OPTIMIZATION OF BATTERY MANAGEMENT SYSTEM FOR NANO SATELLITE

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DEDICATION

I would want to dedicate this work to my God in appreciation of his grace, favor, and faithfulness as well as to my treasure, "my wife," whose support and love are the driving forces behind my achievements.

CERTIFICATION

This is to certify that the thesis titled "Optimization of Battery Management System for Nano-Satellite" was submitted to the school of postgraduate studies, Institute of Space Science and Engineering (ISSE), an affiliate of the African University of science and technology (AUST), Abuja, Nigeria. For the Master's degree is a record of original research carried out by Edet David Kokoette in the department of Systems Engineering.

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ABSTRACT

A Battery Management system (BMS) is tasked to provide optimum and efficient control over the battery in any satellite EPS. Along with Efficiency, these systems also require intelligent safety measures to avoid catastrophic failure when working in the space environment. For a large-scale battery pack, the accumulation of the heat generated during the charging and discharging processes might increase the battery pack's temperature, which will poss a faster acceleration of electrochemical reaction that may cause battery damage. Thus, this study aims to optimize the charging current to minimize the charging time for fast battery charging before the satellite approaches eclipse. The BMS will be utilizing a Social Group Optimization Algorithm on MATLAB Simulink to overcome the state of charge (SOC) problem, improving the battery lifespan.

The result shows that the total time taken for the algorithm to converge is 86.18s, having an optimized current at 2500mA to fast-charge a lithium-ion battery. This produces 524s decrease in the charging time without affecting the capacity and the life cycle for the battery life. The approach accounts for charge time reduction with an efficiency of 95.51%, having an improvement of 2.41% compared to the previous technique used. This

result entitles that this method performed best over the previous technique and is easy to implement on Nano-Satellite, considering all the charging processes, allowing maximum battery protection from overvoltage, overcharging, and overheating conditions.

Keywords: Optimization Battery Power Management Nano satellite.

CHAPTER ONE

INTRODUCTION

1.1BACKGROUND TO THE STUDY

A battery management system (BMS) is essential in small satellites mission to prevent batteries from being overcharged or over-discharged, radiation projection overheating, and overvoltage protection (Jain & Simon, 2005). However, this listed factor could result in extreme damage to the battery. Other factors such as rises in temperature will drastically drain battery capacity and reduce the battery's life span (Mousavi et al., 2016) that may dramatically lead to the end of a satellite mission.

A BMS is a crucial part of various electrical and electronic systems, for example, commercial electronics device and electric vehicles that help to monitor and reports the state of charge (SOC) (Mohammed et al., 2019), (Rahman et al., 2015), state of health (SOH) and remaining useful life for every rechargeable multi-unit batteries cell (Ananthraj & Ghosh, 2021). The battery management system can manage and adapt towards changing batteries characteristics over time since the applications require the parallel or series attachment of multiple unit battery cells (Khan et al., 2016).

Renewable energies are becoming famous worldwide over the last few decades due to the increasing attention on the environmental pollution issue caused by conventional fuels. However, due to natural, economic, and technical issues, renewable energies are becoming more challenging to be implemented in space exploration (Villela et al., 2019).

A battery management system (BMS) effectively incorporates renewable energies into small spacecraft or satellites to overcome this problem. Lithium-ion batteries remain competitive in the world market due to the superior characteristic and performance of high energy efficiency and density. The wide range of the safe operating temperature and the higher rate of charging capability, longer cycle life, and lower self-discharge rate was discussed by (Tomaszewska et al., 2019).

A lithium-ion battery is a power source with lots of electrochemical reactions during charging and discharging. For a large-scale battery pack, the accumulation of the heat generated during the charging and discharging processes might lead to the rise in the battery pack's overall temperature, thus causing the faster acceleration of electrochemical reaction. This electrochemical reaction can reduce the battery lifespan and seriously affect the battery charging capability and safety. Besides, the mechanical abuse, overcharging, and the short circuit issue in high thermal condition of the battery pack may cause battery damage (Lee et

al., 2018). At low ambient temperature, the lithium-ion diffusion capacity inside the battery may decline (Zou et al., 2018).

Furthermore, at different ambient temperatures, cells and modules in a battery pack behave differently, and this causes the imbalance of the electrochemical over time. (Quamruzzaman et al., 2016) explained the difference in the rate of charging and discharging, the state of charge (SOC) between adjacent cells, and the capacity loss. Thus, a battery management system (BMS) is essential to maximize the battery performance by maintaining an optimum state of charge, state of health, safety area of operation (SOA), and operating temperature range (OTR) (Rahimi-eichi, 2006).

Photovoltaic (PV) can be utilized for various aspects. One of the prominent uses is in space exploration “battery charging.” independent domestic electric supply and pumping (Chellakhi et al., 2021).

The goal of the Maximum power point tracking(MPPT) is to extract the total available power produced by the solar panel (PV) in stipulated climatic conditions (temperature and solar irradiation). To control the power supplied by the solar panel, the MPP is integrated by adjusting the duty cycle of the DC-DC converter by the MPPT algorithm. The maximum power point tracking has been employed in different spacecraft missions, such as the National Aeronautics and Space Administration

(NASA) Mars exploration ("NASA Space Exploration," 2015) (Lele, 2016).

There has been a lot of research ongoing to provide an optimum method or means for battery management. Diverse methods and techniques have been applied in the past to optimize the battery state of charge (SOC) and state of health (SOH). In all, the products mentioned can hardly provide best battery management system for Nano-Satellite technology because of the following reasons; part too costly or expensive, functionally not meeting the power demand in space or not space qualified. A poor performance of the battery management system on spacecraft will not optimize the charging current, and minimize the charging time for fast charging of battery as satellite approaches eclipse. Thus a cheaper and more advanced instrument is required to be developed. Therefore, the objectives of this study focus on the implementation of an optimized battery management system on nano satellite

In order to meet the above requirements, a low cost, versatile, portable battery management system was designed, as the existing system used are imported into the country and are expensive.

1.2 STATEMENT OF PROBLEM

The electrical power supply unit is paramount in satellite systems; its primary source is the battery energy technology, as this determines the satellite's life span. Power failure as a result of battery run down that has not been able to recharge. The power failure is a significant limitation in satellite missions. However, this limitation accounts for the problems in designing the battery management system (BMS), which is generally traceable to an inefficient Power Management System (PMS). Cognitive measure in the design process to elongate the lifespan of satellite mission requires critical intervention; in this research, we optimized the time charge of the battery by an improved optimization technique to optimize the charging current whereby minimizing the charging time. As a benefit, will enhance space exploration by utilizing an efficient optimization algorithm, which will dramatically increase the lifespan of Nano-satellite missions.

1.3 SPECIFIC OBJECTIVE OF RESEARCH

The specific objectives were to

i. implement battery management system for Nano satellite
ii. optimize the battery management system
iii. validation of result to existing work

1.4 EXPECTED CONTRIBUTION TO KNOWLEDGE

This study seeks to optimize the performance of the battery management system in the Nano-satellite system. This was achieved by utilizing a new optimization technique on BMS known on as “Social Group Optimization” Algorithm (SGO) to improve the battery's charge time, thereby preventing the battery from undercharging, overcharging, and over-temperature; this will dramatically improve the lifespan of Nano-satellite missions.

1.5 RESEARCH METHODOLOGY

The first step of the project is to implement battery management system using MATHLAB development software. The optimization of the battery management system is carried out using Social Group Optimization technique (SGO) on MATHLAB software, to improve the state of charge of the battery by optimizing the charging current whereby minimizing the charging time.

Furthermore, the objective function and the design constrain are determined and derived with a focus to optimize the battery management system for Nano-satellite. Comprehensive research, on the existing optimization technique for battery management system was reviewed,

and finally the validation of the result is performed by comparing the related studied area with this optimization technique.

The five chapters in this project are in the following order;

- Chapter 1 gives a general introduction of the thesis with emphasis on BMS.
- Chapter 2 discusses related works "literature survey" on BMS system, Optimization algorithm, and battery chemistry.
- Chapter 3 presents the methodology and the design used for this study, "materials and methods."
- Chapter 4 contains the results obtained in this study, "results and discussion."
- Chapter 5 The Summary, conclusion, and recommendation are presented obtained in this chapter.

CHAPTER TWO

LITERATURE REVIEW

2.1 ENERGY CRISIS OF THE WORLD.

Various space industries are working tirelessly towards the advancement in an alternative source of power supply, the avoidance doubt; solar energy has positively impacted the world economy and ecology. However, fossil fuels and greenhouse emissions have become a global threat for sustainable development of an economy and the society at large, this has been affected by climate change due to Harvey emission of carbon dioxide CO_2 (Uba.C.Uchenna, 2019).

The global energy demand is rapidly evolving as natural energy resources such as uranium, petroleum, and gas decrease in production due to advanced technology in this 21st century to eliminate hazardous emissions. The exponential increment in energy costs and environmental constraints led to the development of technological solutions allowing better control of spacecraft in a space environment. The resources and the exploitation of renewable energies in specific Battery technology have a tremendous impact on space exploration.

Within the last two decades, extensive research has been ongoing toward developing an alternate energy source; these technologies emphasize battery components (cells, pack, and module) optimization. (C. L. Liu et al., 2013) For example, development of battery management system,

exploitation of new electrode material, integration of battery life traceability system, development of fast charging scheme (the cell level).

Rechargeable batteries are significantly reliable in energy storage solutions for spacecraft technologies. Among the commonly used rechargeable batteries, the lithium-ion (Li-ion) batteries are a popular choice for applications in domestic electronic appliances (Zou et al., 2018), such as handset consumer electronics, aerospace, vehicles, and energy backup for renewable energy systems, etc., the choice of adopting battery technology account for its advantage to the environment, high energy and power density, high open-circuit voltage (OCV), low self-discharge rate, less maintenance, and immunization of memory effect.

However, a slight increment in charging rates or temperature exceeding the operating region will dramatically accelerate battery degradation or damage the batteries and cause safety incidents. Therefore, the development of safe, efficient, and non-destructive algorithms to fast charge Li-ion batteries is highly desired and has gained increasing interest over the past fifteen years.

A desirable intent to control and monitor the health of the battery life is what led to inventing a Battery Management system.

2.2 REVIEWS OF RELATED WORKS

Recently, researchers have proposed a diverse approach to optimize the battery lifespan by maintaining appropriate battery parameter specifications. The reviewed publication has details on the various techniques used to maximize the performance of battery cell, notwithstanding lots of algorithms has been used to seek the improvement in the charging rate and to balance the cell voltage, (K. Liu et al., 2019) discussed A brief review on critical technologies in the battery management system of electric vehicles in this work various battery models, such as the electric model, thermal model and coupled electro-thermal model are reviewed.

A survey was done on battery state estimations for the state of charge, state of health, and internal temperature. Several keys and traditional battery charging approaches with associated optimization methods are discussed. Further review on Technologies in battery management system authored by (Hamsavarthini & Kanthalakshmi, 2020) identifies in detail the best battery chemistry, charging methods, battery model, cell balancing, and SOC estimation techniques. (Gabbar et al., 2021) made reviews on the Battery Management Systems based on Development and Industrial Standards. His report further provides a framework for

developing a new standard on BMS, especially on BMS safety and operational risk.

At stressful and abuse conditions, especially at high discharge rates and at high operating or ambient temperatures, will affect the performance of batteries, (Rao & Wang, 2011) presents a review on the development of power batteries, including the perspective of clean vehicles and power batteries, mathematical models of battery thermal behavior. The performance in the battery thermal management system was investigated experimentally.

In recent years, lithium-ion batteries have been variably used, and it is the technology of choice from portable gadgets, electric vehicles, grid storage, and satellite. The exponential increase in the design and production of satellites is drastically increasing, with the length of time required to recharge the batteries are still a common concern. The high currents needed to speed up the charging process have been known to reduce energy efficiency and cause accelerated capacity and power fade. (Tomaszewska et al., 2019) reviewed the literature on the physical phenomena that limit battery charging speeds, A review on the critical issues for lithium-ion battery management in electric vehicles was authored by (Lu et al., 2013). This work presents the analysis of literature and, in combination with their practical experience, gives a brief

introduction to the composition of the battery management system (BMS) and its key issues such as battery cell voltage measurement, battery states estimation, battery uniformity, and equalization, battery fault diagnosis (Kim et al., 2019) Reviewed the battery management system for electric vehicles, the author stated that the purpose of the BMS is to guarantee safe and reliable battery operation.

An electric vehicle can be a dynamic or static system that utilizes electrical components. In the case of spacecraft, satellites are electric vehicles. (Cui et al., 2020) authored an application of evolutionary computation algorithm in multidisciplinary design optimization of battery packs for an electric car, targets based on optimization of battery enclose design at pack level using non-dominated sorting genetic algorithm (NSGA-II). In their work, the validated results manifest an outstanding optimization function of NSGA-II and improved enclosure performance.

Moreover, the results presented an enhanced version of NSGA-II when combined with other artificial intelligence algorithms. The results suggest that EC can be integrated into the EV system for monitoring its performance and ensure its safety. (Burt, 2011) discussed the distributed electrical power system in CubeSat applications, which was carried out with an incorporated battery management system, an actual CubeSat electrical power system design based on the centralized architecture is

broken down into its individual components. Issues with battery management rely sincerely upon the kind or type of battery cell used (Karkuzhali et al., 2020); the author has performed intensive research on Lithium-ion (Li-ion) battery & Nickel-metal hydride batteries in terms of aging and the effect of temperature using their state of charge (SOC) and open-circuit voltage (OCV).

There are lots of battery management approaches that have been reviewed (Lelie et al., 2018). After a brief analysis of general requirements, various possible topologies for battery packs and their consequences for the BMS' complexity are examined. It is a standardized method of siting and sizing of battery energy storage systems for the distribution network of distribution system operators (Boonluk et al., 2020); in this work, the adoption of Genetic algorithm (GA) and particle swarm optimization (PSO) was adopted to solve this optimization problem, and the results obtained from these two algorithms were compared. Energy management is critical for improving the performance of electric vehicles (Z. Chen et al., 2015) propose an energy management approach based on a particle swarm optimization (PSO) algorithm. However, different optimization techniques such as Ant Colony System Algorithm, Particle Swarm Optimization (PSO), Taguchi Approach, and Fuzzy Logics are used to find the optimal charge pattern (OCP) of multistage constant-current

charging (MSCCC) method (Khan et al., 2016).The optimization objective is to minimize total energy cost (summation of oil and electricity) from vehicle utilization. (Mohammed et al., 2019) presented a work on the Particle swarm optimization of a hybrid wind, PV, battery energy system, where they applied it to remote areas. The total net present cost (TNPSC) is introduced as the objective function, considering the optimal sizing of the system, high reliability, planning expansion for future development. (Shekar & Anwar, 2019) This author presented a novel real-time SOC estimation of a lithium-ion battery using the particle swarm optimization (PSO) method to a detailed electrochemical model of a single cell. This work also optimizes both the single-cell model and PSO algorithm. The developed algorithm can run on embedded hardware with reasonable utilization of central processing unit (CPU) and memory resources while estimating the SOC with reasonable accuracy was developed in Simulink©, and its performance was theoretically verified in simulation. Experimental data were collected for health and aged Li-ion battery cells to validate the proposed algorithm. Both simulation and experimental results demonstrate that the developed algorithm can accurately estimate the battery SOC for 1C charge and 1C discharge operations for both healthy and aged cells. (T. Wu et al., 2020) prosed an optimized algorithm using the optimized PID parameter applied to the battery charging control system.

(S. C. Wang & Liu, 2015) A PSO-Based Fuzzy-Controlled Searching for the Optimal Charge Pattern of Li-Ion Batteries proposed an FDFE to combine CT and NDC into a unified cost function to properly evaluate the multiple performance characteristics index in the charging problem. An Optimal siting and sizing of battery energy storage were carried out by (Boonluk et al., 2021). He elaborated on the case study of the seventh Feeder at Nakhon Phanom Substation in Thailand. An Optimization of a battery energy storage system using particle swarm optimization for stand-alone microgrids was authored by (Kerdphol et al., 2016). Their research target is to propose an optimum size of BESS by using the PSO method-based frequency control to prevent the microgrid from instability and system collapse after the loss of the utility grid (e.g., blackout or disasters) and minimize the total cost of BESS for 15 years installation in the microgrid. The optimization problem is based on maximizing energy-efficiency between the wheel power and battery pack, not only to maintain but also to improve its value by modifying the state of charge (SOC) (Valladolid et al., 2021). Liquid based cooling systems are configured with a liquid based passive, active moderate and active system for the battery thermal management system (Hannan et al., 2019) proved a lithium-ion battery thermal management system using an optimized fuzzy controller, considering the Chaos embedded particle swarm optimization algorithm (J. H. Chen et al., 2015) proposes this method to

minimize the switching loss of battery in charge and discharge conditions. The battery module in Matlab/Simulink environment is used for a solar charge; multiple modes were compared with traditional common methods. A novel work on real-time estimation of state-of-charge using particle swarm optimization on the electrochemical model of a single cell (Shekar, 2017) This work aims at exploring the real-time estimation and optimization of SOC by applying Particle Swarm Optimization (PSO) to a detailed electrochemical model of a single cell. The goal is to develop a single-cell model and PSO algorithm that can run on an embedded device with reasonable utilization of CPU and memory resources and still estimate SOC with acceptable accuracy. Differential charging of cells with age has turned balance management systems into an important research subject(Velho et al., 2017). The author's method was to propose a new battery management system (BMS) to improve the capacity usage and lifespan of large Li-ion battery packs and a new charging algorithm based on the traditional multistage method. The main advantages of the proposed system are its versatility and ability to implement different charging and balancing methods in a very accessible way. Solar energy is considered one of the main renewable energy sources, even though the energy produced by a photovoltaic array is variable and non-linear depending on the changes in irradiation and temperature (Aljarhizi et al., 2019), reduce the investment costs. In this

work, the required features are achieved by controlling a dc/dc boost converter with two different strategies of control i.e., the maximum power point tracking (MPPT) INC algorithm to benefit as much as possible from solar irradiation and the PI control to secure the battery from the overloading situation. The constant current strategy simply uses a small constant current to charge battery along the whole process to avoid the steep rise in both the battery voltage and temperature in this manner an advanced Lithium-ion battery optimal charging strategy based on a coupled thermoelectric mode was proposed by (K. Liu et al., 2016). Research on the Optimal Charging Strategy for Li-Ion Batteries Based on Multi-Objective Optimization with an aim of demonstrate that the traditional normal and fast charging strategies can only satisfy a small range of EV users' charging demand well while the proposed charging strategy can satisfy the whole range of the charging demand well (Min et al., 2017), Swarm intelligence based State-of-Charge optimization for charging Plug-in Hybrid Electric Vehicles this aimed to obtained for maximizing the highly non-linear objective function indicate that APSO achieves some improvement in terms of best fitness and computation time(Rahman et al., 2015). Usage of the genetic algorithms for solving electric vehicles optimization problem in the scope of smart grid is an extremely actual problem nowadays (Korotunov et al., 2020). Genetic algorithm has been used to optimize the charging capacity of lithium-ion

batteries in small satellites (Jain & Simon, 2005) the author schedules optimizer and propose an FPGA based fitness evaluation function for the algorithm. Modular simulation model of a PV battery system has been developed and integrated into a genetic algorithm framework (Magnor & Sauer, 2016) in order to evaluate optimal sizing of such systems under various boundary conditions their presented work describes the simulation assumptions and presents optimization results for a PV battery system having a DC topology. Turning a kalman filter using genetic algorithm by (Ting et al., 2014), From this work, Ting found that different sets of Q and R values (KF's parameters) can be applied for better performance and hence lower RMS error. Structured optimization of battery thermal management systems using sensitivity analysis and stud genetic algorithms (J. Chen et al., 2021) concluded that the stud genetic algorithm combined with the flow resistance network and heat dissipation models could quickly and efficiently optimize the air-cooled BTMS to improve the cooling performance. The design optimization of the battery holder for electric vehicles (Bao & Zhao, 2018), (Perez et al., 2017) Optimal Charging of Li-Ion Batteries with Coupled Electro-Thermal-Aging Dynamics. The thermal coupled equivalent circuit model provides a vital role in inaccurate and reliable state monitoring and ineffective thermal management of lithium-ion batteries (Q. K. Wang et al., 2017). Today’s batteries deliver a lot of currents. While maintaining a

constant voltage, which can lead to a runaway condition that causes the battery to catch fire (Rahimi-eichi, 2006); as a result, the chemicals used to construct a battery are highly volatile, and a battery impaled with the right object can result in the battery catching fire. Temperature measurements are not just used for safety conditions; they can also determine if it’s desirable to charge or discharge a battery.

