OPTIMIZATION OF BATTTERY MANAGEMENT SYSTEM ON NANO SATELLITE

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CERTIFICATION

This is to certify that the thesis titled **OPTIMIZATION OF BATTTERY MANAGEMENT SYSTEM ON NANO SATELLITE**, submitted to the school of postgraduate studies, African University of Science and Technology (AUST), Abuja, Nigeria for the award of a Master's degree, is a record of an original research carried out by **EDET DAVID KOKOETTE** in the **SYSTEM ENGINEERING DEPARTMENT** of the Institute of Space Science and Engineering (ISSE), an affiliate of AUST.

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Name	**Sign**	**Date**

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BY

A THESIS APPROVED BY THE DEPARTMENT OF SYSTEMS ENGINEERING

RECOMMENDED: _____ **19th November 2021**

Supervisor: Prof. Onuh Spencer Date

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DEDICATION

I like to dedicate this work to God the Almighty for his favor and faithfulness and to my wife, for her love and support are the impetus for my accomplishments.

ACKNOWLEDGEMENT

Firstly, I would like to express my appreciation and gratitude to the Institute of Space Science and Technology for their support. My prefunded gratitude to the director of the “Centre for Satellite Technology and Development” for providing a means, towards the completion of my tuition fee, I would like to thank Dr. Ale Felix for introducing and encouraging me to enroll as pioneer of the ISSE program. My thanks again go’s to my supervisor, Professor Spencer Onuh (Head of Department) for his detailed advice and guidance. I am so thankful to my second supervisor Dr. Essien Ewang for his support, encouragement and valuable assistance. My thanks to my colleagues in the ISSE Group and the Department of System Engineering; I would like to acknowledge the great attitude of all the staff members that I have interacted with at the institute of Space Science and Engineering (NASRDA).

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ABSTRACT

Battery Management Systems (BMS) are tasked so as to provide an 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 space environment. For a large scale of battery pack, the accumulation of the heat generated during the charging and discharging processes might lead to the increase in temperature in the battery pack and thus causing the faster acceleration of electrochemical reaction, this can reduce the battery lifespan and seriously affect the battery charging capability and safety. However, overcharging and the short circuit issue in high thermal condition of battery pack may cause battery damage. For this cause, this thesis aim is to optimizes the charging current so as to minimize the charging time for fast charging of battery before the satellite approaches eclipse, by utilizing a Social Group Optimization Algorithm to overcome the state of charge (SOC) problem whereby improving the battery lifespan. The approached used, account for the reduction of charge time with an efficiency 95.51% compared with other technique used. This entitles that this proposed method performed best over the previous technique and are easy to implement considering all the charging process, which allows maximum protection of the battery from overvoltage, overcharging and overheating conditions. The result shows an almost 9min decrease in the charging time without affecting the capacity and the life cycle which is most significant for the battery life.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND TO THE STUDY

Battery management system (BMS) is essential in small satellite because this prevent batteries from overcharged or over discharged, radiation projection overheating and the like (Jain & Simon, 2005). However this listed factor could result to extreme damage of the battery, other factors such as rises in temperature will drastically drain battery capacity and reducing the life span of the battery(Mousavi et al., 2016), as well dramatically lead to the end of satellite mission. Battery management system is as a crucial part in various electrical and electronic systems, e.g., commercial electronics device and electric vehicles that help to monitors 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 is capable to manage and adapt towards the changing of batteries characteristic over time since the applications require the parallel or series attachment of multiple unit battery cells (Khan et al., 2016).

Renewable energies are becoming popular worldwide over the last few decades due to the increasing attention on the environmental pollution issue caused by the usage of conventional energies. However, due to the natural, economical and technical issues, the renewable energies is becoming more difficult to be implemented in space exploration (Villela et al., 2019). To overcome this problem, battery management system (BMS) is a big solution for incorporate renewable energies into the small space craft or satellite. Lithium ion batteries have the potential to remain competitive in the world market due to the superior characteristic and performance of high energy efficiency and density, wide range of the safe operating temperature, higher rate of charging capability, longer cycle life and lower self-discharge rate