A Battery management system (BMS) is used to monitor and control the charging and discharging of rechargeable batteries, making the operation more economical. (Ananthraj & Ghosh, 2021) The battery management system keeps the battery safe, reliable and increases senility without entering into a damaging state. To maintain the state of the battery, voltage, current, ambient temperature, different monitoring techniques are used. BMS is an essential module that leads to reliable power management, optimal power performance, and a safe vehicle that leads back to power optimization(Salehen et al., 2017). The battery technology literature is reviewed, with an emphasis on key elements that limit extreme fast charging.(Ahmed et al., 2017) With fast charging, the rate of the above process would increase, limiting the cell's life. A novel cell-balancing algorithm that was used for cell balancing of the battery management system (BMS) was proposed in this paper. Cell balancing algorithm is a key technology for lithium-ion battery packs (Piao et al.,

2015). An intelligent controlling method for battery lifetime increment using state of charge estimation in PV battery hybrid system to minimize the rate of frequent charging and discharging cycles that reduce its operational life and affect the battery's performance (Qays et al., 2020). It is important to perform a reliability check for every battery design model (Xu et al., 2018). It proposes a distributed battery management system (BMS) to meet the reliability design requirements, consisting of two parts: the main control module and the sampling module.(Zhang et al., 2016) an online battery internal temperature estimation method is proposed based on a novel simplified thermoelectric model. The battery thermal behavior is first described by a simplified thermal model and battery electrical behavior by an electric model. Then, these two models are interrelated to capture the interactions between battery thermal and electrical behaviors, thus offer a comprehensive description of the battery behavior that is useful for battery management. (Balasingam et al., 2020) A battery management system consists of a battery fuel gauge, optimal charging algorithm, and cell/thermal balancing circuitry. It uses three non-invasive measurements from the battery, voltage, current and temperature, in order to estimate crucial states and parameters of the battery system, such as battery impedance, battery capacity, and state of charge, state of health, power fade, and remaining useful life. (Balasingam et al., 2020) The scope of this Special Issue is to address all

the above issues by promoting innovative design concepts, modeling and state estimation techniques, charging/discharging management, and hybridization with other storage components. (Pany, 2019) A novel battery management system for series parallel connected lithium ion battery pack for electric vehicle application this work presented next-generation Lithium ion batteries with significantly improved performances, including improved specific energy and volumetric energy density, recyclability, charging rate, stability, and safety. Battery modeling for a photovoltaic system with battery management system using fuzzy logic controller, the state of charge and state of health (SoC & SoH) are the state of the battery which can be used for the estimation of the lifetime of the battery (Shalom Irence et al., 2019) the present charge level of a battery is known as the state of charge (SoC) which will be measured typically based on at a particular temperature measured the current which is going in and out from the battery. Prediction and estimation of internal battery states are important tasks for safe operation of batteries. However, due to inherent uncertainties like parameter, model structural and measurement uncertainties, it is especially challenging to make accurate predictions(Mehne & Nowak, 2017) Improving temperature predictions for Li-ion batteries: data assimilation with a stochastic extension of a physically-based, thermo-electrochemical model. In order to optimize the charging of lithium-ion batteries, a multi-

stage charging method that considers the charging time and energy loss as optimization targets has been proposed by (X. Wu et al., 2017)in his work a dynamic model based on a first-order circuit was been established, and the model parameters have been identified. On the basis of the established model, the objective functions of the optimization problem as a weighted sum of charging time and energy loss. A dynamic programming algorithm (DP) has been used to calculate the charging current of the objective function.

Temperature Compensated Model for Lithium-Ion Polymer Batteries With Extended Kalman Filter State of Charge Estimation for an Implantable Charger was proposed by (Lee et al., 2018). In their work, implantable devices become more sophisticated, and their extended functionalities impact their energy requirements. They not only rely on charging for the extra energy but also become ever more sensitive to battery deep discharge or overcharge. (S. C. Wang et al., 2015) an accurate state-of-charge (SOC) estimation plays a fundamental role in ensuring the operational safety of implantable medical devices. Temperature variation can impact the battery model parameters and directly affect the accuracy of SOC estimation. Coulomb counting or ampere-hour counting is the most frequently used method for SOC

estimation by directly integrating battery current over time (Piao et al., 2015).

2.3. BATTERY OVERVIEW

2.3.1 Definition

A battery is a device that converts chemical energy into electrical energy (Cultu, n.d.). This is done through an electrochemical oxidation-reduction reaction of its active materials. This process involves the transfer of electrons from one material to another through an electric circuit. An oxidation-reduction reaction is defined as a reaction in which electrons are transferred(Zou et al., 2018). Oxidation means loss of electrons. Reduction is the process of accepting electrons. The basic electrochemical unit is the "cell." A battery of any number of cells is used depending on the desired output voltage. People tend to misuse the similarity of cell and battery; it is vital to know that a cell is related to one battery. A battery is the combination of cells in a pack noticeable as a battery pack.

2.3.2 Type of battery

The two types of batteries wildly used are primary and secondary batteries. Primary batteries can provide only one continuous or intermittent discharge, meaning that they can’t be reused after discharge; their chemical process is irreversibly changed, and electrical energy is

obtained from the chemical reaction. These batteries are commonly used in domestic electronics such as remote control, wall clock, and the like.

A secondary storage battery is made of several chemical and elemental materials. There is a movement of electrons during charging and discharging, making it chemically reversible. After the battery has discharged, it is brought back to a charged state by causing the current to flow back through the battery in the opposite direction. The electrodes are thus returned to approximately their original state. The most common battery of this type is a lead- (sulfuric) acid battery. Secondary batteries are used as a source of dc.

2.3.3 Cell Structure

A cell generally has two conducting electrodes, one positive and one negative, and an electrolyte. One electrode must be an electron donor (anode), and the other an electron receiver (cathode). An anode is a negative electrode, and a cathode is a positive electrode. Zinc has been the most common anode, although alkali metals such as lithium and sodium are the most effective anodes. The most effective cathodes are fluorine, chlorine, oxygen, sulfur, and metal oxides. The electrolyte must have ionic conductivity. The majority of electrolytes are in liquid form.

2.3.4 Operation of a Primary Cell

To understand how a battery operates, let consider a typical primary cell. The most normal primary cell is the Leclanché cell. It is also called a "zinc-carbon dry cell." It is used for flashlights and portable radios. The negative electrode is zinc, and the positive electrode is a graphite rod surrounded by a densely packed layer of graphite and manganese dioxide. The electrolyte is a moist powder containing zinc chloride. The discharge operation can be represented schematically, as in Figure 2.1

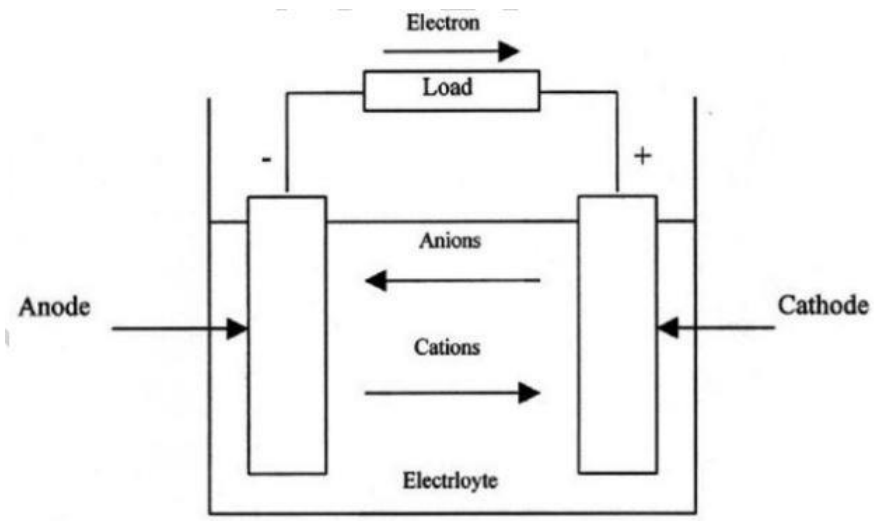

Figure 2.1: Electrochemical operation of a cell (discharge).

The load outside the cell provides a path for electrons to flow from anode to cathode. This flow of electrons causes the anode to be oxidized and the cathode to be reduced. Inside the cell, anions (negative ions) flow to the

anode in the electrolyte, and cations (positive ions) flow to the cathode. The discharge reaction can be written for Leclanchè battery as follows:

Negative electrode oxidation (production of electrons)

$$Zn \rightarrow Zn^{2+} + 2e^{-} \tag{2.1}$$

Positive electrode reduction (gain of electrons)

$$2MnO_2 + 2NH_4^+ + 2e^- \rightarrow Mn_2O_3 + 2NH_3 + H_2O \tag{2.2}$$

The overall reaction becomes,

$$Zn + 2MnO_2 + 2NH_4^+ \rightarrow Zn^{2+}Mn_2O_3 + 2NH_3 + H_2O \tag{2.3}$$

2.3.5. Charge and Discharge of Secondary Batteries

Secondary batteries are different because the process can be reversed, and the battery can be used again. In secondary batteries, the electrodes can be regenerated after depletion. An external source of potential is applied across them to reverse the current flow through the cell. The process of returning them to their original state is called charging. To charge (or recharge) a run-down secondary battery, the voltage of the external source must be more significant than that of the battery in its original state and opposite in polarity.

Consider the lead-acid battery during charging and discharging. The negative electrode is lead(Pb), and the positive electrode is lead dioxide

(PbO2). The electrolyte is a sulfuric acid solution. The discharge operation can be represented schematically as in Figure 2.1. When the external circuit is completed, electrons are released from the anode to the external circuit, and the resulting Pb2+ ions precipitate on the electrode as insoluble lead sulfate. At the cathode, electrons from the external circuit reduce PbO2 to water and Pb2+ ions, precipitating as PbSO4 on that electrode. The discharge reaction can be written as follows:

Negative electrode:

$$\mathrm{Pb^{2+}} + 2\mathrm{e^{-}} \rightarrow \mathrm{Pb} \tag{2.4}$$

$$\mathrm{PbSO_4} \rightarrow \mathrm{Pb^{2+}} + \mathrm{SO_4^{2-}} \tag{2.5}$$

Positive electrode:

$$\mathrm{Pb^{2+}} + 2\mathrm{H_2O} \rightarrow \mathrm{PbO_2} + 4\mathrm{H^{+}} + 2\mathrm{e^{-}} \tag{2.6}$$

$$\mathrm{PbSO_4} \rightarrow \mathrm{Pb^{2+}} + \mathrm{SO_4^{2-}} \tag{2.7}$$

Overall reaction:

$$2\mathrm{PbSO_4} + 2\mathrm{H_2O} \rightarrow \mathrm{Pb} + \mathrm{PbO_2} + 2\mathrm{H_2SO_4} \tag{2.8}$$

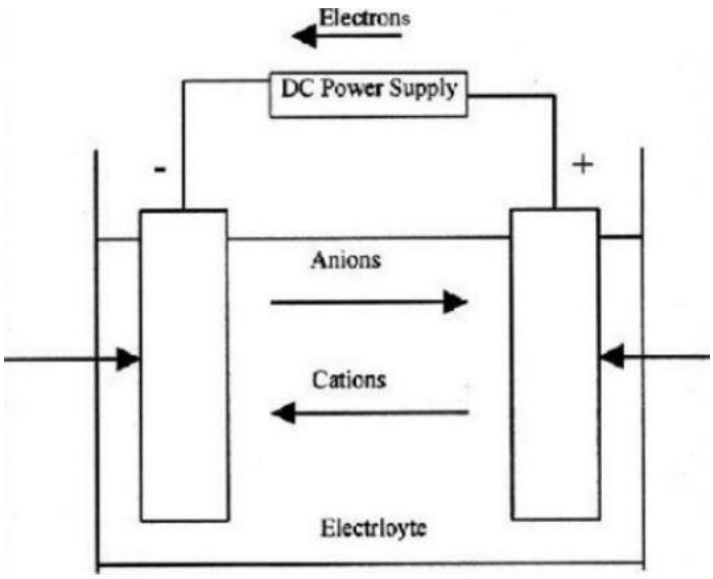

Figure 2.2: Electrochemical operation of a cell (charge)

2.3.6 Traditional Battery and Cell Chemistries

A wide range of different cell chemistries offer different voltages, power, and energy performances. Lithium-ion cells have considerably greater energy density than previous chemistries, making them particularly suitable for satellite applications. They are also considered safer, less toxic, and are more energy-efficient with significantly longer cycle life. Some of the most popular chemistries are presented

Lead-Acid (Pb): Lead-acid batteries are composed of a Lead-dioxide cathode, a sponge metallic Lead anode, and a Sulphuric acid solution electrolyte. This heavy metal element makes them toxic, and improper disposal can be hazardous to the environment. The typical cell voltage is 2 Volts. Lead-acid is a popular low-cost secondary battery, available in

large quantities and various sizes and designs, has good high-rate performance, moderately good low and high-temperature performance, easy state of charge indication, and reasonable charge retention for intermittent charge applications. Cell components are easily recycled. Because of the irreversible physical changes in the electrodes, failure occurs between several hundred and 2,000 cycles.

The main drawbacks of these batteries are their comparatively low energy density, long charging time, and the need for careful maintenance (Rao & Wang, 2011). It is widely used in battery power for energy storage, emergency power, earlier generations of electric and hybrid vehicles, and engine starting, vehicle lighting, and engine ignition (SLI). It still dominates the stop-start battery and e-bike battery market. With continuous improvement and the development of the advanced Lead-acid battery, it will remain competitive.

Nickel Cadmium (NiCd): These cells use nickel hydroxide Ni(OH)2 for the cathode, cadmium Cd as the anode, and alkaline potassium hydroxide for the electrolyte. Standard Ni-Cd cells use an aqueous chemical impregnation process for the fabrication of the electrodes. It has been used for storing electrical energy in spacecraft since the beginning of space exploration. It has a long cycle life, good low-temperature and high-rate performance capability, long shelf life in any state of charge,

and rapid recharge capability. Memory effect is one of its most significant drawbacks, as is a relatively high rate of self-discharge at high temperatures. As cadmium is highly toxic, its use in batteries is now banned, with the exception of medical and some military applications.

Nickel Metal Hydride (NiMH): These cells use nickel hydroxide Ni(OH)2 for the cathode. Hydrogen is used as an active element in a hydrogen-absorbing anode. This electrode is made from a metal hydride, standard alloys of lanthanum, and rare earth that serve as a solid source of reduced hydrogen that can be oxidized to form protons. The electrolyte is alkaline, usually potassium hydroxide. Nickel Metal Hydride cells have a higher energy density than nickel-cadmium cells, rapid recharge capability, long cycle life, and long shelf life in any state of charge. There are minimal environmental problems. However, its high-rate performance is less than that of nickel-cadmium. The poor charge retention, memory effect, and higher cost anodes are the drawbacks. It has been used in computers, cellular phones, and other consumer electronic applications, with the possible exceptions of high-drain power tools and applications where low battery cost is a significant consideration. It was the leading choice for hybrid electric vehicles. However, lithium-ion batteries are gradually taking the market.

Lithium-Ion: Lithium is attractive due to its low equivalent weight and high standard potential and has been used in rechargeable batteries to provide over three times the energy density of traditional rechargeable batteries. The field has seen significant advances in solid-state chemistry to improve performance further. This includes a drive for increased energy density, rate capability, and the ability to provide high power and long cycle life and thermal stability for increased safety. Attention has also focused on fast charge capability and cost reduction through the use of inexpensive raw materials synthetic processes and using materials of low toxicity and environmental banality (Xu et al., 2018). Research and development have focused on many aspects of cell chemistry to improve overall performance. However, enormous attention has been placed on positive cathode materials development as it has a prominent role in determining overall specific energy density. Depending on the electrolyte material choice, lithium-ion batteries can be separated into two categories, liquid lithium-ion cells, which use liquid electrolytes, and solid-state lithium-ion cells, which use inorganic or polymer electrolytes.

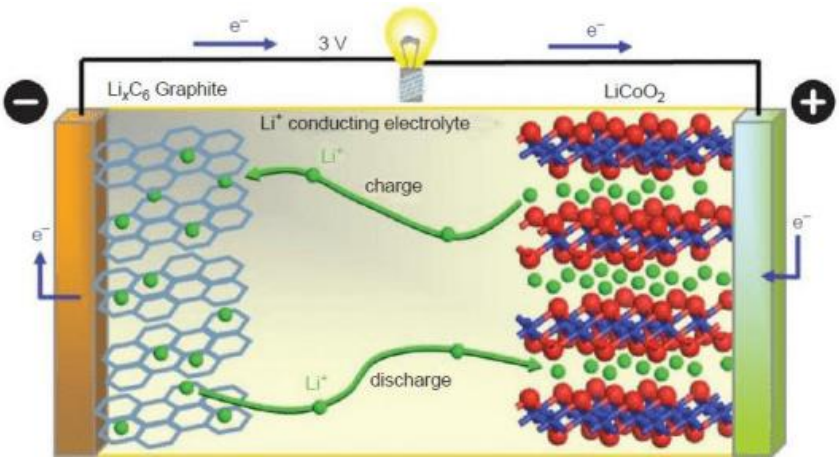

Figure 2.3: Lithium-Ion Battery Cell Structure

Lithium Cobalt Oxide (LCO) - Lithium Cobalt Oxide has been the most widely used positive electrode material in lithium batteries for many years, used for laptops, mobile phones, and tablet batteries. LCO cells provide moderate cycle life (<500 Cycles) and energy density. However, the chemistry is less thermally stable than other transition metal oxide or phosphate chemistries under extreme abuse conditions such as cell puncture or short circuit, making them more susceptible to thermal runaway conditions.

Lithium Cobalt Aluminum Oxide (NCA) - Lithium Nickel Cobalt Aluminum Oxide offers high specific energy density and reasonably good power capabilities. NCA cells are considered somewhat safer than LiCoO2. NCA cells tend to have superior life characteristics to LCO and are more commonly available in some 18650 type cells than in large format automotive cells

Lithium Iron Phosphate (LFP) - Phosphate-based technology lithium-ion materials possess improved thermal and chemical stability than oxides. They are generally perceived to be safer cell chemistry than other Lithium-ion technologies and less susceptible to thermal runaway under abuse conditions. Automotive lithium-ion cells are also durable and stable for long-term cycling. Although Lithium iron phosphate batteries have lower energy density than Oxide systems, they are typically able to support higher currents and thus suited to high power and more extended life applications. They are a significant improvement over lithium cobalt oxide cells in cost, safety, and toxicity.

Lithium Manganese Oxide Spinel (LMO): Lithium Manganese Oxide Spinel provides a higher cell voltage than Cobalt-based chemistries and thermally is more stable. However, the energy density is typically 20% less. Manganese, unlike Cobalt, is a safe and more environmentally benign cathode material due to its low toxicity. Other benefits include lower cost and higher rate capability. However, they suffer from lower overall capacities due to their spinel structure and are unstable at higher temperatures in the lithium-based electrolyte.

Lithium Nickel Cobalt Manganese Oxide (NCM): Although no single cell chemistry currently ticks all the boxes of energy, power, cost, safety, and life, the mixed metal oxide systems and in particular those based on

NCM type chemistry can be optimized to give high specific energy or high specific power whilst being considered safer and more cost-effective than LCO and LFP but with reasonable life expectancy.

Lithium Titanate Oxide (LTO): These cells replace the negative graphite electrode with lithium titanate. This negative electrode material is compatible with any of the above positive electrode materials but is commonly used with Manganese-based materials. They offer superior rate capability and power combined with a wide operating temperature range. They are considered a safer alternative to the graphite material due to higher potential Li/Li+ than conventional graphite and therefore have a degree of inbuilt overcharge protection. However, lithium titanate batteries tend to have a slightly lower energy density than graphite-based systems.

2.3.6 Battery Capacity

The total quantity of charges involved in the electrochemical reaction determines the battery's capacity and is measured in terms of ampere-hours (Ah). The ampere-hour capacity is a function of active materials in the battery.

The battery's capacity is also expressed on an energy basis by multiplying ampere-hours by the voltage of the battery. Specific energy is the amount of energy the battery stores per unit mass at a specified discharge rate,

also called gravimetric energy density. It is usually measured in watt-hours per kilogram. Similarly, the ampere-hour or watt-hour capacity on a volume basis can be calculated. Energy density is defined as the amount of energy a battery can deliver per unit volume at a specified discharge rate; also called volumetric energy density, it is usually measured in watt-hours per liter. Another concept used in connection with capacity is specific power. It is the power a battery can deliver per unit mass at a specified state of charge, usually 20 percent. It is also called gravimetric power density. It is generally measured in watts per. Similarly, power density is the amount of power a battery can deliver per unit volume at a specified state of charge - usually 20 percent. It is also called volumetric power density and is generally measured in watts per liter.

2.4. TYPES OF LITHIUM-ION BATTERIES

There are several types of lithium-ion batteries available today (Lu et al., 2013). However, there are a few that stand out due to their long life, specific power, and overall level of safety, specifically when it comes to satellite systems (Issn et al., 2021). The three most relevant to satellite systems are Lithium Manganese Oxide (LiMn2O4), Lithium Iron Phosphate (LiFePO4), and Lithium Nickel Manganese Cobalt Oxide (LiNiMnCoO2); the abbreviations for these types of lithium-ion batteries

are LMO, LFP, and NMC, respectively. This thesis will focus mainly on NMC and LFP 18650 (NMC).

2.5. THE BATTERY MODEL

Building a proper model is usually the starting point for BMS design, control, and optimization (K. Liu et al., 2019). Over the years, numerous battery models with various levels of accuracy and complexity have been developed. These models are based on their classification, which can be primarily categorized as;

- Battery electric model
- Battery thermal model
- Battery coupled model

In this thesis, we will focus on The Battery Electrical Model, the first electrical-circuit model was proposed by (Hageman, 1993). He used simple PSpice circuits to simulate nickel-cadmium, lead-acid and alkaline batteries. The core of the models for the different types of batteries is the same: A capacitor represents the battery's capacity. A discharge rate normalizer determines the lost power at high discharge currents

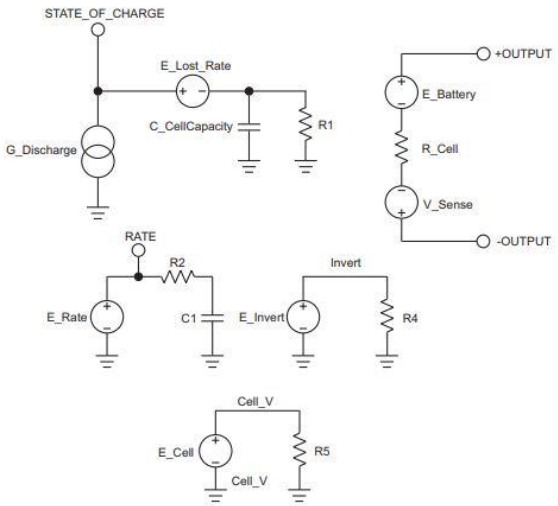

Figure 2.4: Basic functional schematic covering all the modeled cell types

This basic schematic requires minor changes to complete the models for each specific cell (Moura & Perez, 2014).

- A circuit to discharge the capacity of the battery,
- A voltage versus state-of-charge lookup table,
- A resistor represents the battery's resistance.

Figure 2.4 shows the basic circuits used to model an arbitrary cell. Minor changes have to be made to complete the model for a specific cell type. Although the models are much simpler than the electrochemical models and therefore computationally less expensive, it still takes some effort to configure the electrical-circuit models. Especially the lookup tables used in the model require many experimental data on the battery's behavior.

Furthermore, the models are less accurate, having an error of approximately 10%.

2.5.1. The Equivalent Circuit of a lithium-ion Battery Model.

Various equivalent circuit models such as the Rint model, the RC model, the Thevenin model, or the PNGV model are now widely used (He et al., 2011).

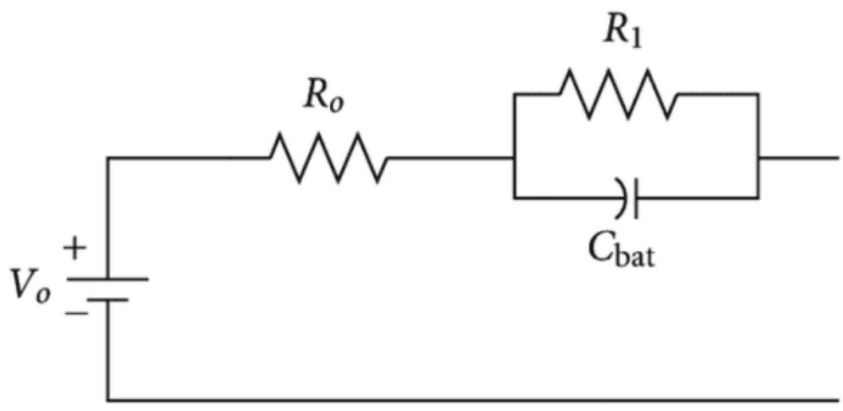

Figure 2.5: A simple equivalent circuit of a battery

Electrical models' accuracy lies between electrochemical and mathematical models (around 1- 5% error), are electrical equivalent models using a combination of voltage sources, resistors, and capacitors. There have been many electrical models of batteries, from lead-acid to polymer Li-Ion batteries. Most of these electrical models fall under three basic categories: Thevenin model, impedance model, and runtime-based models(M. Chen & Rincón-Mora, 2006).

2.5.2. Thevenin Based Electrical Model:

A Thevenin based model uses a series resistor (R-Series) and an RC parallel network figure (5) (RTransient and CTransient) to predict battery response to transient load events at a particular state of charge (SOC) by assuming the open-circuit voltage (VOC (SOC)) is constant.

Impedance-Based Electrical Model: Impedance-based models employ the method of electrochemical impedance spectroscopy to obtain an AC-equivalent impedance model in the frequency domain and then use a complicated equivalent network (ZAC) to fit the impedance spectra. The fitting process is complicated, complex, and non-intuitive. In addition, impedance-based models only work for a fixed SOC and temperature setting, and therefore they cannot predict DC response or battery runtime.

Runtime-Based Electrical Model: Runtime-based models use a complex circuit network to simulate battery runtime and DC voltage response for a constant discharge current in SPICE-compatible simulators. They can predict neither runtime nor voltage response for varying load currents accurately.

2.5.3. The battery management system (BMS)

The goal of a BMS system is to maximize the battery's life, efficiency, and safety. This is done through performing a wide variety of tasking, including cell monitoring, protection, charge state estimation, and

performance maximization. The complexity of the BMS, defined by features performed by the system, depends on the application and balancing energy efficiency and charge capacity with cost and complexity. As seen in Figure 2.1, the whole range of tasks will be discussed in this chapter so that an understanding of the BMS design can be obtained.

- Monitoring the battery
- Providing battery protection
- Estimating the battery's operational state
- Continually optimizing battery performance
- Reporting functional status to external devices

2.6 WORKING PRINCIPLES OF A BATTERY MANAGEMENT SYSTEM

Battery management systems do not have a fixed or unique set of criteria that must be adopted. The technology design scope and implemented features generally correlate with:

- The costs, complexity, and size of the battery pack
- Application of the battery and any safety, lifespan, and warranty concerns

- Certification requirements from various government regulations where costs and penalties are paramount if inadequate functional safety measures are in place

There are divers BMS design features, with significant battery pack protection management and capacity management. The Battery pack protection management has two essential arenas: electrical protection, which implies not allowing the battery to be damaged via usage outside its SOA, and thermal protection, which involves passive or active temperature control to maintain or bring the pack into its SOA.

2.6.1 Electrical Management Protection: Current

Monitoring battery packs current and cell or module voltages are a good conduct of electrical protection. The electrical Safe operation area (SOA) of any battery cell is bound by current and voltage. Figure 2.6 illustrates a traditional lithium-ion cell SOA.

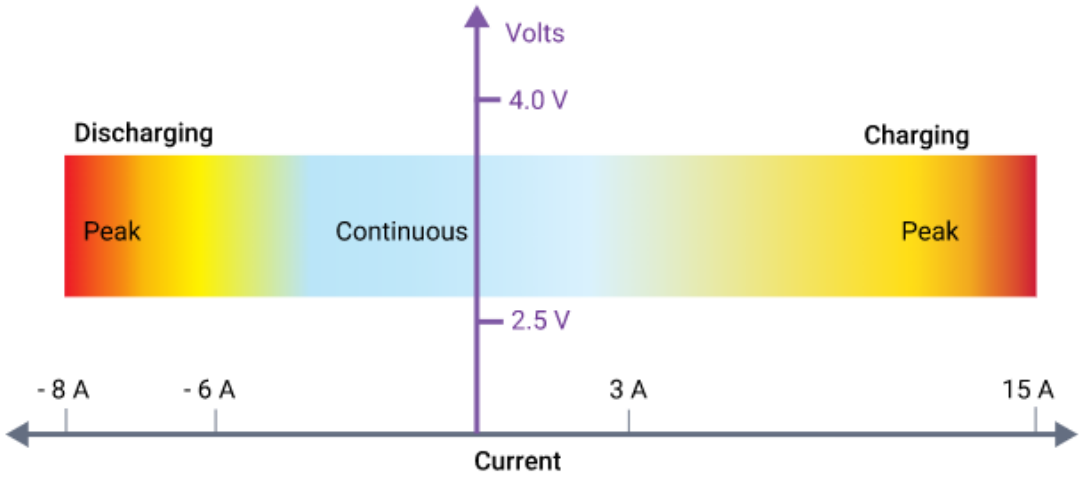

Figure 2.66: Safe Operating Area of a Lithium-ion Battery

Lithium-ion cells process different current limits for charging than for discharging, and both modes can handle higher peak currents, albeit for short time periods.

2.6.2 Electrical Management Protection: Voltage

Figure 2.6 shows that a lithium-ion cell must operate within a certain voltage range. These SOA boundaries will ultimately be determined by the intrinsic chemistry of the selected lithium-ion cell and the temperature of the cells at any given time. Moreover, since any battery pack experiences a significant amount of current cycling, discharging due to load demands and charging from a variety of energy sources, these SOA voltage limits are usually further constrained to optimize battery lifespan. The BMS must know what these limits are and will command decisions based upon the proximity to these thresholds. For example, when

approaching the high voltage limit, a BMS may request a gradual reduction of charging current, or may request the charging current be terminated altogether if the limit is reached.

2.6.3 Thermal Management Protection: Temperature

In figure 2.7, it may appear that lithium-ion cells have a wide temperature operating range, but overall battery capacity diminishes at low temperatures because chemical reaction rates slow down remarkably. With respect to capability at low temperatures, they do perform much better than lead-acid or NiMh batteries; however, temperature management is prudently essential since charging below 0 °C (32 °F) is physically problematic. The phenomenon of plating of metallic lithium can occur on the anode during sub-freezing charging. This is permanent damage and not only results in reduced capacity, but cells are more vulnerable to failure if subjected to vibration or other stressful conditions. A BMS can control the temperature of the battery pack through heating and cooling.

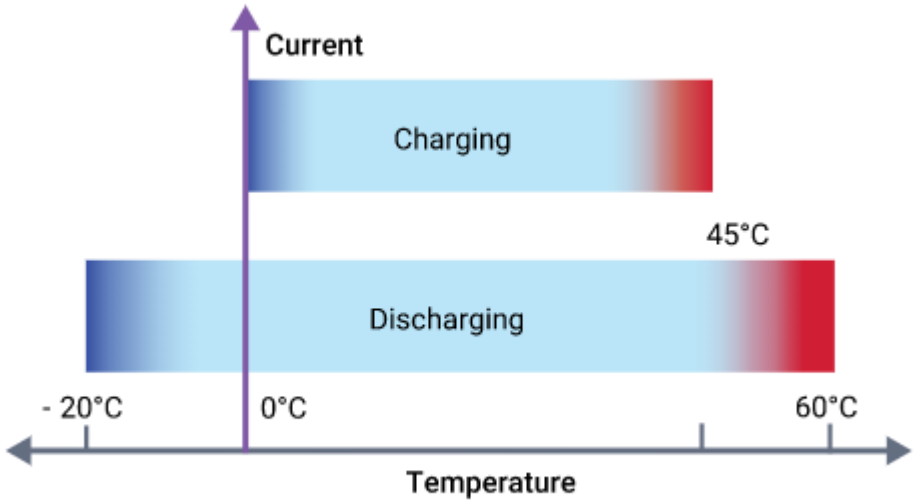

Figure 2.77: Thermal Characteristics of a Lithium-ion Battery

2.7 TYPES OF BATTERY MANAGEMENT SYSTEMS

Battery management systems range from simple to complex and can embrace a wide range of different technologies to achieve their prime directive to "take care of the battery." However, these systems can be categorized based upon their topology, which relates to how they are installed and operate upon the cells or modules across the battery pack.

2.7.1 Centralized BMS Architecture

Has one central BMS in the battery pack assembly. All the battery packages are connected to the central BMS directly. The structure of a centralized BMS is shown in Figure 6. The centralized BMS has some

advantages. It is more compact, and it tends to be the most economical since there is only one BMS. However, there are disadvantages of a centralized BMS. Since all the batteries are connected to the BMS directly, the BMS needs a lot of ports to connect with all the battery packages. This translates to lots of wires, cabling, connectors, etc. in large battery packs, which complicates both troubleshooting and maintenance.

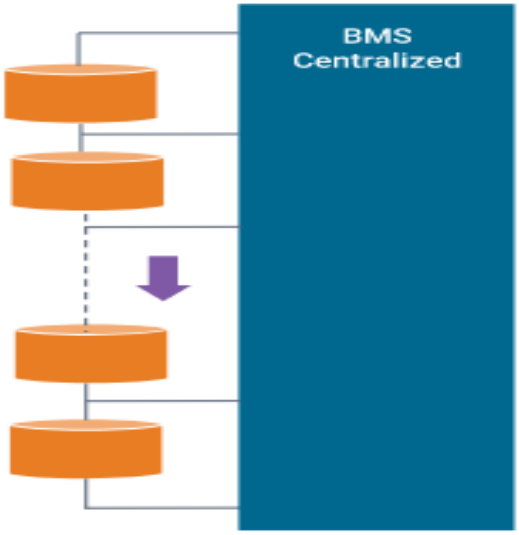

Figure 2.88: Centralized BMS

2.7.2 Modular BMS Topology

Similar to a centralized implementation, the BMS is divided into several duplicated modules, each with a dedicated bundle of wires and connections to an adjacent assigned portion of a battery stack. See Figure 2.9. In some cases, these BMS sub modules may reside under a primary

BMS module oversight whose function is to monitor the status of the sub modules and communicate with peripheral equipment. The advantages of this topology are that troubleshooting and maintenance is easier, and extension to larger battery packs is straightforward. The disadvantage is that the overall costs are slightly higher, and there may be duplicated unused functionality depending on the application.

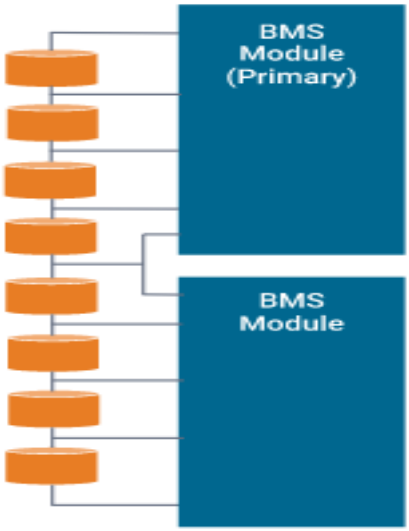

Figure 2.99: Modular BMS Topology

2.7.3 Primary/Subordinate BMS

This is similar to the modular topology, however, in this case, the slaves are more restricted to just relaying measurement information, and the Master is dedicated to computation and control, as well as external communication. It has an advantage of costs to be lower because of the

simpler functionality of the slaves and has less overhead and fewer unused features.

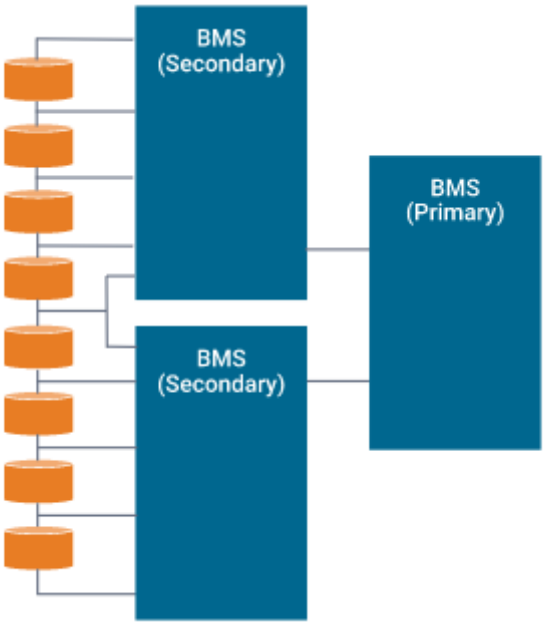

Figure 2.1010: Primary/Subordinate BMS

2.7.4 Distributed BMS Architecture

This architecture is quite different from other types of BMS because the electronic hardware and software are encapsulated in modules that interface to the cells via bundles of attached wiring. A distributed BMS incorporates all the electronic hardware on a control board placed directly on the cell or module that is being monitored. This alleviates the bulk of the cabling to a few sensor wires and communication wires between adjacent BMS modules. Consequently, each BMS is more self-contained, and handles computations and communications as required. However,

despite this apparent simplicity, this integrated form does make troubleshooting and maintenance potentially problematic, as it resides deep inside a shield module assembly. Costs also tend to be higher as there are more BMSs in the overall battery pack structure.

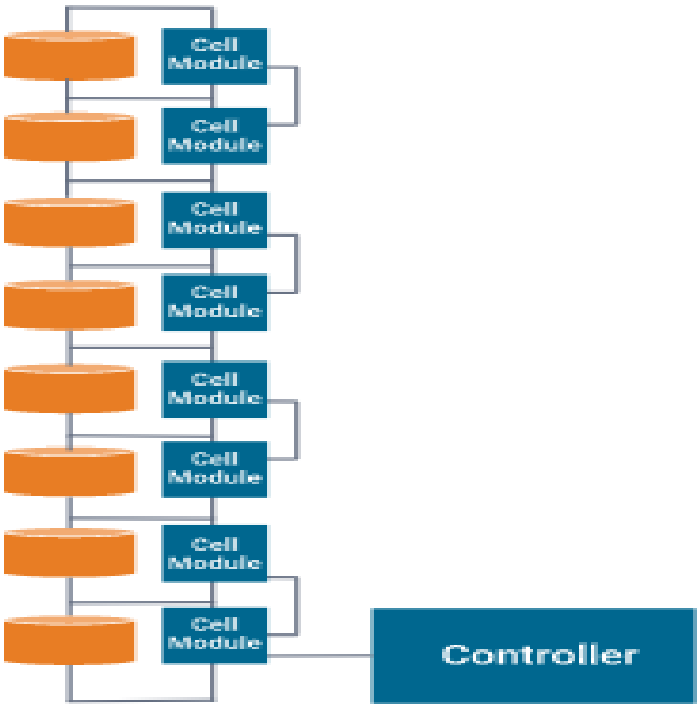

Figure 2.1111: Distributed BMS Architecture

2.8 THE IMPORTANCE OF BATTERY MANAGEMENT SYSTEMS

Functional safety is of the highest importance in a BMS. It is critical during charging and discharging operation, to prevent the voltage, current, and temperature of any cell or module under supervisory control from exceeding defined SOA limits. If limits are exceeded for a length of

time, not only is a potentially expensive battery pack compromised, but dangerous thermal runaway conditions could ensue. Moreover, lower voltage threshold limits are also rigorously monitored for the protection of the lithium-ion cells and functional safety. If the Li-ion battery stays in this low-voltage state, copper dendrites could eventually grow on the anode, which can result in elevated self-discharge rates and raise possible safety concerns. The high energy density of lithium-ion powered systems comes at a price that leaves little room for battery management error.

Performance of the battery pack is the next highest important feature of a BMS, and this involves electrical and thermal management. To electrically optimize the overall battery capacity, all the cells in the pack are required to be balanced, which implies that the SOC of adjacent cells throughout the assembly are approximately equivalent. This is exceptionally important because not only can optimal battery capacity be realized, but it helps prevent general degradation and reduces potential hotspots from overcharging weak cells. Lithium-ion batteries should avoid discharge below low voltage limits, as this can result in memory effects and significant capacity loss. Electrochemical processes are highly susceptible to temperature, and batteries are no exception. When environmental temperature drops, capacity and available battery energy roll off significantly. Consequently, a BMS may engage an external in-

line heater that resides on, say, the liquid cooling system of an electric vehicle battery pack, or turn-on resident heater plates that are installed underneath modules of a pack incorporated within a helicopter or other aircraft. Additionally, since charging of frigid lithium-ion cells is detrimental to battery life performance, it is important to first elevate the battery temperature sufficiently. Most lithium-ion cells cannot be fast-charged when they are less than 5°C and should not be charged at all when they are below 0°C. For optimum performance during typical operational usage, BMS thermal management often ensures that a battery operates within a narrow Goldilocks region of operation (e.g. 30 – 35°C). This safeguards performance, promotes longer life, and fosters a healthy, reliable battery pack.