(Tomaszewska et al., 2019). Lithium ion battery is a power source with lots of electrochemical reactions during the process of charging and discharging. For a large scale of battery pack, the accumulation of the heat generated during the charging and discharging processes might lead to the rise in the overall temperature in the battery pack and thus causing the faster acceleration of electrochemical reaction, this 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 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 temperature, cells and modules in a battery pack behave differently and this causes the imbalance of the electrochemical over time, the difference in the rate charging and discharging, a difference in the state of charge (SOC) between adjacent cells, and the capacity loss (Quamruzzaman et al., 2016). Thus, a battery management system (BMS) is essential to maximize the battery performance by maintaining optimum state of charge, state of health, safety area of operation (SOA) and operating temperature range (OTR), (Rahimi-eichi, 2006). The extraction of Photovoltaic (PV) can be utilized for various aspects, one of the prominent used is in space exploration “battery charging”. independent domestic electric supply, and pumping (Chellakhi et al., 2021). The goal of an MPPT is to extract the available maximum power produced by the solar panel (PV) in stipulated climatic conditions (temperature and solar irradiation). In order to control the power supplied by the solar panel, thence 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 space craft mission such as the NASA mars exploration (“NASA Space Exploration,” 2015), (Lele, 2016).

There has been lot of research on going to provide an optimum method or means for battery management, diverse method and technique has been applied in the past to optimize the battery state of charge (SOC) and state of health (SOH).

1.2 STATEMENT OF PROBLEM

The electrical power supply unit is paramount in satellite systems; its main source is the battery energy technology, as this determines the life span of the satellite. Power failure as a result of battery run down, that is not been able to recharge, has been found to be a major limitation in satellite missions, however this limitation accounts for the problems in the design of 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 critically intervention; in this research we proposed a method for optimizing the time charge of battery by an improve state of charge estimation with the use of a hybridized algorithm. This, 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 are as follows;

I. To implement battery management system on Nano satellite
II. To optimized 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 battery management system in Nano-satellite system by developing a new optimization technique to improve the charge time of the battery thereby preventing the battery from undercharge, overcharge and over temperature; this will dramatically improve the lifespan of Nano-satellite missions.

1.5 RESEARCH METHODOLOGY

Intensive research on the existing optimization technique for battery life optimization was carried out in order to find an optimum method. MATLAB will be used to perform the optimization. The optimization function and the design constraints are determined and are introduced to the SGO algorithm to obtain the Best Cost or Cost Function of optimal current required to charge the battery.

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 discussions of 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, with the avoidance of doubt solar energy has positively impact the world economy, and ecology, although fossil fuels and greenhouse emissions have become 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 demand for energy is rapidly evolving as natural energy resources such as uranium, petroleum, and gas decreased in production due to an advance in technology in this 21th century to eliminate hazardous emission. The exponential increment in energy costs and environmental constraints is what led to the development of technological solutions allowing better control of spacecraft in space environment, the resources and the exploitation of the renewable energies in specific Battery technology has tremendously impact space exploration. Within the last two decades, extensive research is ongoing toward development of an alternate energy source; these technologies are emphasizing on 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, transportation 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, slight increment in charging rates or temperature exceeding operating region will dramatically accelerate battery degradation or damage the batteries and cause safety incidents. The development of safe, efficient, and non-destructive algorithms to fast charge Li-ion batteries is therefore highly desired and has gained an increasing interest over the past fifteen year.

A desirable intent to control and monitor the health of the battery life is what leads to invent of battery Management system.

2.2 REVIEWS OF RELATED WORKS

Recently there has been diverse approach proposed by researcher to optimized the battery lifespan by maintaining an appropriate battery parameter specifications, review publication has details on the various techniques used to optimizes the performance of battery cell, notwithstanding lots of algorithm has been used to seek the improvement in the charging rate and balancing the cell voltage, (K. Liu et al., 2019) discussed A brief review on key 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. Surveyed was done on battery state estimations for the state of charge, state of health and internal temperature. Several key and traditional battery charging approaches with associated optimization methods are discussed. Further review on Technologies in battery management system authored by (Hamsavarthini & Kanthalakshmi, 2020) where he identify in details 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 technology of choice from portable garget, electric vehicles, grid storage and satellite. The exponential increase in design and production of satellites are 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) reviews the literature on the physical phenomena that limit battery charging speeds, A review on the key issues for lithium-ion battery management in electric vehicles was authored by (Lu et al., 2013) This work present, 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.

Electric vehicle can be dynamic or static system that utilizes electrical component, in the case of spacecraft, satellite are electric vehicles. (Cui et al., 2020) authored an application of evolutionary computation algorithm in multidisciplinary design optimization of battery packs for electric vehicle, 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 performance of the enclosure. Moreover, the results presented an improved performance of NSGA-II when combined with other artificial intelligence algorithms. The results suggest that EC can be integrated in 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 deeply in the kind or type of battery cell used, (Karkuzhali et al., 2020) has done intensive research on Lithium ion (Li-ion) battery & Nickel metal hydride battery in terms of aging and effect of temperature using their state of charge (SOC) and open circuit voltage (OCV).