2.9 THE BENEFITS OF BATTERY MANAGEMENT SYSTEMS

An entire battery energy storage system, often referred to as BESS, could be made up of tens, hundreds, or even thousands of lithium-ion cells strategically packed together, depending on the application. These systems may have a voltage rating of less than 100V, but could be as high as 800V, with pack supply currents ranging as high as 300A or more. Any mismanagement of a high voltage pack could trigger a life-threatening, catastrophic disaster. Consequently, therefore BMSs are

absolutely critical to ensure safe operation. The benefits of BMSs can be summarized as follows.

2.9.1 Functional Safety

Hands down, for large format lithium-ion battery packs, this is particularly prudent and essential. But even smaller formats used in, say, and laptops, have been known to catch fire and cause enormous damage. Personal safety of users of products that incorporate lithium-ion powered systems leaves little room for battery management error.

2.9.2 Life Span and Reliability

Battery pack protection management, electrical and thermal, ensures that all the cells are all used within declared SOA requirements. This delicate oversight ensures the cells are taken care of against aggressive usage and fast charging and discharging cycling, and inevitably results in a stable system that will potentially provide many years of reliable service.

2.9.3 Performance and Range

BMS battery pack capacity management, where cell-to-cell balancing is employed to equalize the SOC of adjacent cells across the pack assembly, allows optimum battery capacity to be realized. Without this BMS feature to account for variations in self-discharge, charge/discharge cycling, temperature effects, and general aging, a battery pack could eventually render itself useless.

2.9.4 Diagnostics, Data Collection, and External Communication.

Oversight tasks include continuous monitoring of all battery cells, where data logging can be used by itself for diagnostics, but is often purposed to the task for computation to estimate the SOC of all cells in the assembly. This information is leveraged for balancing algorithms, but collectively can be relayed to external devices and displays to indicate the resident energy available, estimate expected range or range/lifetime based on current usage, and provide the state of health of the battery pack.

2.9.5 Cost and Warranty Reduction.

The introduction of a BMS into a BESS adds costs, and battery packs are expensive and potentially hazardous. The more complicated the system, the higher the safety requirements, resulting in the need for more BMS oversight presence. But the protection and preventive maintenance of a BMS regarding functional safety, lifespan and reliability, performance and range, diagnostics, etc. guarantees that it will drive down overall costs, including those related to the warranty.

2.10. CELL MONITORING

The most basic and critical task of the BMS is to monitor the battery cells operating parameters, including voltage, current, and temperature. The monitoring of these parameters enables the BMS to make decisions regarding the remaining features. The first measurement taken is voltage.

This measurement is needed to ensure the cell remains insides of its safe operating area, SOA, during charge and discharge cycles. The voltage measurements' rate depends on its application and must be balanced at the expense of making faster systems. Additionally, the voltage measurement's accuracy depends on the state of charge (SOC) vs. open-circuit voltage (OCV) of the battery chemistry being used. The OCV plateau determines the necessary accuracy so that the BMS system can accurately estimate the SOC.

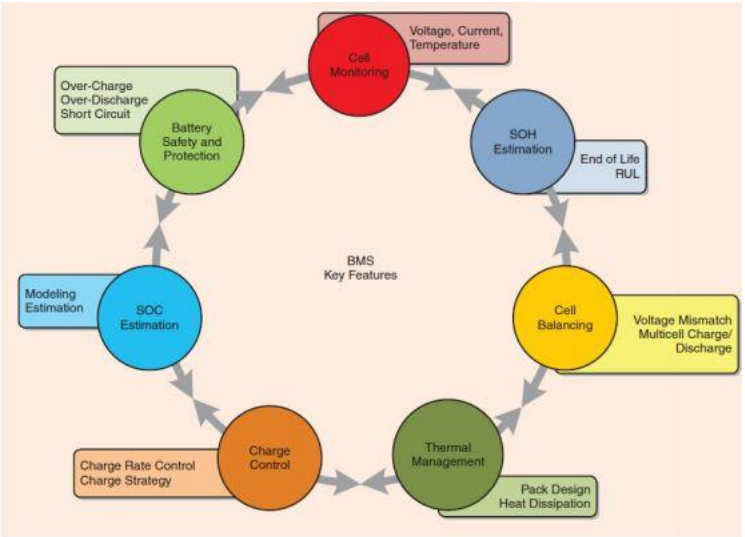

Figure 2.1212: *Key features of BMS*

The second type of measurement is cell temperature. Li-ion cells are prone to thermal runaway. The BMS system monitors the cell temperature to control battery pack current or cooling systems when necessary. The final measurement needed by many BMS systems is the current draw. This measurement is required in order to calculate the depth

of discharge (DOD), state of charge (SOC), impedance, and IR compensation.

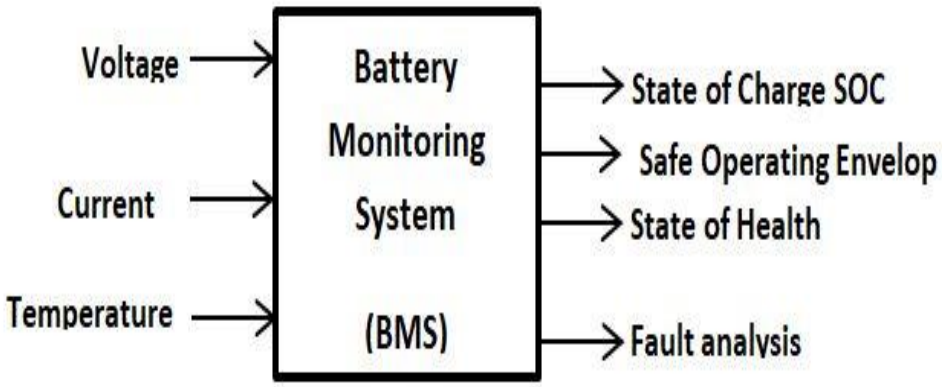

Figure 2.1313: *BMS task*

Additionally, the current measurement can help increase the system's lifetime by preventing excess current draw and operation of the cells outside of their SOE. In addition to measures, a BMS needs to protect the cells. Especially for Lithium-ion chemistries, the battery system mustn't operate outside their SOE. By ensuring the systems pack current, cell voltage, and temperature, both peak and continuous, the system can run safely. However, suppose the system begins to operate outside of the SOE. In that case, the BMS can interrupt the charging or discharging current to take corrective actions necessary to ensure safe and long work conditions (Rahimi-eichi, 2006). These operating parameters are used for two main tasks; maintaining safe operation and state estimation. Two main types of protectors can accomplish the safe operation. The first is a

designated protection circuit. This circuit is directly connected to the cell, and no processor logic is linked to its operation. The protection circuitry uses device-level comparators and will cease current flow into and out of the battery if it begins to operate outside of its designated operating conditions. The advantage of this design is its robust and efficient design, with power consumption seen as low as 9μW (Boonluk et al., 2020). This technology is convenient for simple BMS designs where state estimation is not required. However, if state estimation or additional system control are desired, the operating parameters need to be sent to a microprocessor. The second type is a system-level protector. A master module receives the cell operation parameters and makes a pack-wide determination using software and control algorithms to determine whether the operation needs to be stopped.

2.10.1. State of Health Estimation

State of Health (SOH) is an indicator of predicted life expectancy that allows a BMS to create strategies to prolong system life. This is not a measurable parameter but one that must be calculated from the cell operating parameters. One such example determines the SOH by finding the internal resistance through an equivalent circuit model, adapted from cell operating parameters and approximating the Ohmic resistance. When

a cell is nearing the end of its cycle life, the recorded changes in cell impedance can dictate how a BMS should manipulate charge and discharge through IR compensation.

2.10.2. Cell Balancing

As previously mentioned, Lithium-ion batteries have very strict SOA about the cell voltage. When a cell begins to charge, the charge capacity rises along with the cell voltage until the maximum voltage is reached, and then the charging must stop. However, manufacturing variances lead to discrepancies in internal impedance and maximum capacity. The battery's self-discharge rate will lead to differences in the SOC even when supplied with the same charging current. This leads to imbalances in cell voltage, and the cells cannot reach their maximum potential charge capacity. Additionally, when the battery is discharged, the discharge is limited by the first cell in a series string to get the minimum voltage, leaving the remaining cells half charged. This issue will propagate, leading to a continued loss in battery pack capacity unless the cells are balanced. Cell Balancing is a continuous field of research that falls into two main categories passive and active cell balancing, with the majority falling within the latter. The goal of balancing a battery pack is to quickly and efficiently equalize all of the cells SOC. The first category is passive cell balancing. This category balances cells by dissipating energy of fully

charged cells so the remainder can continue to charge. This technique equals energy consumption five times greater than active balancing techniques, assuming average converter efficiency (Baroniti). While this balancing scheme is slow and inefficient, its simplicity leads to its use in specific applications. The second balancing category is active cell balancing, defined by shuttling charge between cells to balance the cells SOC. This balancing system has three main subsystems Capacitor, Inductor / Transformer, and converter. Capacitor-based cell balancing is typically referred to as charge shuttling. This topology uses switches and capacitors to shuttle charge from the highest charged cell to the lowest. Research into this construction balances the number of switches with the number of capacitors attempting to limit the balancing time and switching energy. The second subcategory is inductor/transformer-based cell balancing which uses magnetic energy conversion with the benefit of a higher balancing time at the cost of component price and high switching frequency; you need capacitors across the batteries to filter the high frequencies. Similar to the last subcategory, this system attempts to balance the number of inductors and switches. With a single-tier system, a single inductor can be used for quick balancing with a complicated switching platform, or multiple switches can be used in an attempt to balance the two. Multi-tier systems, currently being researched, use far less complex control algorithms and use less energy than single-tier

systems at the additional expense of increased inductor count. The final subcategory is converter balancers. This subcategory uses voltage converters to balance the charge between batteries. The type of converter used depends on the application, and each has its own set of properties, but all are energy efficient but use complex control algorithms. One new converter being looked at is the wave trap converter which uses LC oscillators to select and shuttle charges between the cells. This system gives the ability to rapidly shuttle the amount at the cost of expensive and complicated controls. While the main focus is on the circuitry that balances the cells, research is still needed and being conducted on how currents flow between the batteries when they are connected. This type of research will allow for a better understanding of batteries and enable further control strategies.

2.10.3. Thermal Management

Li-Ion cells are prone to thermal runaway, so the BMS system must be able to stop battery current, directly or through request, to allow the battery system to allow for system cooling. Additionally, operating the batteries at extreme temperatures impacts the cell life of those batteries by maintaining the SOA cell life can be enhanced.

2.10.4. Charge Control

The discharge and charge rates of the batteries are determined based upon the application. However, cell chemistry also impacts the safe charge rates of the cells, and if these rates are exceeded, a degradation of capacity will occur and shorten cell life. The most common charge control strategy used is a constant current constant voltage, CC-CV; this strategy is simple yet efficient in maximizing the charge capacity of the cell. The constant current starts this protocol by maintaining a safe and desirable charge rate. Then when the cell has reached its maximum SOA voltage, a constant voltage is applied to add charge without increasing the voltage of the cell. However, research is still being conducted into more efficient means of charging and discharging a battery. One charging technique is a CC-CC-CV, where there are two levels of charging current an initial lower current and a secondary higher current. This technique allows for a decrease in charging time while minimizing the stress on the battery. Another technique involves using pulsed charging currents, allowing for a higher average current and allowing the battery to recover during the charged pulses.

2.10.5. State of Charge Estimation

State of Charge, SOC, is a critical battery parameter; however, it cannot be measured. SOC is a parameter, generally given in a percentage, which

refers to the amount of charge capacity remaining, delivered in milliamp hours, maH. Discharge capacity is the amount of current a battery can discharge over time. While multiple models can lead to a SOC estimation, including OCV, Coulomb counting methods, and BP neural network, all of them look at discharge characteristics and try to fit them into a mathematical model to predict the remaining charge. Research in this field involves increasing the accuracy of these models while decreasing the rate of the data points needed; such models include the fractional-order model and the estimation method presented by (Shekar 2017).

2.10.6. Modeling Estimation

Accurate prediction of remaining cell capacity is critical for applications in Nano-Satellite. The BMS can use the battery model to create a precise SOC estimation. While continued research is needed to further facilitate accurate and efficient battery models, they can still play an essential role in a BMS (Shalom Irence et al., 2019). Current research is focused on creating an accurate equivalent circuit model. While the mathematical and chemical models are relatively well known and produce highly accurate results, the models take a long time to calculate. The equivalent circuit model would provide a sufficient model to the BMS that can operate at quicker refresh intervals.

2.11. BATTERY CHARGING APPROACH

When a battery energy source is exhausted, or its terminal voltage drops below the cut-off voltage or SOC declines to 20% or lower, the discharging process should be stopped, and the battery needs to be recharged. The charging performance for various batteries is shown in Table 2. Incorrect operations such as over-discharging overcharging or improper charging will speed up the degradation process of the battery dramatically. Compared with other battery types, the Li-ion battery has relatively stable performance but less cycle life at high-temperature conditions. At the same time, no permission is allowed for being charged below freezing.

Table 2. 1: Charging performance of various batteries

Battery type	**Charging Performance**
Li-ion	1) High temperature can improve charging speed but damage to battery lifetime 2) Charging is dangerous at pretty low temperatures, well below freezing
Lead-acid	1) Higher temperature leads to a lower –threshold by three mV/^{0}C; 2) Charging at 0.3 C or less below freezing

NiMH, NiCd	1) Charging acceptance decreases from 70% at 45 ^{0}C to 45% at 60 ^{0}C, respectively; 2) 0.1 C charging rate between -17 ^{0}C and 0^{0}C 3) 0.3 C charging between 0^{0}C and 6^{0}C

According to (Kerdphol, 2017), with enough accurate estimations of battery SOC, SOH, and temperature, proper battery charging approaches can be effectively designed further to charge a battery from initial state to final SOC target value. Meanwhile, the charging approaches can also protect batteries from overheating, prolong service life, and improve utilization.

2.11.1 Conventional battery charging approach

There are some conventional charging approaches to solve the battery charging problem with numerous objectives and termination conditions. Four traditional charging approaches that have been widely utilized to charge batteries in satellites are listed in the Figure below.

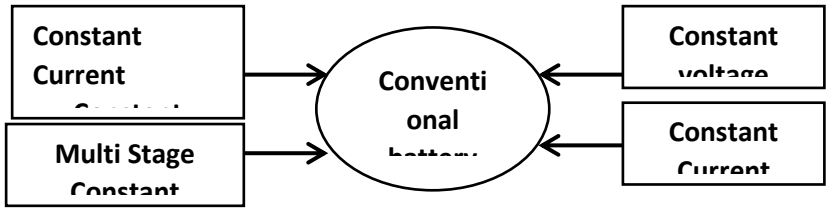

Figure 2.1414: *Conventional charging approach*

These typical approaches can be mainly classified as constant current (CC) charging, constant-voltage (CV) charging, constant-current constant-voltage (CC-CV) charging, and multi-stage constant-current (MCC) charging. In the following, a particular emphasis is placed upon the CCCV charging and MCC charging approaches. The CC charging is a rough but straightforward approach that adopts a low constant current rate to charge the battery during the whole charging process. The CC charging is terminated when the time-to-charge reaches a predefined threshold. This charging approach was first introduced to charge NiCd or NiMH batteries (K. Liu et al., 2019)and is also widely used for Li-ion batteries (Tomaszewska et al., 2019). However, the behaviors of batteries are highly dependent on the current rate in CC charging. Hence the main challenge for the CC charging approach is to search for a suitable charging current rate capable of equilibrating battery charging speed and capacity utilization. For the sizeable current rate in CC charging, the charging speed is improved, but the battery aging process will be aggravated accordingly.

For a low current rate in CC charging, high capacity utilization is achieved. Still, the too low current rate will slow down the battery charging speed, and further harm the convenience of its sage. Another simple conventional charging approach is CV charging which adopts a

predefined constant voltage to charge batteries. The primary superiority of using CV charging is to avoid over-voltage and irreversible side reactions in the charging process, further prolonging battery cycle life. When the CV charging is applied, the charging current will gradually reduce due to the low acceptance with progressing recharge. However, this approach needs a high current rate to keep the constant terminal voltage at the early stage of the charging process, which is easy to causes the battery lattice to collapse, and battery poles broke. The CV charging approach's common problem is selecting a proper value for charging speed, electrolyte decomposition, and capacity utilization. Reference (Khan et al., 2016) summarizes the characteristic of CV charging. It concludes that the CV charging approach is capable of effectively improving the charging speed but bringing significant damages to the battery capacity. This is primarily caused by the sharp increase of charging current when the battery is charged from low SOC. The start current is far more significant than the acceptable range of the battery, leading to the battery lattice frame collapses, and further aggravating the pulverization of the active substance in the battery pole. But as battery capacity increases, the charging current will reduce dramatically. The charging speed for the CV approach is relatively fast due to a high average battery current during the SOC interval from 0.15 to 0.8, and the charging current will reduce very slightly when SOC reaches 0.9. By

integrating CC charging and CV charging, a hybrid charging approach named CC-CV has been proposed, as shown in the Figure below.

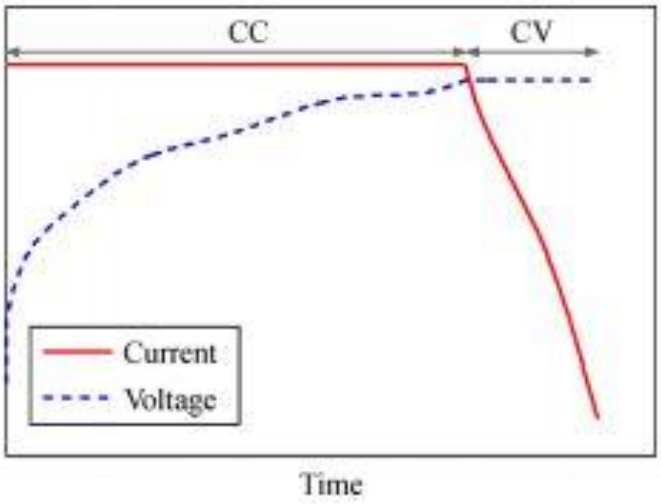

Figure 2.1515: *Battery current and voltage of CC-CV charging approach*

In this approach, a battery is firstly charged by a predefined constant current in the CC phase, and the battery voltage will increase to the maximum safe threshold. Afterward, the battery enters into the CV phase with a predefined constant voltage, entailing the continuous step down of the charging current. This CV phase will end until a terminal value of the decreasing current or a goal capacity is reached. The standard CC-CV approach is first utilized to charge a lead-acid battery with the preset values of constant current and a constant voltage recommended by battery manufacturers and is also extended to charge Li-ion battery with some modifications. Because of higher terminal voltage and charging acceptance for Li-ion battery, constant current in Li-ion battery CC-CV

charging applications should be much larger than that of lead-acid battery, which is usually chosen from 0.5 to 3.0 C (S. C. Wang et al., 2015). In the CC-CV charging process, the CC stage and CV stage can be complementary in some ways. The CV stage will effectively compensate the capacity loss caused by the large electrochemical polarization in the CC stage. Hence the CC-CV charging approach is superior to the sole CC and sole CV charging in the applications of spacecraft and has been selected as a benchmark to compare with the performance of other newly developed battery charging approaches(Xu et al., 2018). Although the standard CC-CV charging approach is easy to apply, the challenging issue is to set the appropriate constant current rate at the CC stage and constant voltage value at the CV stage. The battery charging speed of the CC-CV approach is primarily determined by the constant current rate. In contrast, the capacity utilization of battery charging is mainly affected by the values of constant voltage and termination. For constant current rate in CC-CV, on the one hand, a high value of current rate may cause lithium plating, further to cause low efficiency of energy conversion, and battery temperature may exceed permissible levels especially in high power applications. On the other hand, low charging current may decrease battery charging speed and affect the convenience of satellite. Therefore, it is vital to design a proper CC-CV approach to improve the overall charging performance and guarantee the operation safety of

battery. Another popular traditional charging approach is the MCC charging, as shown in Fig. 6. This approach has been successfully developed to charge numerous types of battery such as lead acid battery, NiMH battery and Li-ion battery. The mainly difference between MCC charging and CC-CV charging is that in MCC charging, the multi-stage series of monotonic charging currents are injected into battery during total charging process. This series of charging currents should be gradually reduced as the form of various constant currents stages ($I_{CC1}>I_{CC2}> \ldots >I_{CCN}$). When terminal voltage goes up to a default voltage threshold by the constant current in one stage, charging procedure will turn into another constant current stage and then a new less constant current rate will be utilized accordingly.

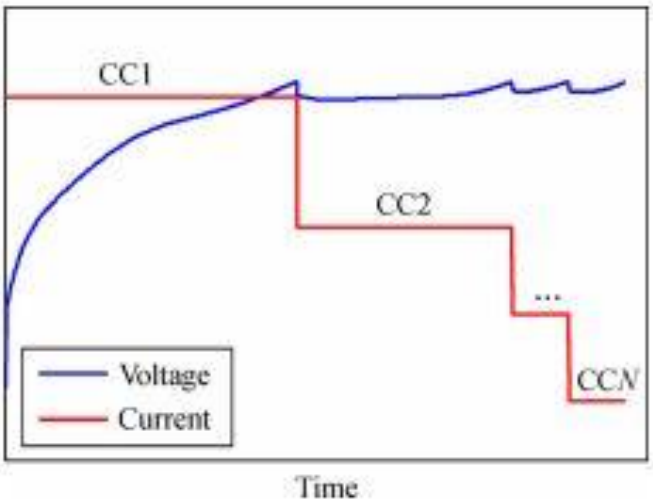

Figure 2.1616: *Battery current and voltage of MCC charging approach*

This decreased process of charging current will continue until battery terminal voltage reaches the last default voltage threshold under the condition of minimum current. The charging speed for the standard MCC approach will usually be a bit slower than the traditional CC-CV approach with the same initial current.

Table 2. 2: Comparison of traditional battery charging approaches

Approach	**Advantages**	**Disadvantages**	**Key Elements**
CC	Easy to implement	Capacity utilization Is low	1) Charging constant current rate; 2) Terminal condition
CV	1) Easy to implement; 2) Stable terminal voltage	Easy to cause the lattice collapse of battery	1) Charging constant voltage; 2) Terminal condition
CC-CV	1) Capacity utilization is high; 2) Stable terminal voltage Easy to implement;	Difficult to balance objectives such as charging speed, energy	1) The constant current rate in CC phase; 2) Constant voltage in CV phase;

		loss, temperature variation	3) Terminal condition
MCC	1) Easy to implement 2) Easy to achieve fast charging.	Difficult to balance objectives such as charging speed, capacity utilization, and battery lifetime	1) The number of CC stages 2) Constant current rates for each stage

Table 2.2 briefly compares the conventional charging approaches mentioned above, while the advantages, disadvantages, and key elements to design these approaches are summarized. All in all, for rough charging approaches, including sole CC charging and CV charging, the implementation costs are relatively low, with just a few parameters that need to be considered. However, these simple charging approaches would cause many charging problems, such as battery lattice collapse and battery poles being broken. It is significantly challenging to equilibrate battery capacity utilization and to charge speed by using just the sole CC or CV charging approach to further improve charging performance, such

as avoiding over-voltage, enhancing capacity utilization, and achieving fast charging, some hybrid charging approaches, including CC-CV and MCC are developed. The open problem for using these hybrid approaches is to search the proper current and voltage values to efficiently equilibrate conflicting objectives such as charging speed, energy loss, temperature variation, and battery lifetime. Besides, the analysis of electrochemical reactions such as lithium plating during these charging processes is still at its primitive stage and will be a thriving area of research in space applications.

2.12 STATES OF CHARGE ESTIMATION TECHNIQUES

SOC is analogous to the fuel gauge in an automobile, making it a crucial measurement in designing any device that uses a battery. However, there is no direct and easy method to measure SOC. In all cases, it must be estimated or determined by establishing SOC as a function of other measurable signals like Voltage, Current, and Cell Temperature, etc. This paradigm makes SOC estimation one of the most researched topics. There are a wide variety of techniques available for SOC estimation. They can be broadly classified into three categories, which are:

- The non-model-based method is like Ampere hour counting.
- Computational Intelligence and Optimization-based methods, like Fuzzy logic, Particle Swarm Optimization.

- Estimation-based methods, like variations of Kalman filter using equivalent circuit and state-space models.

The Computational Intelligence & Optimization and Estimation-based methods are considered online estimation methods as the SOC is estimated in real-time. Some of these techniques are discussed in this section.

2.12.1 Ampere Hour Counting

Ampere hour counting or Coulomb Counting is the most popular and easy technique to determine SOC. The charge is directly proportional to the current supplied during charging and the current withdrawn during the discharge operation. The current can be integrated as shown in equation 2.4 to determine the SOC.

$$\mathbf{SOC = SOC_O + \frac{1}{C_N}\int_{t_0}^{t}(I_{batt} - I_{loss})dt} \qquad (16)$$

Where SOC_0 is the initial SOC, C_N is the rated capacity. I_{batt} Is the current and. I_{loss} is the current loss in the system. The equation shows that this technique is subject to inaccuracies in charge/discharge current measurement, knowledge of accurate initial SOC, and rated capacity. If the accurate initial SOC and Capacity are unknown, it could lead to an offset in estimated SOC. Inaccurate current measurement can add up over time due to integration, leading to the drift of estimated SOC from the

actual SOC. This can be overcome by resetting the SOC when certain conditions like full charge are reached. But to achieve such a condition, for example, in an electric vehicle application, would be impractical.

2.12.4 Estimation Based

There is a good number of online estimation techniques proposed for the estimation of SOC. Kalman Filter method and its variants are one of the essential methods. A series of papers have proposed the Extended Kalman filter method to estimate battery states like SOC, power fade, and capacity fade, and instantaneous available power. The general requirement for such an estimation technique is the definition of SOC as a function of measurable signals like Voltage or Current. However, the battery parameters for different chemistries, different operating conditions, and different health conditions must be determined. Many techniques are employed to determine the battery parameters, from the off-line least squared method to the online PSO-based method. More modern methods like Moving Horizon Estimator and Particle Swarm Optimization have been proposed to estimate SOC.

2.12.3 Open Circuit Voltage

Open Circuit Voltage (OCV) is the voltage across the battery/cell terminal under no-load conditions SOC bears a linear relationship to OCV. This property makes OCV a suitable candidate to determine SOC

directly. However, this technique would be appropriate only in applications where there are rest periods to take the OCV readings. Lead-acid battery, having a very linear relation with SOC, is a good candidate for this technique but for batteries like Li-ion (LiFePO4) where the OCV is flat in lower operating voltages, 2.o to 3.65V, which corresponds to 20% - 80%, even a small error in measurement of OCV would lead to large estimation errors. For the reasons mentioned above, this technique would not be suitable.

2.13 EXISTING BATTERY MANAGEMENT SYSTEM

Recently, numerous studies have been made and published by researchers on optimization techniques for battery management. This section of the study presents the result of the existing battery management system algorithm used. (Jain & Simon, 2011) utilized the Genetic Algorithm for charge optimization of lithium-ion batteries in Small Satellites; he proposed a power management scheme primarily for scheduling loads to various subsystems for power utilization and optimization. (He et al., 2011) utilized model parameters, which are identified with a genetic algorithm, to find the optimal time constant of the model, and the evaluations on five models are carried out from the point of view of the dynamic performance and the state of charge (SOC) estimation. It was observed that the errors resulting from the SOC initial value are

significantly reduced, and the actual SOC is convergent within an acceptable error.

(C. L. Liu et al., 2013) developed a PSO-based fuzzy logic optimization of dual performance characteristic indices for fast charging of Lithium-ion batteries; their experimental findings show that the resulting pattern can charge the batteries to over 90% available capacity within 50 minutes. Compared with the conventional constant current-constant voltage (CC-CV) method, the devised scheme has more than 80% charging time reduction, 21% more life cycles, and over 0.4% charging efficiency increase. (Wang & Liu, 2014) proposes a searching strategy based on particle swarm optimization (PSO), combined with a fuzzy-deduced fitness evaluator (FDFE), to find the optimal multistage charging pattern that delivers the most discharged capacity within the shortest charging time. Their experimental results show an obtained way of charging the batteries to over 88% capacities within 51 min. Compared with the conventional constant current–constant voltage (CC-CV) method. The charging time, obtained life cycle, and charging efficiency is improved by approximately 56.8%, 21%, and 0.4%. (Ting et al., 2014) In this work, a state-space battery model is derived mathematically to estimate a battery system's state-of-charge (SOC). Subsequently, Kalman filter (KF) is applied to predict the dynamical behavior of the battery

model. Results show an accurate prediction as to the accumulated error in terms of root-mean-square (RMS). Their work discovered that different sets of Q and R values (kalman filters parameters) could be applied for better performance and lower RMS error.

(Z. Chen et al., 2015) worked on an energy management approach based on a particle swarm optimization (PSO) algorithm. Their optimization objective is to minimize total energy cost (summation of oil and electricity) from vehicle utilization. The main drawback of optimal strategies is that they can hardly be used in real-time control. To solve this problem, a rule-based approach containing three operation modes is proposed first. Then the PSO algorithm is implemented on four threshold values in the presented rule-based strategy. The proposed approach has been verified by the US06 driving cycle under the MATLAB/Simulink software environment. (Kerdphol et al., 2016) their work depicts a new method to evaluate an optimum size of Battery Energy Storage System (BESS) at minimal total BESS cost by using particle swarm optimization (PSO)-based frequency control of the stand-alone microgrid. Results show that the optimum size of the BESS-based PSO method can achieve a higher dynamic performance of the system than the optimum size of BESS-based analytic approach and the conventional size of BESS.

(Magnor & Sauer, 2016) this author presented a paper describing the simulation assumptions and presented optimization results for a PV battery system with a DC topology. (L. Chen et al., 2017) their study aims to develop a novel estimation approach based on the Grey model and Genetic Algorithms without the need for a high-fidelity battery model demanding high computation power for experimental verification. (K. Liu et al., 2017) this author proposed an advanced optimal charging strategy to develop the optimal constant-current-constant-voltage (CCCV) charge current profile, which gives the best trade-off for the objective functions of battery management. (Djamel et al., 2018) Proposed a low-cost electrical power supply (EPS) for Nano-Satellites constellation of belt and road countries. The main focus of their presentation is to investigate the field relating to Electrical Power Systems (EPS) for Nano-satellites. A simulation model of the Satellite EPS with the solar panel as the main source and the battery storage as the secondary source was developed in MATLAB-SIMULINK.

(Hannan et al., 2019) presents a thermal management system for a lithium-ion battery to maintain a regulated thermal process in the battery pack. A robust control algorithm was proposed using a particle swarm optimization (PSO) fuzzy logic controller for the battery thermal management system. The system performance was evaluated by the

overshoot, undershoot, and settling time and compared with the PID and simple fuzzy system to validate the results. From the performance results and comparisons, the proposed PSO-based fuzzy system can yield the most negligible overshoot of 0.497 % and settling time of 32 min 13 s during the heating subroutine; an undershoot of 0.975 %, and a settling time of 28 min 46 s during the cooling subroutine. Moreover, it is also capable of maintaining a uniform temperature among the battery modules in the pack. These results prove that the PSO-based fuzzy system is a robust control system that efficiently enhances the lithium ion battery temperature regulating system's performance.

(Shalom Irence et al., 2019) This paper focuses on how solar energy has been harvested and stored to supply power to the required load demand continuously.

(Shekar & Anwar, 2019) This paper presents a novel real-time SOC estimation of a lithium-ion battery by applying the particle swarm optimization (PSO) method to a detailed electrochemical model of a single cell. This also optimizes both the single-cell model and PSO algorithm. The developed algorithm can run on embedded hardware with reasonable utilization of central processing unit (CPU) and memory resources while estimating the SOC accurately.

(Yixiao Wang, Yong Li, Li Jiang, 2019) The author presented an optimization algorithm to search for an optimal five-stage constant-current charging pattern. The goal is to maximize the objective function for this charging pattern based on the charging capacity, time and energy efficiency. The proposed charging pattern was 2.5% lower than that of the CC-CV method; the charging time and efficiency are improved by 15.6%, and 0.47%, the maximum temperature increase of the battery is $0.8^{o}C$.

2.13.6 Social Group Optimization (SGO)

There are many behavioral traits such as honesty, dishonesty, caring, compassion, courage, fear, justness, fairness, tolerance or respectfulness, etc., lying dormant in human beings, which need to be harnessed and channelized in the appropriate direction to enable him/her to solve complex tasks in life (Satapathy & Naik, 2016). Few individuals might have the required level of all these behavioral traits to solve, effectively and efficiently, complex problems in life. But very often, complex issues can be solved with the influence of characteristics from one person to another or from one group to other groups in society. It has been observed that human beings are great imitators or followers in solving any task. Group solving capability has emerged to be more effective than

individual capability in exploiting and exploring different traits of each individual in the group to solve a given problem. Based on this concept, a new optimization technique is proposed, named social group optimization (SGO). In SGO, each person (a candidate solution) is empowered with some sort of knowledge having a level of capacity for solving a problem. SGO is another population-based algorithm similar to other algorithms discussed in the previous section. For SGO, the population is considered as a group of persons (candidate solutions).

Each person acquires knowledge and, thereby, possesses some level of capacity for solving a problem. This corresponds to the 'fitness.' The best person is the best solution. The best person tries to propagate knowledge amongst all persons, which will, in turn, improve the knowledge level of the entire members of the group. The procedure of SGO is divided into two parts. The first part consists of the 'improving phase'; the second consists of the 'acquiring phase.' In the 'improving phase,' the knowledge level of each person in the group is enhanced with the influence of the best person in the group. The best person in the group has the highest level of knowledge and capacity to solve the problem. And in the 'acquiring phase,' each person enhances his/her expertise with the mutual interaction with another person in the group and the best person in

the group now. The basic mathematical interpretation of this concept is presented below.

Let $X_{j,}$ j = 1, 2, 3, N be the persons of social group, i.e., social group contains N persons. Each person X_j is defined by $X_j = X_{j1}, X_{j2}, X_{j3},..., X_{jD}$), where D is the number of traits assigned to a person which determines the dimensions of a person and f_j, j = 1, 2,...N are their corresponding fitness values, respectively.

2.13.6.1 Improving phase

The best person (gbest) in each social group tries to propagate knowledge among all persons, which will, in turn, help others to improve their knowledge in the group.

Hence, $gbest_g = \min\{ f_i , i = 1, 2, ... N\}$ at generation g for solving a minimization problem.

In the improving phase, each person gets knowledge (here, knowledge refers to a change of traits with the influence of the best person's characteristics) from the group's best (gbest) person. The updating of each person can be computed as follows:

$For\ i\ =\ 1{:}\,N$

$\quad For\ j = 1{:}\,D$

$$Xnew_{i\,j} = c * Xold_{i\,j} + r * (gbest(j) - X\,old_{i\,j})$$

(17)

End for

End for

Where r is a random number, $r \sim U(0,1)$

Accept $Xnew$ if it gives a better fitness than $Xold$. Where c is known as the self-introspection parameter. Its value can be set from $0 < c < 1$.

2.13.6.2 Acquiring phase

In the acquiring phase, a person of social group interacts with the best person ($gbest$) of that group and also interacts randomly with other persons of the group for acquiring knowledge. A person acquires new knowledge if the other person has more knowledge than him or her. The best knowledgeable person (here known as person having 'gbest') has the most significant influence on others to learn from him/her. A person will also acquire something new from other persons if they have more knowledge than them in the group. The acquiring phase is expressed as given below:

$$gbest = min\{f\,(X_i), i = 1, 2, \ldots N\}$$

(X_i's are updated values at the end of the improving phase)

$For\ i\ =\ 1{:}\ N$

Randomly select one person X_r, $where\ i\ \neq r$

$$If\ f(X_i)\ <\ f\ (X_r)$$

For j = 1: D

$$Xnew_{\ i,j} =\ X\ old_{\ i,j} +\ r1\ *(X_{i,j}\ -\ X_{r,j} + r2\ *\ (gbest_j\ -\ X_{i,j})$$

(18)

End for

Else

$For\ j\ =\ 1:\ D$

$$Xnew_{i,}{:} =\ Xold_{i,}{:} + r1\ *\ X_{r,}{:} - X_{r,}{:} + r2\ *\ (gbest_J -\ X_{i,j})$$

End for

End If

Accept $Xnew$ if it gives a better fitness function value.

End for

where r1 and r2 are independent sequences,$r1\ \sim\ U(0,1)\ and\ r2\ \sim\ U(0,1)$. These sequences are used to affect the stochastic nature of the algorithm, as shown above in Eq. (18). The flowchart in figure 2.10

2.14 IMPLEMENTATION OF SGO FOR OPTIMIZATION

The step-wise procedure for the implementation of SGO is given in this section.

Step 1:

Enumeration of the problem and Initialization of parameters Initialize the population size (N), number of generations (g), number of design variables (D), and limits of design variables (U_L , L_L). Define the optimization problem as: Minimize f (X). $Subject\ to\ =\ (x_1, x_2, x_3\ , \ldots\ldots, x_D\ ), so\ that\ X_j\ =$ $(x_{j1}, x_{j2}, x_{j3}\ , \ldots\ldots, x_{jD})$, Where $f\ (X)$ is the objective function, and X is a vector for design variables such that $L_{L,i} \leq\ x, i\ \leq\ U_{L,i}$

Step 2: Initialize the population

A random population is generated based on the features (number of parameters) and the size of the population chosen by the user. For SGO, the population size indicates the number of persons, and the features indicate the number of traits. This population is articulated as:

$$\text{Population}\ =\ \begin{bmatrix} x_{1,\ 1} x_{1,2} x_{1,3} & \cdots & x_{1,D} \\ \vdots & \ddots & \vdots \\ x_{N,\ 1} x_{N,2} x_{N,3} & \cdots & x_{N,D} \end{bmatrix}$$

(19)

Calculate the fitness of the population $f\ (X)$.

Step 3: Improving Phase

Then, determine $gbest_g$ Using Eq. (18), which is the best solution for that iteration. As in the improving phase, each person gets knowledge from their group's best, i.e., gbest

$For\ i\ =\ 1{:}\ N$

$For\ j\ =\ 1{:}\ D$

$$Xnew_{ij} :=\ c * Xold_{ij} + r\ *\ (gbest(j) -\ Xold_{i,j})$$

End for

End for

The value of c is the self-introspection factor. The value of c can be empirically chosen for a given problem. We have set it to 0.2 in this work after a thorough study of our investigated issues, and r is a random number, $r\ \sim\ U(0, 1)$.

Accept $Xnew$ if it gives a better function value.

Step 4: Acquiring phase

As explained above, in the acquiring phase, a person of the social group interacts with the best person, i.e., gbest of the group, and also interacts

randomly with other persons of the group to acquire knowledge. The mathematical expression is defined in the “Acquiring phase.”

Step 5: Termination criterion

Stop the simulation if the maximum generation number is achieved; otherwise, repeat Steps 3–4.

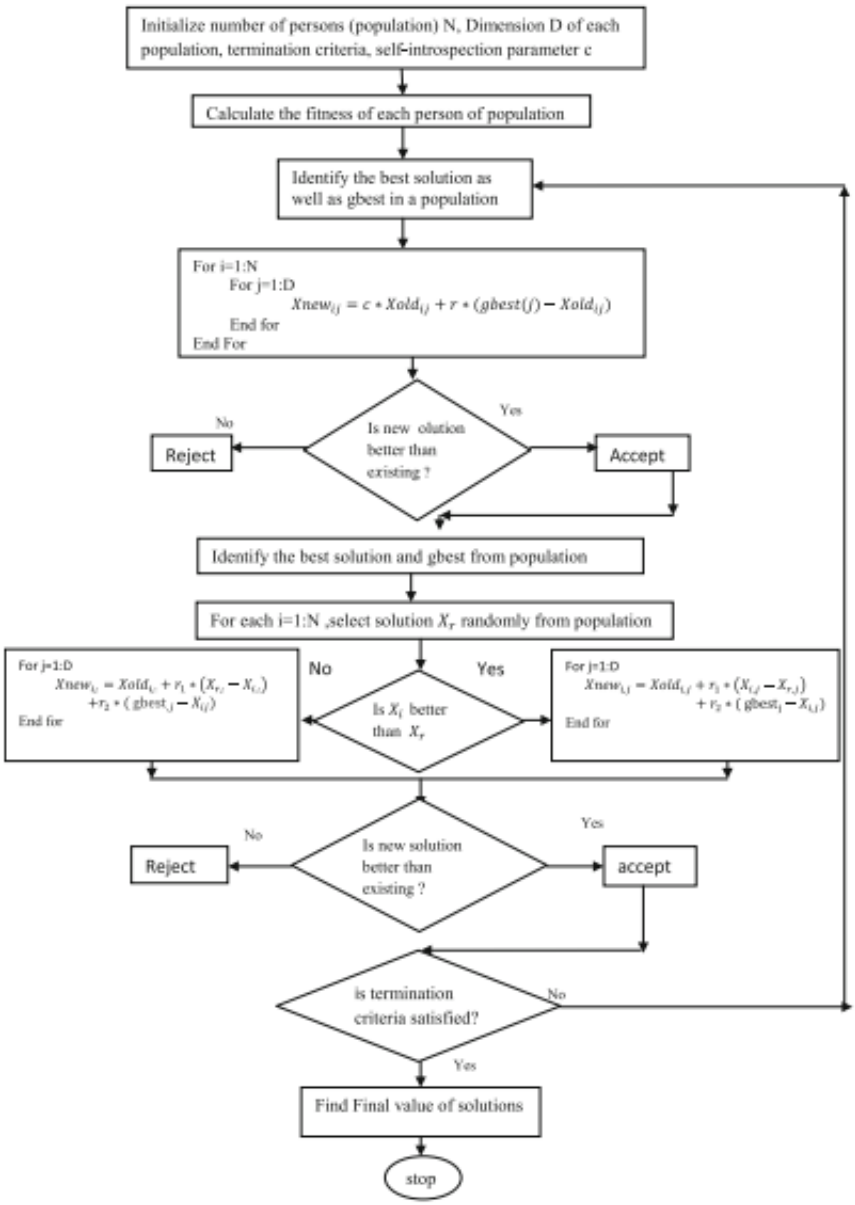

Figure 2.1717: *Flow chart of SGO Algorithm*

As this optimization technic was developed and published in 2016, there has been a lot of studies been carried out using the SGO algorithm. (Das et al., 2020) utilized the SGO to optimize problems relating to Civil Engineering, where damage analysis of different modeled civil engineering structures and a real-life American Society of Civil Engineers (ASCE) benchmark structure using a stiffness-based objective function. (Rani & Suri, 2021) this author proposed the SGO for exposing numerous artificial faults in the software, whereas (Feng et al., 2016) provided a feedback intelligence algorithm called the social group entropy optimization (SGEO) algorithm is proposed for solving optimization tasks. The proposed algorithm is based on the social group model, the status optimization model, and the entropy model. (Chakravarthy, 2021) presented work on “Circular antenna array optimization using modified social group optimization algorithm” the main objective of the work process is to synthesize radiation patterns with suppressed SLL while the BW being equal to the uniform distribution. (Jasmine et al., 2021) applied inertia weight strategies to SGO.