There are lots of battery management approaches which has 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 distribution network of distribution system operators (Boonluk et al., 2020) in this work the adoption of Genetic algorithm (GA) and particle swarm optimization (PSO) were 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) proposes 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. Particle swarm optimization of a hybrid

wind/tidal/PV/battery energy system was applied to remote area (Mohammed et al., 2019), The total net present cost (TNPSC) is introduced as the objective function, taking into consideration 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 by 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 so that the developed algorithm can run on an 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 healthy and aged Li-ion battery cells in order to validate the proposed algorithm. Both simulation and experimental results demonstrate that the developed algorithm is able to 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 optimized PID parameter which is 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 charge problem. An Optimal siting and sizing of battery energy storage was carried out by (Boonluk et al., 2021) where he elaborate on the case Study 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 in order 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 focused 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 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 solar charge, multiple charge modes where compared with traditional common methods. A novel work on real-time estimation of state-of-charge using particle swarm optimization on the electro-chemical 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 which can run on an embedded device with reasonable utilization of CPU and memory resources and still be able to estimate SOC with acceptable accuracy. Differential charging of cells with age has turned balancing management systems into an important research subject(Velho et al., 2017) the author method was to proposes 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 as 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 in 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, it was 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) this work concluded that the stud

genetic algorithm combined with the flow resistance network and heat dissipation models can quickly and efficiently optimize the air-cooled BTMS to improve the cooling performance. The design optimization of battery holder for electric vehicle (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 not only in accurate and reliable state monitoring, but also in effective thermal management of lithium-ion batteries (Q. K. Wang et al., 2017). Today's batteries deliver a lot of current 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 be used to 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 which makes the operation more economical. (Ananthraj & Ghosh, 2021) Battery management system keeps the battery safe, reliable and increases the senility without entering into damaging state. In order to maintain the state of the battery, voltage, current, ambient temperature different monitoring techniques are used. . BMS is an essential module which leads to reliable power management, optimal power performance and safe vehicle that lead back for 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 life of the cell. A novel cell-balancing algorithm which was used for cell balancing of battery management system (BMS) was proposed in this paper. Cell balancing algorithm is a key technology for lithium-ion battery pack (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 reduces its operational life and affects its performance of the battery (Qays et al., 2020). It is important to perform reliability check for every battery design model (Xu et al., 2018) proposes a distributed battery management system (BMS) to meet the reliability design requirements which consist of two parts that is 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 function 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 operation 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 by means of an electro-chemical 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 important to known that a cell is related to one battery and a battery is the combination of cells in a pack noticeable as 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 reuse after discharge that is its chemical process are 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 are movement of electrons during charging and discharging making its 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). Anode is the negative electrode and the cathode is the positive electrode. Zinc has been the most common anode, although the most effective anodes are alkali metals such as lithium and sodium. 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, it is easiest to look at a common primary cell. The most familiar primary cell is the Leclanché cell. It is also called "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 1

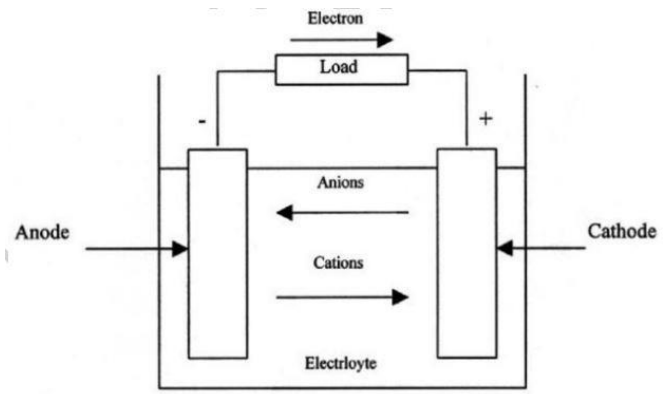

Figure 2.1: Electrochemical operation of a cell (discharge).

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, in the electrolyte, anions (negative ions) flow to the anode 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)

$$\mathrm{Zn} \rightarrow \mathrm{Zn}^{2+} + 2\mathrm{e}^{-} \quad (1)$$

Positive electrode reduction (gain of electrons)

$$2\mathrm{MnO}_2 + 2\mathrm{NH}_4^{+} + 2\mathrm{e}^{-} \rightarrow \mathrm{Mn}_2\mathrm{O}_3 + 2\mathrm{NH}_3 + \mathrm{H}_2\mathrm{O} \quad (2)$$