CHAPTER THREE

METHODOLOGY

3.1 INTRODUCTION

This chapter will explain the materials and methods used in this project. It will be including the description of the control strategy for charging time optimization, SGO steps for optimization, problem formulation, optimization model construction and solution, performance architecture**,** design optimization, and flowchart execution explanation.

Figure 3.1 shows the battery management system block diagram, which explains the control strategy block diagram in Fig. 3.2.

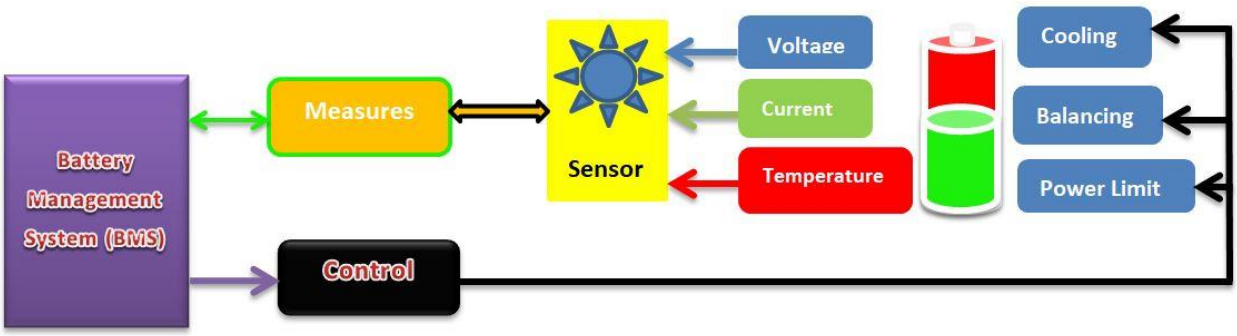

Figure 3.118: *Block diagram of a BMS*

The above figure presents the block diagram of the BMS, a sensor receives battery parameters (which are voltage, current, and temperature) into the BMS, and this now compares the initial state of charge (SOC) of the battery and then performs cooling, balancing and power limiting

controls. The system is a closed-loop system with a feedback mechanism.

Figure 3.2 presents the control system for charge optimization. The control system analyzes input of the battery parameter; this input is converted to analog values.

We consider three particles (Voltage, Current, and Temperature) associated with the actual properties: SOC, SOH, and SOE. These three variables are adjusted for each particle according to its own experience and the experience of its neighbors. Each particle operates through in the solution area and recalls the best objective function value (SOC), which has been discovered; the fitness value is saved and known.

3.1.1 Control Strategy for Charging Time Optimization

In this study, the constant-current constant-voltage (CCCV) charging strategy was optimized, the charging profile can be divided into several CC and CV phases. We present three objective functions: battery charging time, energy loss, and battery temperature change. The constraints considered during the charging process are finding the optimal current to minimize the time required to move the state of charge (SOC) from a low-level SOC to its desired level with a short time.

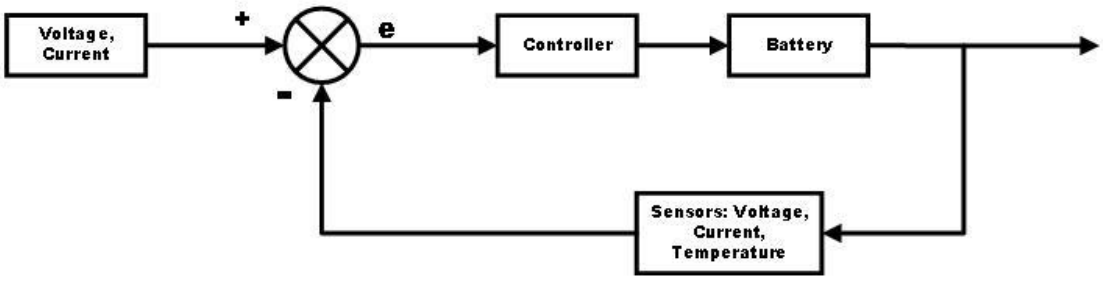

Figure 3.219: *Demonstration of the control strategy flow*

3.1.2 Battery Parameter

The battery used in this work is manufactured by Ultrafire Battery Company. It is a 18650 battery with a capacity of 7800mAh, as in figure 3.3.

Figure 3.320: Lithium-ion batteries

Table 3.1 illustrates the fundamental characteristic of the lithium-ion battery with a nominal capacity of 7800mAh and a minimum capacity of 7459mAh. It has a discharge cut-off characteristic of 2.5V with an internal impedance less than $70m\Omega$.

Table 3. 1: The Basic Characteristics of the battery

Capacity（25±5℃）	Nominal Capacity： 7800mAh (0.52A Discharge， 2.75V) Typical Capacity：2550mAh（0.52A Discharge， 2.75V） Minimum Capacity：7450mAh (0.52A Discharge， 2.75V)
Nominal Voltage	3.7V
Internal Impedance	≤ 70mΩ
Discharge Cut-off Voltage	2.5V
Max Charge Voltage	4.20±0.05V
Standard Charge Current	0.52A
Rapid Charge Current	1.3A
Standard Discharge Current	0.52A
Rapid Discharge Current	1.3A
Max Pulse Discharge Current	2.6A
Weight	46.5±1g
Max. Dimension	Diameter(Ø): 18.4mm Height (H): 65.2mm
Operating Temperature	Charge: 0 ~ 45℃ Discharge: -20 ~ 60℃
Storage Temperature	During 1 month: -5 ~ 35℃ During 6 months: 0 ~ 35℃

3.1.3 SGO Steps for Optimization

The step-wise procedure for the implementation of SGO is given in this section.

Step 1:

Enumeration of the problem and Initialization of parameters Initialize the population size (N), number of generations (g), number of design variables (D), and limits of design variables (U_L , L_L). Define the optimization problem as: Minimize f (X). $Subject\ to\ = (x_1, x_2, x_3\ , \ldots\ldots, x_D\ ), so\ that\ X_j\ =$

$(x_{j1}, x_{j2}, x_{j3}, \ldots\ldots, x_{jD})$, Where $f\ (X)$ is the objective function, and X is a vector for design variables such that $L_{L,i} \leq\ x, i\ \leq\ U_{L,i}$

Step 2: Initialize the population

A random population is generated based on the features (number of parameters) and the size of the population chosen by the user. For SGO, the population size indicates the number of currents, and the features indicate the number of traits. This population is articulated as:

Step 3: Improving Phase

In the improving phase, each person gets knowledge from their group's best

Step 4: Acquiring phase

In the acquiring phase, the fitness value of the social group interacts with the best Fitness Value, i.e., the best of the group, and interacts randomly with other Values of the group for acquiring knowledge. The mathematical expression is defined in Acquiring phase.

3.2 PROBLEM FORMULATION

3.2.1 Optimization Model Construction and Solution

Formulating the problem of battery charging, and the critical optimization function is to be considered; this function is known as the performance

index. The Performance Index will be designed to minimize time by coupling the effort required and keeping the input as close to the maximum value as possible without violating the boundary conditions. The battery charging time is a crucial charging performance index, and it is wise to minimize its charge time as possible. Another key consideration of this index parameter is the battery energy loss, i.e., the power consumption, during the charging process. It can be understood that immense energy loss results in a thermal runaway; this means that the battery eventually will experience a drop in its charging Efficiency. The battery charging time and energy loss are critical issues when optimizing the battery.

An increase in battery temperature can quickly lead to degradation of the battery, so it is crucial in preventing this situation and the need to maintain the temperature of a battery according to its manufacturer specifications. However, let's consider the battery charging time, energy loss, and temperature as the objective function for optimizing the charging process. The cost functions relating to the battery charging time C_T and energy loss $E_{\emptyset l}$ can be calculated respectively as follows:

$$\mathfrak{C}_{C_T} = T_{st} * \mathfrak{B}_{t_f} \tag{3.1}$$

$$V(\mathfrak{B}) = V_1(\mathfrak{B}) + V_2(\mathfrak{B}) + R * I(\mathfrak{B}) + U_{ocv} \tag{3.2}$$

$$\mathfrak{C}_{E_{\emptyset l}} = T_s * \sum_{\mathfrak{B}=0}^{\mathfrak{B}_{t_f}} (i^2(\mathfrak{B}) * R(\mathfrak{B}) + \frac{V_1^2(\mathfrak{B})}{R_1(\mathfrak{B})} + \frac{V_1^2(\mathfrak{B})}{R_2(\mathfrak{B})}) \quad (3.3)$$

Table 3. 2: First Term Parameter Definitions

$\mathfrak{C}_{C_T\ and}\ \mathfrak{C}_{E_{\emptyset l}}$	Cost function.
T_{st}	Is the sampling period (in seconds) during the battery charging process
$\mathfrak{B}_{t_f}$	Denotes the time when the battery capacity reaches its final target.
T_s	The battery charging time
V_1, V_2	RC network Voltage.

Considering the battery lumped thermal model by (K. Liu et al., 2017), we can simply define the battery internal temperature rise index as

$\tilde{T}_{in}(\mathfrak{B}) = T_{in}(\mathfrak{B}) - T_{amb}$ And the battery surface temperature rise index$\tilde{T}_{sh}(\mathfrak{B}) = T_{sh}(\mathfrak{B}) - T_{amb}$.

The expression for the battery thermal model is given as;

$$\begin{cases} D_1 * \dot{T}_{in} = i^2 * R + \mathfrak{B}_1 * (T_{sh} - T_{in}) \\ D_1 * \dot{T}_{sh} = \mathfrak{B}_1 * (T_{sh} - T_{in}) + \mathfrak{B}_2 * (T_{amb} - T_{sh} \end{cases}$$

(3.4)

By adopting $Q = i^2 * R$

Where Q is the battery dissipation, the above equation becomes;

$$\begin{cases} T_{in}(\mathfrak{B}+1) = \left(1 - T_s * \frac{\mathfrak{B}_1}{D_1}\right) * T_{in}(\mathfrak{B}) + T_s * \frac{\mathfrak{B}_1}{D_1} * T_{sh}(\mathfrak{B}) + \frac{T_s}{D_1} * i^2(\mathfrak{B}) * R \\ T_{in}(\mathfrak{B}+1) = T_s * \frac{\mathfrak{B}_1}{D_2} * T_{in}(\mathfrak{B}) + \left(1 - T_s * (\frac{\mathfrak{B}_1+\mathfrak{B}_2}{D_2}\right) * T_{sh}(\mathfrak{B}) + \mathfrak{B}_2 * T_s * \frac{T_{amb}}{D_2} \end{cases}$$

(3.5)

From the above equation (3.5)

Put $\tilde{T}_{in}(\mathfrak{B}) = T_{in}(\mathfrak{B}) - T_{amb}$ and $\tilde{T}_{sh}(\mathfrak{B}) = T_{sh}(\mathfrak{B}) - T_{amb}$.

$$\begin{cases} \tilde{T}_{in}(\mathfrak{B}+1) = \left(1 - T_s * \frac{\mathfrak{B}_1}{D_1}\right) * \tilde{T}_{in}(\mathfrak{B}) + T_s * \frac{\mathfrak{B}_1}{D_1} * T_{sh}(\mathfrak{B}) + \frac{T_s}{D_1} * i^2(\mathfrak{B}) * R \\ = A_1 * \tilde{T}_{in}(\mathfrak{B}) + B_1 * T_{sh}(\mathfrak{B}) + C * R(\mathfrak{B}) * i^2(\mathfrak{B}) \\ \tilde{T}_{in}(\mathfrak{B}+1) = T_s * \frac{\mathfrak{B}_1}{D_2} * T_{in}(\mathfrak{B}) + \left(1 - T_s * (\frac{\mathfrak{B}_1+\mathfrak{B}_2}{D_2}\right) * T_{sh}(\mathfrak{B}) + \mathfrak{B}_2 * T_s * \frac{T_{amb}}{D_2} \\ A_2 * \tilde{T}_{in}(\mathfrak{B}) + B_2 * \tilde{T}_{sh}(\mathfrak{B}) \end{cases}$$

Now the temperature rise index can be formulated as

Assuming $T_{in}(0) = T_{amb}$ and $T_{sh}(0) = T_{amb}, then\ \tilde{T}_{in}(0)$

$= 0, \tilde{T}_{sh}(0) = 0$

The cost function for the temperature rise $\mathfrak{C}_{TR}$ $becomes$;

$$\mathfrak{C}_{T_{rise}} = T_s * (\sum_{\mathfrak{B}=0}^{\mathfrak{B}_{tf}} \tilde{T}_{in}(\mathfrak{B}) + \sum_{\mathfrak{B}=0}^{\mathfrak{B}_{tf}} \tilde{T}_{sh}(\mathfrak{B}))$$

(3.6)

The objective function $\mathfrak{C}_{charge}$ is the combination of the cost functions as stated in the above equations.

$$\mathfrak{C}_{charge} = \mathfrak{C}_{C_T} + \mathfrak{C}_{E_{\emptyset l}} + \mathfrak{C}_{T_{rise}} \tag{3.7}$$

$$\mathfrak{C}_{charge} = T_s * \mathfrak{B}_{t_f} + T_s * \sum_{\mathfrak{B}=0}^{\mathfrak{B}_{t_f}} (i^2(\mathfrak{B}) * R(\mathfrak{B}) + \frac{V_1^2(\mathfrak{B})}{R_1(\mathfrak{B})} + \frac{V_1^2(\mathfrak{B})}{R_2(\mathfrak{B})}) +$$

$$T_s * (\sum_{\mathfrak{B}=0}^{\mathfrak{B}_{tf}} \tilde{T}_{in}(\mathfrak{B}) + \sum_{\mathfrak{B}=0}^{\mathfrak{B}_{tf}} \tilde{T}_{sh}(\mathfrak{B})) \tag{3.9}$$

T_s Is the sampling period of the battery; it is processed in one second.

3.3 DESIGN OPTIMIZATION

The design optimization goal of the charging process is to locate a global charging current profile $i(\mathfrak{B})$ to minimize the cost or objective function $\mathfrak{C}_{charge}$ during the battery charging process. Let's consider voltage, current, and battery SOC level limits as our optimization constraints because this parameter must be achieved during the optimal charging process.

$\mathfrak{C}_{charge}$ *is subjected to the following equations*.

$$\begin{cases} SOC(\mathfrak{B}) = SOC(\mathfrak{B}-1) - \frac{T_s}{C_n} * i(\mathfrak{B}-1) \\ V_1(\mathfrak{B}) = a_1 * V_1(\mathfrak{B}-1) - b_1 * i(\mathfrak{B}-1) \\ V_2(\mathfrak{B}) = a_2 * V_2(\mathfrak{B}-1) - b_2 * i(\mathfrak{B}-1) \\ A_1 * \tilde{T}_{in}(\mathfrak{B}) + B_1 * T_{sh}(\mathfrak{B}) + C * R(\mathfrak{B}) * i^2(\mathfrak{B}) \\ A_2 * \tilde{T}_{in}(\mathfrak{B}) + B_2 * \tilde{T}_{sh}(\mathfrak{B}) \end{cases}$$

(3.10)

$$V(\mathfrak{B}) = V_1(k) + V_2(\mathfrak{B}) + i(\mathfrak{B}) * R(\mathfrak{B}) + U_{ocv}$$

(3.11)

$$\begin{cases} SOC(0) = S_0 \\ \tilde{T}_{in}(0) = 0 \end{cases} \qquad \begin{matrix} Soc(t_f) = S_{t_f} \\ \tilde{T}_{sh}(0) = 0 \end{matrix}$$

$$\begin{cases} i_{min} \leq i(\mathfrak{B}) \leq i_{max} \\ V_{min} \leq v(\mathfrak{B}) \leq V_{max} \end{cases}$$

Table 3. 3: Second Term Parameter Definitions

S_0	initial SOC state during the battery charging process
S_{t_f}	final SOC state during the battery charging process
i_{max}	lower bound limits of charge current $i(\mathfrak{B}), and\ V(\mathfrak{B})$
i_{min}	and upper bound limits of charge current

	$i(\mathfrak{B}), and\ V(\mathfrak{B})$
V_{max} & V_{min}	the minimum and maximum bounds of $V(\mathfrak{B})$

For proper optimization, we will separate this strategy CCCV approach into CC charging approach and then CV charging approach, the battery will start charging at a phase of constant current (CC) technique, here there is a continuous increase of the battery voltage until its approaches $V_{max}\ bound$. At this point, the circuitry switching, the CC is transferred to CV to continue charging until the battery capacity matches the requirement of the SOC. As the voltage increase, the current gradually decreases, and the dynamics of the CV charging current $i_{CV}(\mathfrak{B})$ is derived as;

From Ohms law $V = IR$.

$$i_{CV}(\mathfrak{B}) = \frac{(V_{max} - V_1(\mathfrak{B}) - V_2(\mathfrak{B}) - U_{ocv})}{R(\mathfrak{B})} \tag{3.12}$$

For$\mathfrak{B} = \mathfrak{B}_{cc}, \mathfrak{B}_{cc} + 1, \ldots \mathfrak{B}_{tf},$

The charging current profiles $i_{CV}(\mathfrak{B})\ is\ thus\ c$alculated, the objective function $\mathfrak{C}_{charge_cV}$is then calculated based on the charging profile.

$$Minimize\ \mathfrak{C}_{charge\_cV} = \mathfrak{C}_{charge\_cc} + \mathfrak{C}_{charge\_cv} \tag{3.13}$$

$$\mathfrak{C}_{charge_{cc}} = w_t * T_{-t} * \mathfrak{B}_{-cc} + w_E * T_s * \sum_{\mathfrak{B}=0}^{\mathfrak{B}_{cc}-1} f_{\emptyset E}(\mathfrak{B}) + w_T * T_s * \sum_{\mathfrak{B}=0}^{\mathfrak{B}_{cc}-1} f_{TR}(\mathfrak{B}) \quad (3.14)$$

$$\mathfrak{C}_{charge_{cv}} = w_t * T_{-t} * (\mathfrak{B}_{-tf} - \mathfrak{B}_{-cc}) + w_E * T_s * \sum_{\mathfrak{B}=0}^{\mathfrak{B}_{cc}-1} f_{\emptyset E}(\mathfrak{B}) + w_T * T_s * \sum_{\mathfrak{B}=0}^{\mathfrak{B}_{cc}-1} f_{TR}(\mathfrak{B}) \quad (3.15)$$

Subject to:

$$\begin{cases} SOC(0) = S_0 & Soc(t_f) = S_{t_f} \\ \tilde{T}_{in}(0) = 0 & \tilde{T}_{sh}(0) = 0 \end{cases}$$

$$\begin{cases} i_{min} \leq i(\mathfrak{B}) \leq i_{max} \\ V_{min} \leq i(\mathfrak{B}) \leq V_{max} \end{cases}$$

$$f_{\emptyset E}(\mathfrak{B}) = i^2(k) * R(\mathfrak{B}) + \frac{V_1^2(\mathfrak{B})}{R_1(\mathfrak{B})} + \frac{V_2^2(\mathfrak{B})}{R_2(\mathfrak{B})} \quad (3.16)$$

$$f_{TR}(\mathfrak{B}) = w_{in} * \tilde{T}_{in}(k) + w_{sh} * \tilde{T}_{sh}(k) \quad (3.17)$$

Table 3. 4: Third Term Parameter Definitions

$\mathfrak{B}_{cc}$	Is the time taken for the battery terminal voltage $V(\mathfrak{B})$ to first approach the constant voltageV_{max}.
$\mathfrak{B}_{tf}$	Is the time taken for which the battery reaches its final charge stage

w_t	Represent the battery charging time weight
w_E	Represent the battery energy loss weight,
w_T	is the battery temperature weight
w_{in}, w_{sh}	Are for the two battery temperatures weights, the interior temperature and the surface temperature.

The optimization problem is aimed at optimizing the charging current profile $i_{Cc}(\mathfrak{B})$ to minimize the objective function $\mathfrak{C}_{charge}$. However $i_{Cc}(\mathfrak{B})$ can be determined by an optimization algorithm, it should be noted that the resistance $R(\mathfrak{B}), R1(\mathfrak{B}), R2(\mathfrak{B}), and\ voltage\ V1(\mathfrak{B}), \mathrm{V2}(\mathfrak{B})$ this are the parameters which are used to calculate the objective function $\mathfrak{C}_{charge}$. To solve the battery optimal charging problem formulated in equations (3.10) and (3.11), respectively, this will utilize the SGO optimization method to find the battery optimal charging profile is presented.

3.4 **PERFORMANCE ARCHITECTURE**

Some parameters of the battery defer along the charging process, e.g., the battery OCV varies with the SOC level, and battery resistances R_1, R_2, R_3 also, vary with the battery temperature and SOC level. The objective function for the battery charging process has to be optimized under time-

varying and nonlinear conditions. This presents a significant challenge for traditional analytical optimization techniques such as the variation method to solve complicated optimization problem. SGO algorithm is employed in this work to solve the nonlinear, time-varying, complex battery optimal charging problem. The optimization process undergoes three phases: the searching phase, the improving phase, and the acquiring phase. In the searching phase, a search is done to find the best charging profile of current (I); in the improving phase, the generation of a new solution and the calculation of new fitness is initiated by applying greedy selection. This will select the initial charging profile by comparing. The acquiring phase will find a new solution, then calculate the new fitness, apply greedy selection then lastly memorize the best solution. It is convenient and straightforward to adopt this optimization algorithm for battery optimal charging strategy since there are no algorithm-specific parameters that need to be adjusted by the user for the algorithm implementation. In this thesis, instead of using analytic optimization methods, SGO is adopted to search for the best charge current in the constant-current (CC) process through its two phases, aiming to minimize the objective function $\mathfrak{C}_{charge}$ described is discussed in section 3.2 and to obtain the suitable charge current profile for optimal battery charging.

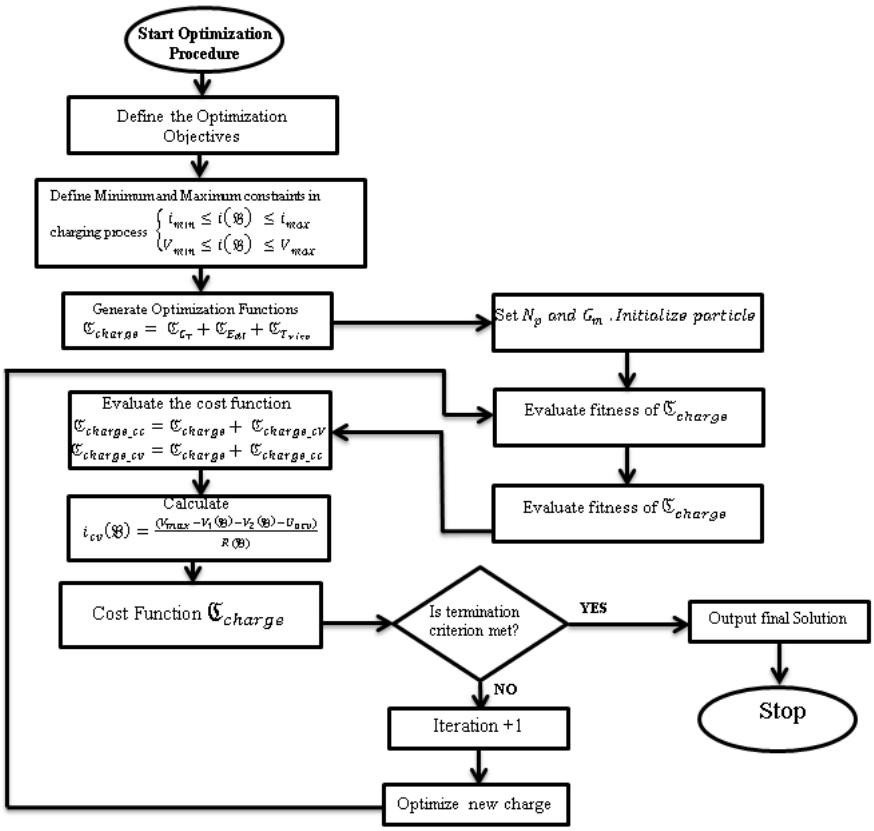

Figure 3.421: *Flowchart of implementing the Social group optimization Algorithm methods for battery optimal charging strategy*

3.4.1: Flowchart Execution Explanation

Step 1: Define the optimization objectives, define minimum and maximum constraints in the charging process, and then generate optimization function $\mathfrak{C}_{charge} = \mathfrak{C}_{C_T} + \mathfrak{C}_{E_{\emptyset l}} + \mathfrak{C}_{T_{rise}}$.

Step 2: Set the battery charging initial SOC level, set N_p and G_m and evaluate the fitness of cost function $\mathfrak{C}_{charge}$respectively.

Step 3: evaluate the cost function $\mathfrak{C}_{charge\_cc}$ and $\mathfrak{C}_{charge\_cv}$ then

calculate the constant voltage current i_{cv} then evaluate the optimization $\mathfrak{C}_{charge}$.

Step 4: At the CC stage, calculate the objective fitness $\mathfrak{C}_{charge\_cc}$ in each generation using equation (3.14) until the terminal voltage reaches the maximum thresholdV_{max}, then the battery charging process will enter the CV stage; at the CV stage, determine the charge current profile using equation (3.12) in each generation and then calculate the objective fitness $\mathfrak{C}_{charge\_cv}$ using equation (3.15) until the battery SOC level reaches its final $S_{\mathfrak{B}_{tf}}$ now evaluate the final objective function $\mathfrak{C}_{charge}$according to the sub-objective fitness $\mathfrak{C}_{charge\_cc}$ and $\mathfrak{C}_{charge\_cv}$. Check whether the maximum number of iterations is achieved, and the loop is terminated once the condition; update the charge current in the CC stage using the corresponding. When the terminal voltage reachesV_{max}, terminate the CC stage; when the battery SOC level reaches $S_{\mathfrak{B}_{tf}}$ which means the battery has been charged to the targeted capacity, terminates the CV stage. When the termination criteria have been satisfied, end the whole optimization process.

$$Objective\ function\ \ \mathfrak{C}_{charge} = \mathfrak{C}_{C_T} + \mathfrak{C}_{E_{\emptyset l}} + \mathfrak{C}_{T_{rise}}.$$

$$\text{Constrain} \begin{cases} i_{min} \leq i(\mathfrak{B}) \leq i_{max} \\ V_{min} \leq v(\mathfrak{B}) \leq V_{max} \\ T_{min} \leq T(\mathfrak{B}) \leq T_{max} \end{cases} = \begin{cases} 1 \leq i(\mathfrak{B}) \leq 3 \\ 2.5 \leq v(\mathfrak{B}) \leq 4.2 \\ 15 \leq T(\mathfrak{B}) \leq 45 \end{cases}$$

CHAPTER FOUR

RESULT AND DISCUSSION

This chapter will discuss the results of the SGO method implemented on MATLAB as achieved and data generated, tabulated, and analyzed. The validation of the performance of SGO algorithm is analyzed. Then, the results are compared with the Particle Swarm Optimization (PSO) algorithm based on the previous study.

4.1. EXPERIMENTAL SETUP

The experiments are carried out by using MATLAB programming to obtain the optimal current profile. Data generated is shown in Table 4.1. These show the run-time simulation data obtained from forty (40) iteration for time and current values at 1.707s and 2.500 mA, respectively. The time implies the number of circles for the algorithm to converge at 2.500 mA to provide the optimum current.

Table 4. 1: Data from simulation

Iterations	Time(S)	Current (mA)
1	2.041929	2.0768
2	1.813085	1.8106
3	1.56295	2.0776
4	1.60678	2.08

5	1.532463	2.2694
6	1.559693	2.4462
7	1.559693	2.4678
8	1.521017	2.5362
9	1.572812	2.5363
10	1.561421	2.5376
11	1.563954	2.524
12	1.686069	2.5181
13	1.586211	2.5018
14	1.718018	2.5027
15	1.608261	2.504
16	1.570283	2.5047
17	1.525606	2.5061
18	1.572762	2.5051
19	1.541606	2.5069
20	1.54953	2.5089
21	1.505475	2.5094
22	1.550263	2.5094
23	1.573758	2.5095
24	1.538826	2.5097
25	1.542541	2.5098

26	1.541823	2.5093
27	1.54039	2.5098
28	1.555551	2.5098
29	1.545795	2.5098
30	1.561551	2.5098
31	1.5187	2.5098
32	1.54746	2.5098
33	1.534055	2.5098
34	1.550207	2.5098
35	2.064708	2.5098
36	1.842818	2.5098
37	1.824358	2.5098
38	1.776321	2.5098
39	1.832513	2.5098
40	1.706928	2.5098

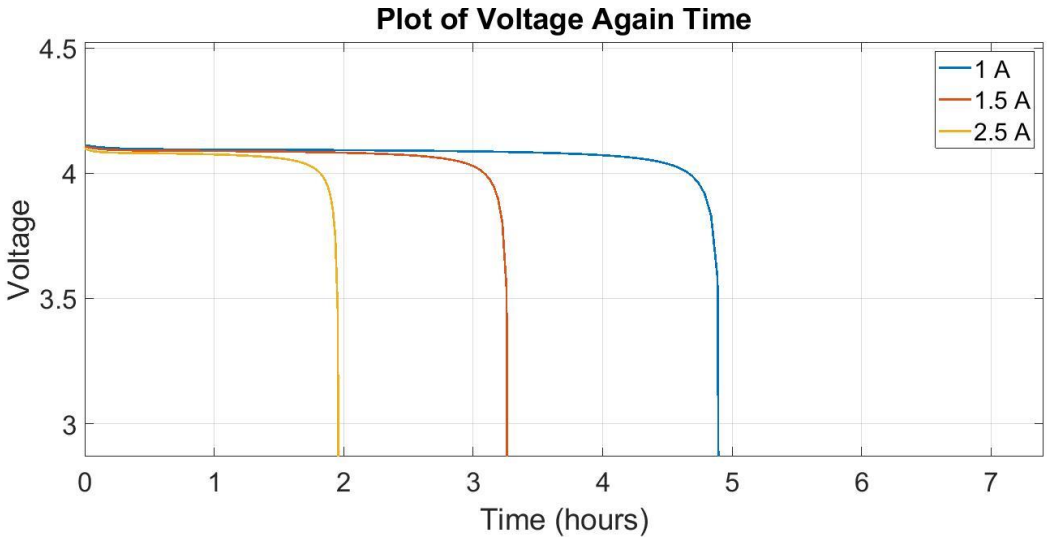

Figure 22: Effect of temperature on nominal current discharge characteristics

Figure 4.1 depicts the voltage profile against time that identifies the current characteristics during discharge, when the battery is fully charge at 4.2V. It is observed that the discharge characteristics with respect to time differ. This is because of the variation in the current profile. For a current of 1A, it will take 4hr58m to discharge. This means that if the power consumption of a Nanosatellite is 2.5A, the discharge time of the battery will be 1.59minutes. This time is sufficient during eclipse activity.

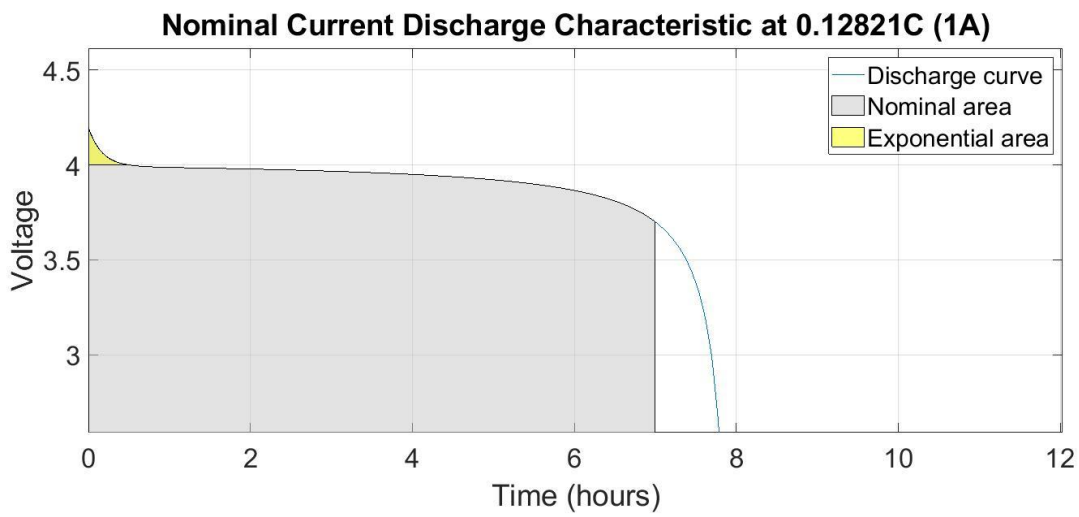

Figure 4.223:Discharge characteristics

Figure 4.2 presents the discharging curves of the battery at 1A. The curves show that the battery was charged at its total capacity of 7800mAh using the technique.

This indicates a decrease in charging time without affecting its life cycle and charge capacity. The simulation was performed using MATLAB Simulink to validate the approach.

4.2. SIMULATION VALIDATION

Figure 4.3 depicts the fitness value after 40 iterations of the best current profile easily performed with the SGO algorithm.

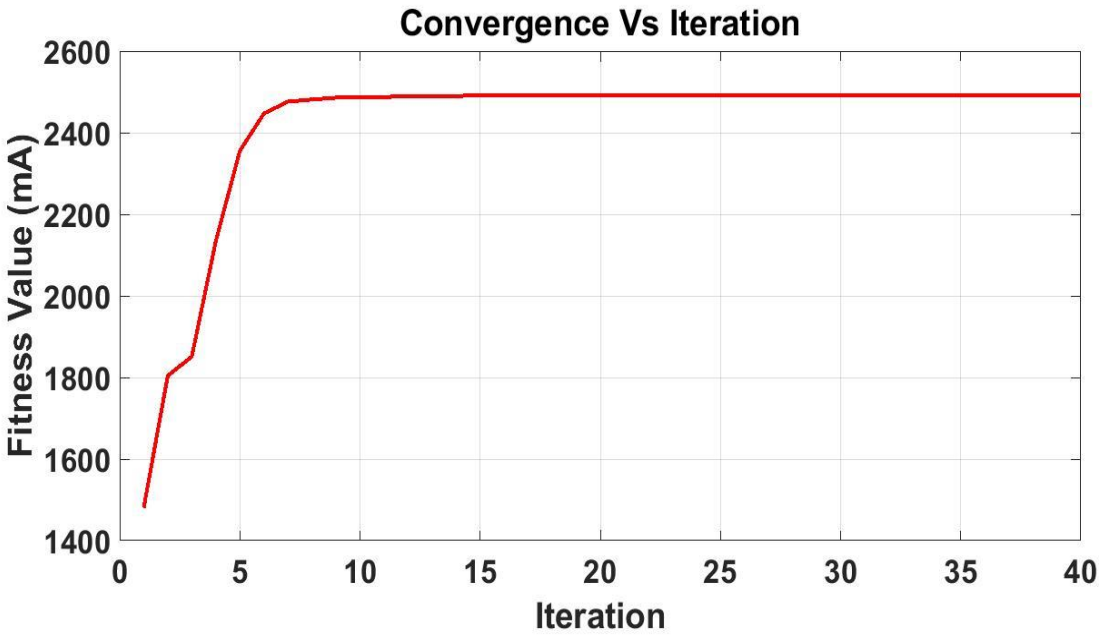

Figure 4.324: A Plot to Show the fitness value charging of Current after 40 Iteration.

This shows the fitness value of the current in mA. The graph's fitness varies with an increment in current from 1430mA to 1800mA during the first and third iteration. The algorithm tries to improve its initial state by performing the greedy section and acquiring knowledge from the previous iteration, as in section 2.8.1. After the tenth iteration at 2430mA, the fitness value converges at its optimal value at 2500mA. This implies that an early stage of convergence. The best fitness value is no longer updated after 40 iterations, which means the convergence of the SGO algorithm as the best value is achieved at 2500mA; this signifies an optimal charging current.

In general, after more iteration, the optimal current begins to increase linearly as the number of iterations increases. The convergence of the SGO algorithm is scientifically affecting the time complexity of the algorithm. For this purpose, we have chosen the fortieth iteration since the algorithm no longer converges at that point. Demonstrating that the searching algorithm can obtain a global optimization solution with fast convergence performance.

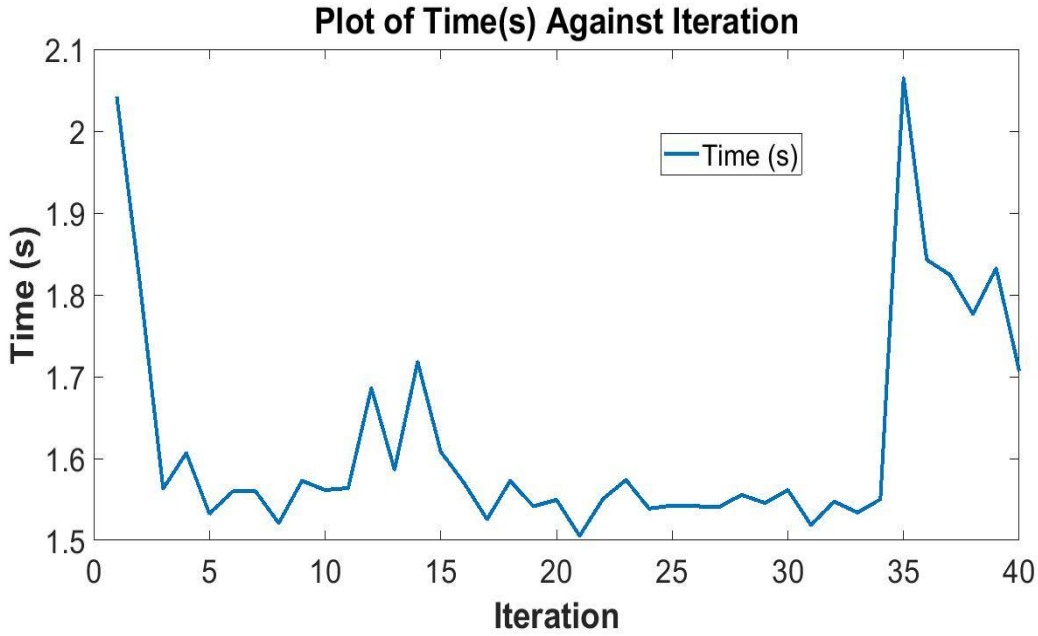

Figure 4.425: A Plot to Show the Time of Convergence

Figure 4.4 shows the actual running time (in seconds) against the number of iterations concerning Figure. 4.3. The plot is generated from the run time of the fitness values in Table 4.1. Based on the number of iteration, the plot is used to analyze the behavior of the current profile, as illustrated in Figure. 4.6. We observed from the figure that during the

improving phase of the SGO, the algorithm tries to acquire knowledge from different current profiles. The process of attaining the best solution for each iteration differs from the other as a function of time. This results in the fluctuation in the run time between the 10th iteration and the 34th iteration.