The overall reaction becomes,

$$\mathrm{Zn} + 2\mathrm{MnO}_2 + 2\mathrm{NH}_4^{+} \rightarrow \mathrm{Zn}^{2+}\mathrm{Mn}_2\mathrm{O}_3 + 2\mathrm{NH}_3 + \mathrm{H}_2\mathrm{O} \quad (3)$$

2.2.5. 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 direction of 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 larger 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 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, which also precipitate as PbSO4 on that electrode. The discharge reaction can be written as follows:

Negative electrode:

$$Pb^{2+} + 2e^{-} \rightarrow Pb \quad (9)$$

$$PbSO_4 \rightarrow Pb^{2+} + SO_4^{2-} \quad (10)$$

Positive electrode:

$$Pb^{2+} + 2H_2O \rightarrow PbO_2 + 4H^{+} + 2e^{-} \quad (11)$$

$$PbSO_4 \rightarrow Pb^{2+} + SO_4^{2-} \quad (12)$$

Overall reaction:

$$2PbSO_4 + 2H_2O \rightarrow Pb + PbO_2 + 2H_2SO_4 \quad (13)$$

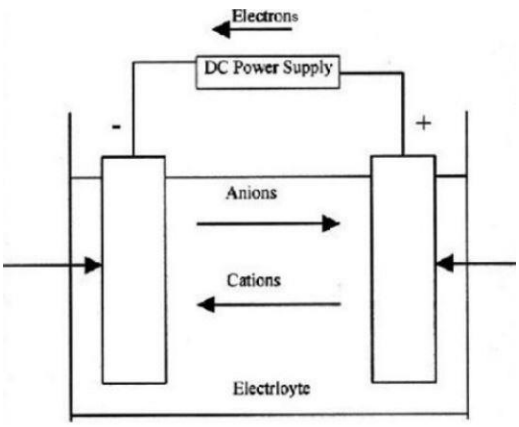

Figure 2.2: Electrochemical operation of cell (charge)

*2.3.*5 Traditional Battery and Cell Chemistries

There is a wide range of different cell chemistries that 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 an 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 in a variety of sizes and designs, has good high-rate performance, moderately good low and high temperature performance, easy state of charge indication and good 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 for 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 an 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 biggest drawbacks, as is a fairly high rate of self-discharge at high temperature. 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, usually alloys of lanthanum and rare earths 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 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 the major consideration. It was the main 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 in effort to improve performance further. This includes a drive for increased energy density, rate capability and the ability to provide high power, as well as long cycle life and thermal stability for increased safety. Attention has also focused on fast charge capability as well as 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 has focused on many aspects of cell chemistry to improve overall performance. However, large attention has been placed on positive cathode materials development as it has a large role to play in determining overall specific energy density. Depending on the electrolyte material choice, lithium-ion batteries can be separated into two categories, the liquid lithium-

ion cells, which use liquid electrolytes, and the solid-state lithiumion cells, which use inorganic or polymer electrolytes.

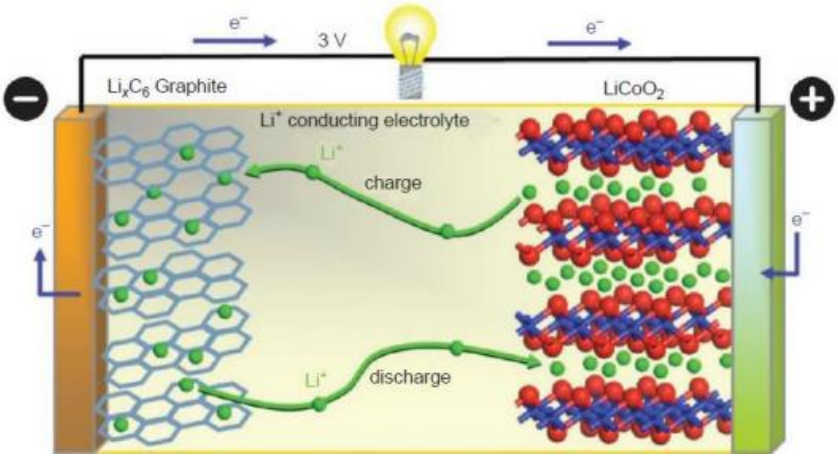

Figure 2.3: Lithium Ion Battery Cell Structure

Lithium Cobalt Oxide (LCO) - Lithium Cobalt Oxide has been the most widely used positive electrode material in lithium batteries for many years, being used for laptop, mobile phone 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 condition.

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 characteristic to LCO and is 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 and 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 to 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 longer life applications. They are a significant improvement over lithium cobalt oxide cells in terms of 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 as a result of their spinel structure and are unstable at higher temperatures in 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 and/or high specific power whilst being considered safer and more cost effective than LCO and LFP but with reasonable life expectation.

Lithium Titanate Oxide (LTO): These cells replace the graphite negative electrode with lithium titanate. This negative electrode material is compatible with any of the above positive electrode materials but is commonly used in conjunction with Manganese-based materials. They offer superior rate capability and power combined with wide operating temperature range. They are considered a safer alternative to the graphite material due to higher potential vs 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 capacity of a battery and is measured in terms of ampere-hours (Ah). The ampere-hour capacity is a function of active materials in the battery.

The capacity of a battery is also expressed on energy basis by multiplying ampere-hours by the voltage of the battery. Specific energy is defined as the amount of energy a 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 usually 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 usually measured in watts per liter.

2.3. TYPES OF LITHIUM ION BATTERIES

There are several types of lithium ion batteries available today, (Lu et al., 2013) although 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 system (Issn et al., 2021). The three most relevant to satellite system 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).

2.4. 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 models were 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 capacity of the battery. A discharge rate normalizer determines the lost capacity at high discharge currents

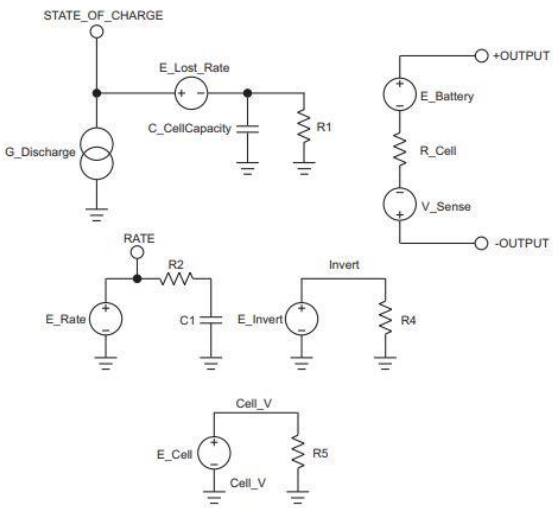

Figure 4: Basic functional schematic covering all the modeled cell types

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 representing the battery's resistance.

Figure 3 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 much experimental data on the battery's behavior. Furthermore, the models are less accurate, having an error of approximately 10%.

2.4.1. The Equivalent Circuit of a lithium ion Battery Model.

There are 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).

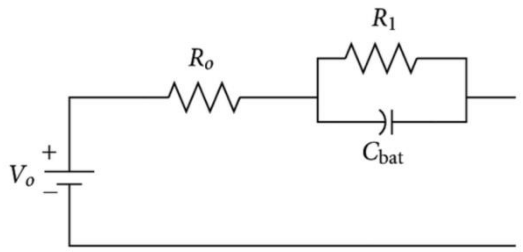

Figure 2.5: A simple equivalent circuit of a battery

Electrical models accuracy of which 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).

2.4.2. Thevenin Based Electrical Model:

A Thevenin based model, uses a series resistor (RSeries) 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 difficult, 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.

2.4.3. The battery management system (BMS)

The goal of a BMS system is to maximize the life, efficiency and safety of the battery. 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, is dependent on the application, as well as balancing energy efficiency and charge capacity with cost and complexity. The whole range of tasks, as seen in Figure 2.1 will be discussed in this chapter, so that an understanding of the WBMS, design can be obtained.

2.4.4. 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 in regards to 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 rate of the voltage measurements are dependent upon its application and must be balanced at the expense of making faster systems. Additionally the accuracy of the voltage measurement is dependent upon 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 SOC can be accurately estimated by the BMS system.

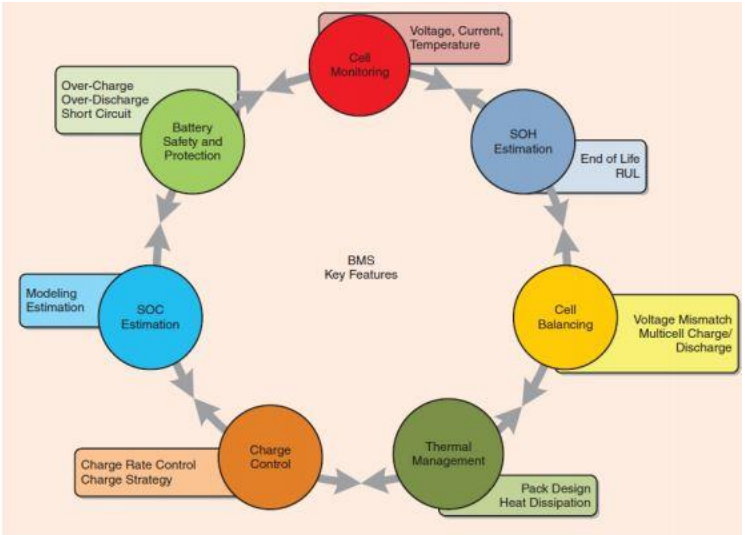

Figure 2.6: Key features of BMS

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 pack current or cooling systems when necessary. The final measurement needed by many BMS systems is the current draw. This

measurement is needed to calculate depth of discharge (DOD), state of charge (SOC), impedance, and IR compensation.