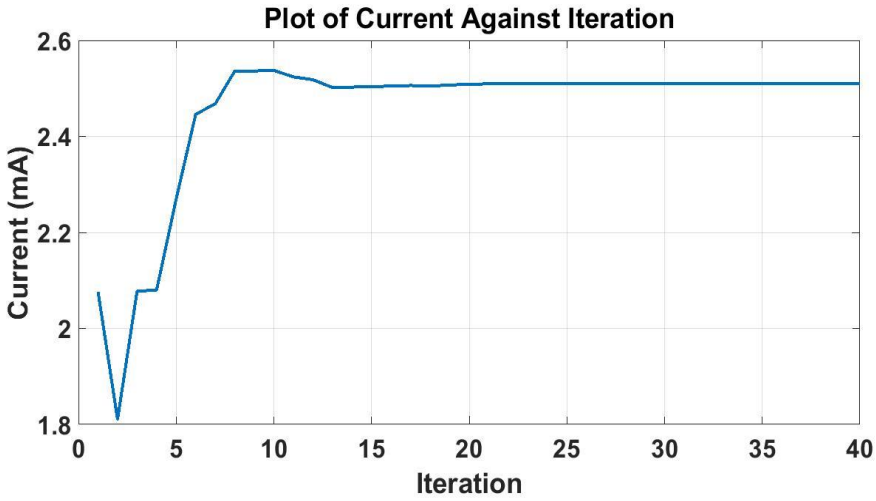

Figure 4.526: A Plot to Show the Convergence of Current

Figure 4.5 demonstrates the convergence of current at 40th iteration which is a confirmation in Figure 4.3. This shows the actual current in mA against Iteration. The data is generated and plotted from Table 4.1. This expresses that for each iteration, there is a change in current, and this change is a function of time and iteration. This shows that the algorithm run time increases linearly with the number of iteration.

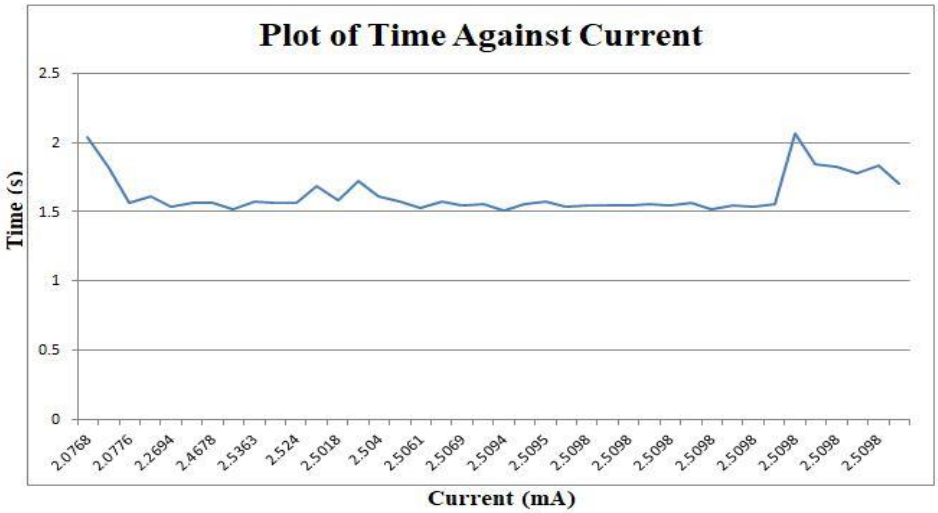

Figure 4.627: A Plot to show the relationship of Time against current

The result in Figure 4.6, shows the time series against the current which varies spontaneously with the numbers of iteration from 2.077mA at its first iteration to 2.500mA at its 40th iteration. In this study, it is observed that after the 40th iteration the time begins to drop sporadically, this is because the current has attained its optimal point of convergence which shows a good qualitative agreement with figure:4.3, and figure 4.7.

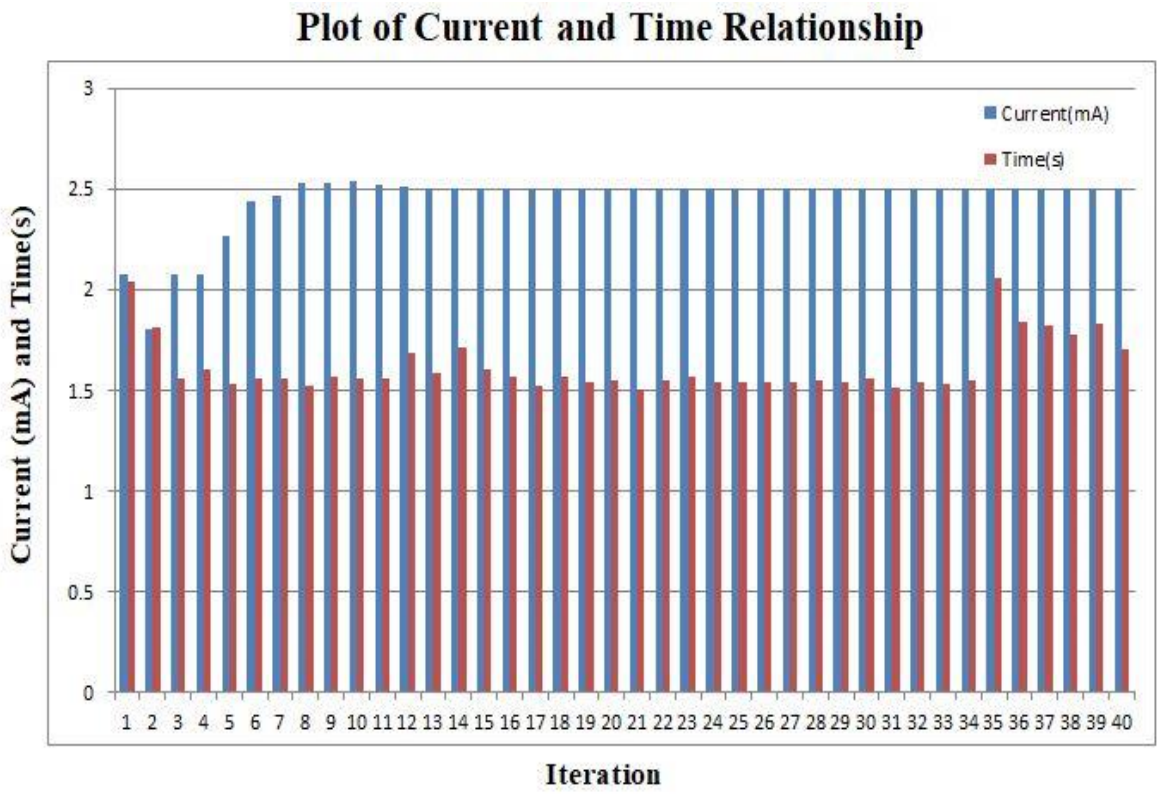

Figure 4.728: A Detailed Plot of Current and Time Relationship

It can be observed from Fig. 4.7 how the current varies significantly with time from the first iteration. The current 2.0768mA corresponded to 2.041929s, and this continues progressively in a stepwise manner to the 12th iteration. Thereafter, at the 11th iteration, the graph became linearly constant at a current profile of 2.5mA. The time series against the current is observed in Figure 4.6. This is confirmed in Figure.4.7, with iteration against current having the same tendency.

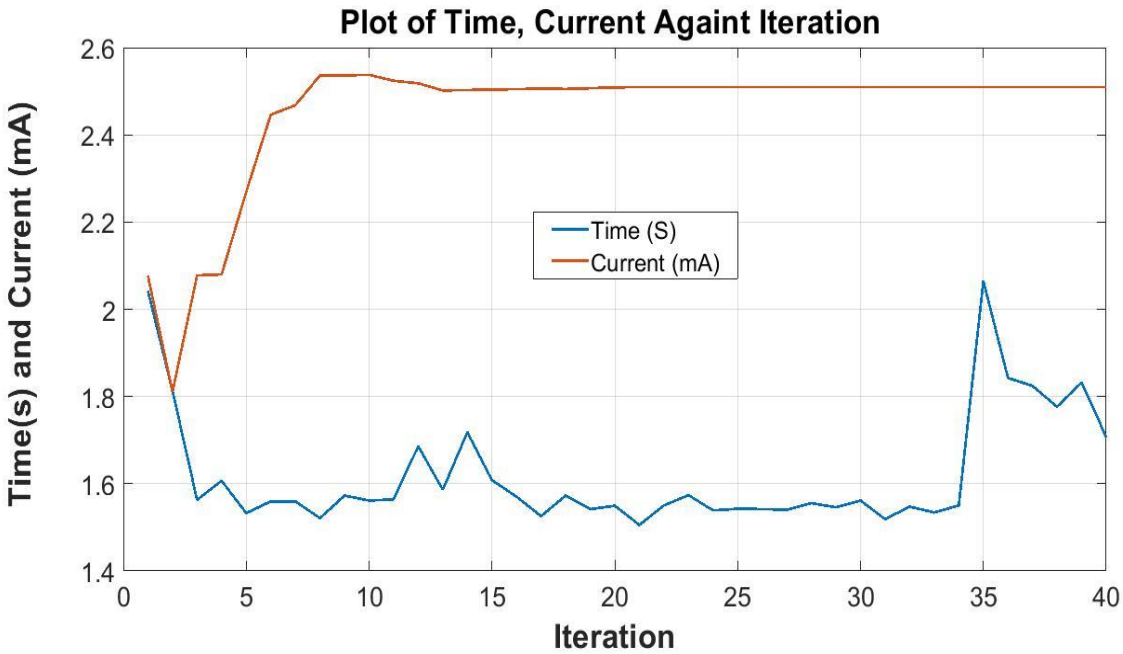

Figure 4.829: A Plot to Show the Relationship of Current, Time, and Convergence.

Figure 4.8 illustrates the summary relationship of Current, Time, and Convergence. Figures. 4.3 and 4.4 show the objective function has an effect on the fitness function. The objective function is aimed to find an optimal current profile to charge a lithium-ion battery effectively. This is achieved by optimizing the charging current to suit the battery, thereby minimizing the charge charging time. This prevents the battery from overcharging, under charge, overheating, and overcurrent.

In the Figure. 4.6, the iteration shows a decrease in the current and time. This is because the algorithm searches for the best cost or optimal charging profile to charge the battery. The time and current corresponding to the first iteration are 2.042s and 2.077mA, respectively.

At this point on the plot, there is an exponential increase in current, ending at the third iteration with a current value of 2.077mA and a converging time of 5.418s. Between the fourth and tenth iteration, the current behaves like a stepwise function, signifying an improvement in the charging current. The time required for the current stepwise is the summation of the time within the fourth and the tenth iteration, which is 9.381s—considering the 11th and 15th iteration with 2.524mA and 2.504mA, respectively. At this interval, the algorithm is checking to perform greedy selection leading to two triangular waves that correspond to 1.564s and 1.608s in the Figure. 4.6. At the 16th iteration, the current rose to 2.5047mA.

However, observation in figure 4.3 shows that the current no longer changes after this iteration due to the constant current (CC) charging pattern, leading to convergence. The algorithm tries to memorize the best-charging current between the 34th and 35th iteration. This requires a more significant time of 3.614915s for storing. Thereafter, another noticeable stepwise decrease between the 35th and 40th iteration after converging. This indicates that the shoring process of the algorithm has been completed, and therefore, the time begins to drop sporadically. Thus, take a total time of 86.17612s for the algorithm to converge.

4.3 **COMPARISON WITH PREVIOUS STUDIES**

This study was compared with the PSO-based Optimization for Constant-Current Charging Pattern for Li-ion Battery (Yixiao Wang et al., 2019).

4.3.1 Data Analysis

The evaluation of the performance of the charging pattern was carried out by a comparative simulated experiment of PSO technique in this method.

As shown in Table 4.2 for PSO based method, the charging time and charging efficiency is 3024s and 93.10%, respectively.

From this study, charging time is 2500s with charging efficiency of 95.51%, showing a reduction in charging time of 524s that account for an improvement over the previous study.

Table 4. 2: Comparison of The Charging Techniques

Method	**Charging Time/s**	**Charging Efficiency (%)**
PSO based method (Yixiao Wang et al, 2019)	3024	93.10
SGO Technique	2500	95.51
Improvement	524	2.41

As shown in section 3.1.2, the charge capacity the battery used in the SGO technique, is 7800mAh with a discharge capacity of 7450mAh. Therefore the charging efficiency is obtained by equation 4.1 that provides 2.41% efficiency over the previous study.

$$\boldsymbol{Charging\ Efficiency} = \frac{\boldsymbol{discharge\ capacity(mAh)}}{\boldsymbol{Charge\ capacity(mAh)}} \times \mathbf{100}$$

(4.1)

$$= \frac{\mathbf{7450}\boldsymbol{mAh}}{\mathbf{7800}\boldsymbol{mAh}} \times \mathbf{100\%} = \mathbf{95.51\%}$$

The charging time of the battery was decreased without affecting its life cycle and charge capacity with the aid of the SGO technique. By adopting this method, the charging time is decreased by 524 seconds. The performance of SGO is dependent on the system accuracy; this SGO method has several advantages over the previous technique which are; easy to implement and consideration of all battery statuses during charging, which allows for maximum battery protection from overvoltage, overcharging, and overheating conditions. The most significant finding, which has the biggest implications for battery life, is that the charging time was reduced by 524 seconds while maintaining capacity and life cycle.

CHAPTER FIVE

CONCLUSION

An approach for optimizing the battery management system for a Nano-satellite was carried out. The Social Group Optimization technique was used to perform the optimization. The method used is proven to be able to optimize the state of charge of a battery pack. In this work, the objective functions and the design constraint were derived. This approach was programmed in MATLAB. The methodology was implemented using a single-cell lithium-ion battery. The technique used accounts for a reduction in a charge time of 541(s) seconds, with an efficiency of 95.51%. The efficiency has an improvement of 2.41% compared with the previous technique. The total time taken for the algorithm to converge is 86.17612s, having an optimized current at 2500mA. The experimental result shows that this charging technique is faster and safer by a current of 2500mA in 86.17612s than traditional techniques. Thus, 524s shows an improvement over the previous study, which will accelerate the charging process of the Nano satellite as it gets closer to the eclipse

5.1 RECOMMENDATION AND FUTURE WORK

The technology will be put into practice in real time in the lab, with several battery types undergoing state of charge tests. It will be implemented to include a real-time battery monitoring system based on computer visualization.

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APPENDIX

MATLAB code for the optimization of battery management system.

```
% Function
```

Function

```
function Iopt = fun(X)

 x1 = X(:,1);

 x2 = X(:,2);

 x3 = X(:,3);

 % Objective function

 %C_charge= C_(C_T )+C_(E_(?l) )+C_(T_rise )

 Iopt = 2.*x1 + 95.51.*x2 + 46.5.*x3;

 end
```

```
% State of charge optimization Algorithm
% Constrain LB = [−0.9  2.5], Ub = [3  4.2]
% where lb is the lower bound and ub is the upper bound
  % variable respectively
```

```
format short

clear all

clc

%

D = 2; % Dimesion of the problem.

lb = [1 2.5 15]; % lower bound of the variables.

ub = [3 4.2 45]; % upper bond of the variables.

N = 20; % State of Charge (SOC)

c = 1; % self introspection parameter (0,1)

%

%   for x = 1:10

%       disp(x)

%   end

%

max_iter = 100; % maximum number of iteration

cR = 5000; % Battery Discharge Capacity

tC = 7800; % Battery charge capacity


% Generate initial State of Charge (SOC)

for i = 1:N
```

```
    for j = 1:D
        pos(i,j) = lb(:,j) + rand.*(ub(:,j)-lb(:,j));
    end
end

fx = fun(pos);
```

Improving Phase

In the improving phase the charging current with respect to time is

```
%enchaced by the influence of the best previous charging current.
% Where cX & X are old current solution, Inew is new Current solution
value
% c refers to self-introspection parameter. cϵ(0,1)
for iter = 1:max_iter
                    [best,bestind] = min(fx);
  Xbest = pos(bestind,:);
  for j = 1:size(pos,10)
      X = pos(j,:);
      Inew = c.*X + rand(size(X)).*(Xbest - X);
        % check bounds
for kk=1:size(Inew,2)
```

```
    if Inew(kk) > ub(kk)
        Inew(kk) = ub(kk);
    elseif Inew(kk) < lb(kk)
        Inew(kk) = lb(kk);
    end
end
% perform greedy delection
%
    fnew = fun(Inew);
    if fnew < fx(j,:)
        pos(j,:) = Inew;
        fx(j,:) = fnew;
    end
%
  end
%
```

ACQUIRING PHASE

Here the charge enhances its initial state with the mutual iteration by acquiring old state of charge then the best charging current is reached in the process of time.

```
[bestG indG] = min(fx);

[bestG indG] = min(fx);

gbest = pos(indG,:);

%

%

%for i = 1:size(pos,10)

for i = 1:N

    X = pos (i,:);        % for new solution "i"

    partner = ceil(rand*N); % choose the partner

end

 while (partner == i)

        partner = ceil(rand*N);

 end

    Xp = pos(partner,:);

    fp = fun(Xp);
```

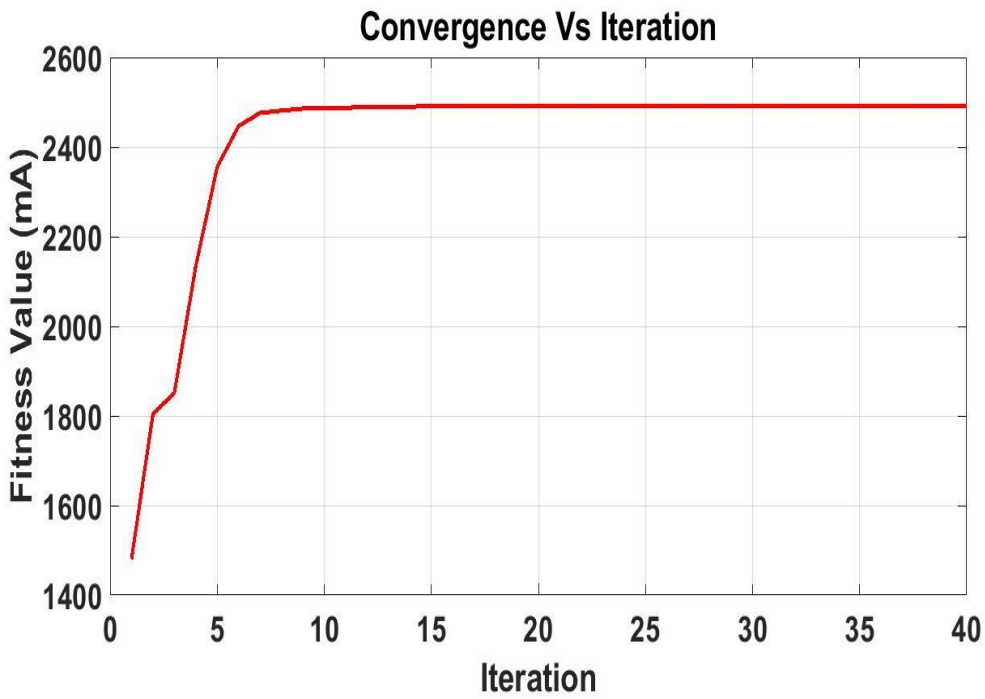
```
    if fx(i,:) > fp

        Inew = X + rand(size(X)).*(X-Xp) + rand (size(X)).*(gbest - X);

    else
```

```
        Inew = X-rand(size(X)).*(X-Xp) + rand(size(X)).*(gbest - X);
    end
     % check the bounds to vary if it lies on the bound or not.
        for kk = 1:size (Inew,2)
            if Inew(kk) > ub(kk)
                Inew(kk) = ub(kk)
            elseif Inew(kk) < lb(kk)
                Inew(kk) = lb(kk);
            end
        end
% perform the greedy selection
        fnew = fun(Inew);
        if fnew > fx(i,:)
            pos(i,:) = Inew;
            fx(i,:) = fnew;
        end
```

MEMORIZE THE BEST CHARGING CURRENT

```
 [optval, optind] = min(fx); % finding the best one
      BestFx(iter) = optval;  %best objective find value
      BestX(iter,:) = pos(optind,:); % best solution
 %
```

```
plot(BestFx, 'r','lineWidth',2);

xlabel('Iteration');

ylabel('Fitness Value');

title('Convergence Vs Iteration');

set(gca,'FontSize',20);

grid on;
```




```
end
```

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ABBREVIATIONS

BMS	Battery Management System
EPS	Electrical Power Supply
SGO	Social Group Optimization
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
CC	Constant Current
CV	Constant Voltage
CC-CV	Constant Current Constant Voltage
EV	Electric Vehicles
NiMH	Nickel Metal Hydride
LTO	Lithium Titanate Oxide
NCM	Lithium Nickel Cobalt Manganese Oxide
Li-ion	Lithium Ion
SOC	Stage of Charge
SOH	State of Health
OCV	Open Circuit Voltage

DOD	Depth of Discharge
SOE	Safe Operating Environment
OTR	Operating Temperature Range
SOA	Safely Operation Area
MPPT	Maximium Power Point Tracking