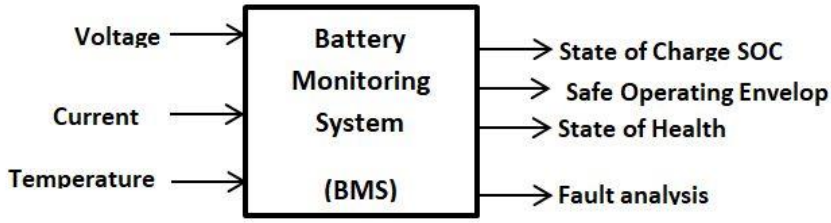

Figure 2.7: BMS task

Additionally, the current measurement can help increase the lifetime of the system by preventing excess current draw and operation of the cells outside of their SOE. In addition to measurements, a BMS needs to provide protection for the cells. Especially for Lithium ion chemistries it is critical that the battery system does not operate outside of their SOE. By ensuring the systems pack current, cell voltage and temperature, both peak and continuous, the system is able to run in a safe manner. However, if the system begins to operate outside of the SOE the BMS is able to interrupt the charging or discharging current in order 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. Safe operation can be accomplished by two main types of protectors. The first is a designated protection circuit. This circuit is directly connected to the cell and no processor logic is connected 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 10 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 than the operating parameters need to be sent to a microprocessor. The second type is a system level protector, where a master module is

receiving the cell operation parameters and making a pack-wide determination using software and control algorithms whether operation needs to be stopped.

2.4.5. 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 the use of 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 to a BMS should manipulate charge and discharge though IR compensation.

2.4.6. Cell Balancing

As previously mentioned LIBs have very strict SOA with regard to cell voltage. When a cell begins to charge, the charge capacity begins to rise 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, maximum capacity, and 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 reach the minimum voltage, leaving the rest of the cells partially charged. This issue will begin to 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 has equalization energy consumption five times greater than active balancing techniques, assuming average converter efficiency (Baroniti). While this balancing scheme is slow and inefficient, the simplicity of operation leads to it use in certain applications. The second balancing category is active cell balancing, defined by shuttling charge between cells in order to balance the cells SOC. This balancing system has three main subsystems Capacitor, Inductor / Transformer, and converter. Capacitor based cell balancing is normally referred to 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 cost of component price and high switching frequency, you need capacitors across the batteries to filter the high frequencies. Similar to the previous 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 with the attempt to balance the two. Multi-tier systems, currently being researched, use far less complicated 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 is dependent upon the application and each has their 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 charge between the cells. This system gives the ability to rapidly shuttle the charge 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 topics such as how currents flow between the batteries when they are connected. This type of research will allow for a better understanding about batteries and enable further development of control strategies.

2.4.7. 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, in order to allow the battery system to allow for system cooling. Additionally operating the batteries at extreme temperatures impact the cell life of those batteries, by maintaining the SOA cell life can be enhanced.

2.4.8. Charge Control

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 a 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, and then when the cell has reached its maximum SOA voltage a constant voltage is applied to add additional 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 the 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.

2.4.9. State of Charge Estimation

State of Charge, SOC, is a critical parameter of the battery; however, it cannot be measured. SOC is a parameter, normally given in terms of a percentage, that refers to the amount of charge capacity remaining, given in milliamp hours, maH. Discharge capacity is the amount of current a battery is able to discharge over time. While there are multiple models that can lead to an SOC estimation, including OCV, Coulomb counting methods and BP neural network , all of them look at discharge characteristics and try to fit them to a mathematical model in order 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).

2.4.7. Modeling Estimation

Accurate prediction of remaining cell capacity is critical for applications in Nano-Satellite. The BMS can use the battery model to create an accurate SOC estimation. While continued research is needed to further facilitate accurate and efficient battery models they can still play an important 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 fairly 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 is able to operate at quicker refresh intervals.

2.8. 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 over charging or improper charging will speed up the degradation process of the battery dramatically. Compared with other types of battery,

the Li-ion battery has fairly stable performance but less cycle life at high-temperature conditions, while 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 temperature, well below freezing
Lead acid	1) Higher temperature leads to lower –threshold by 3 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), the enough accurate estimations of battery SOC, SOH and temperature, proper battery charging approaches can be effectively designed, further to charge battery from initial state to final SOC target value. Meanwhile, the charging approaches can also protect batteries from overheating, prolong the service life and improve the capacity utilization.

2.8.1 Conventional battery charging approach

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

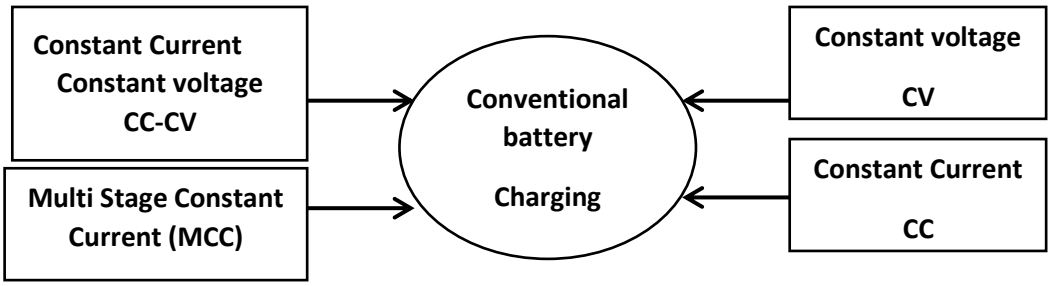

Figure 8: Conventional charging approach

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 place up on the CCCV charging and MCC charging approaches. The CC charging is a simple but rough approach which adopts a small constant current rate to charge battery during the whole charging process. The CC charging is terminated when the time-to-charge reaches a predefined threshold. This charging approach is 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 CC charging approach is to search a suitable charging current rate which is capable of equilibrating battery charging speed and capacity utilization. For large current rate in CC charging, the charging speed is improved but the battery aging process will be aggravated accordingly. For small current rate in CC charging, high capacity utilization is achieved but too low current rate will slow down the battery charging speed and further have a negative effect on the convenience of its sage. Another simple conventional charging approach is the CV charging which totally adopts a predefined constant voltage to charge batteries. The primary superiority of using CV charging is to avoid over-voltage and irreversible side reactions which may occur in the charging process, further to prolong battery cycle life. When the CV charging is applied, the charging current will gradually reduce due to the low acceptance with

progressing recharge. This approach however needs a high current rate in order to keep constant terminal voltage at the early stage of the charging process, which is easy to cause the battery lattice collapse, and battery poles broken. The common problem of CV charging approach is also to select a proper value for charging speed, electrolyte decomposition and capacity utilization. Reference (Khan et al., 2016) summarizes the characteristic of CV charging, and it concludes that CV charging approach is capable of effectively improving the charging speed but bringing great damages to the battery capacity. This is primarily caused by the sharp increase of charging current when battery is charged from low SOC. The start current is far larger than the acceptable range of the battery, leading to the battery lattice frame collapses, and further aggravating the pulverization of the active substance in battery pole. But as battery capacity increases, the charging current will reduce dramatically. The charging speed for 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 Figure blow.

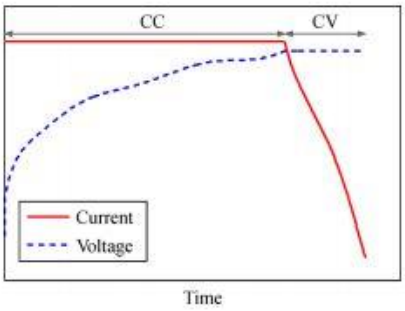

Figure 2.9: Battery current and voltage of CC-CV charging approach

In this approach, a battery is firstly charged by a predefined constant current in CC phase and the battery voltage will increase to the maximum safe threshold. Afterwards, 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 lead acid battery with the preset values of constant current as well as constant voltage which are 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 the applications of Li-ion battery CC-CV charging 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 CC-CV charging process, CC stage and CV stage can be complementary in some ways, the capacity loss caused by the large electrochemical polarization in CC stage will be effectively compensated by CV stage. Hence the CC-CV charging approach is superior to the sole CC as well as sole CV charging in the applications of space craft, and has been selected as a benchmark to compare with the performance of other newly developed battery charging approaches(Xu et al., 2018). Although 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. Battery charging speed of CC-CV approach is primarily determined by the constant current rate, while 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, 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}> … >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.

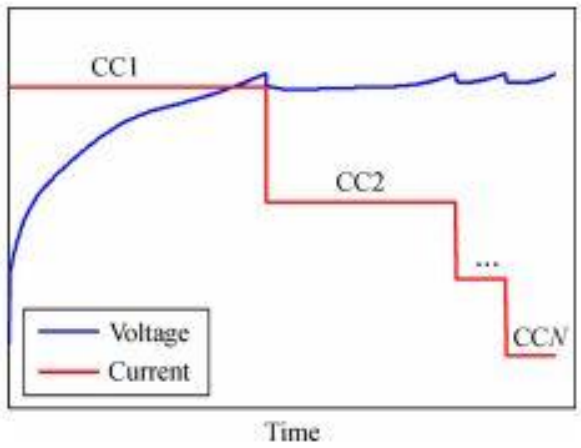

Figure 2.10: Battery current and voltage of MCC charging approach

This decrease 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 standard MCC approach will be usually a bit slower than the standard 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 loss, temperature variation	1) Constant current rate in CC phase; 2) Constant voltage in CV phase; 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 gives a brief comparison of 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 need to be considered. However, these simple charging approaches would cause many charging problems such as battery lattice collapse, and battery poles broken. It is significantly difficult to equilibrate battery capacity utilization and charging speed by using just sole CC or CV charging approach. In order 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 reaction such as lithium plating during these charging process are still at its primitive stage and will be a thriving area of research in the field of space applications.

2.9 STATES OF CHARGE ESTIMATION TECHNIQUES

SOC is analogous to the fuel gauge in an automobile, which makes it a very 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:

- Non-model based method 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.

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

2.9.1 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 discharge operation. The current can be integrated as shown in the equation 2.4 to determine the SOC.

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

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. From the equation, it is clear 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, then it could lead to an offset in estimated SOC. Inaccurate measurement of current 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.

2.9.2 Open Circuit Voltage

Open Circuit Voltage (OCV) is the voltage across the battery/cell terminal under no load condition. SOC bears a linear relationship to OCV. This property makes OCV a suitable candidate to directly determine SOC. However, this technique would be suitable 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, 2.0 to 3.65V which corresponds to 20% - 80%, even a small error in measurement of OCV would lead to large estimation errors. For the aforementioned reasons this technique would not be suitable for online estimation.

2.9.3 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 important methods. A series of papers have proposed the Extended Kalman filter method to estimate battery states like SOC, power fade, 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 parameters of the battery for different chemistries, different operating conditions, and different health conditions must be determined. A wide variety of 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 for the estimation of SOC.

2.10 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 required level of all these behavioral traits to be capable of solving, effectively and efficiently, complex problems in life. But very often, complex problems can be solved with the influence of traits from one person to other or from one group to other groups in the 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 upon this concept, a new optimization technique is proposed which is named as 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 is corresponding 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 in the group. The procedure of SGO is divided into two parts. The first part consists of the 'improving phase'; the second part consists of the 'acquiring phase'. In '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 is the one having the highest level of knowledge and capacity to solve the problem. And in the 'acquiring phase,' each person enhances his/her knowledge with the mutual interaction with another person in the group and the best person in the group at that point in time. 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 and each person X_j is defined by $X_j = X_{j1}, X_{j2}, X_{j3},..., X_{j\,D}$), 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.

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

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

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

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

$$Xnew_{i\,j}\ = c\ *\ Xold_{i\,j}\ + r\ *\ (gbest(j) - X\ old_{i\,j}) \qquad (17)$$

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 self-introspection parameter. Its value can be set from $0\ <\ c\ <\ 1$.

2.10.2 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 greatest influence on others to learn from him/her. A person will also acquire something new from other persons if they have more knowledge than him or her 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

$$Xnew_{\ i,j} =\ X\ old_{\ i,j} +\ r1\ *(X_{i,j}\ -\ X_{r,j} + r2\ *\ (gbest_j\ -\ X_{i,j}) \qquad (18)$$

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 two independent random 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

2.11 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 population chosen by user. For SGO, the population size indicates the number of persons and the features indicate the number of traits of a person. This population is articulated as:

$$\text{Population}\ =\ \begin{bmatrix} x_{1,\ 1} x_{1,2} x_{1,3} & \cdots & x_{1,D} \\ \vdots & \ddots & \vdots \\ x_{N,\ 1} x_{N,2} x_{N,3} & \cdots & x_{N,D} \end{bmatrix} \tag{19}$$

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 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 thorough study of our investigated problems and r is a random number, $r \sim U(0,1)$.

Accept $Xnew$ if it gives better function value.

Step 4: Acquiring phase

As explained above, in the acquiring phase, a person of social group interacts with the best person, i.e., gbest of the group and also interacts randomly with other persons of the group for acquiring knowledge. The mathematical expression is defined in “Acquiring phase”.

Step 5: Termination criterion

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

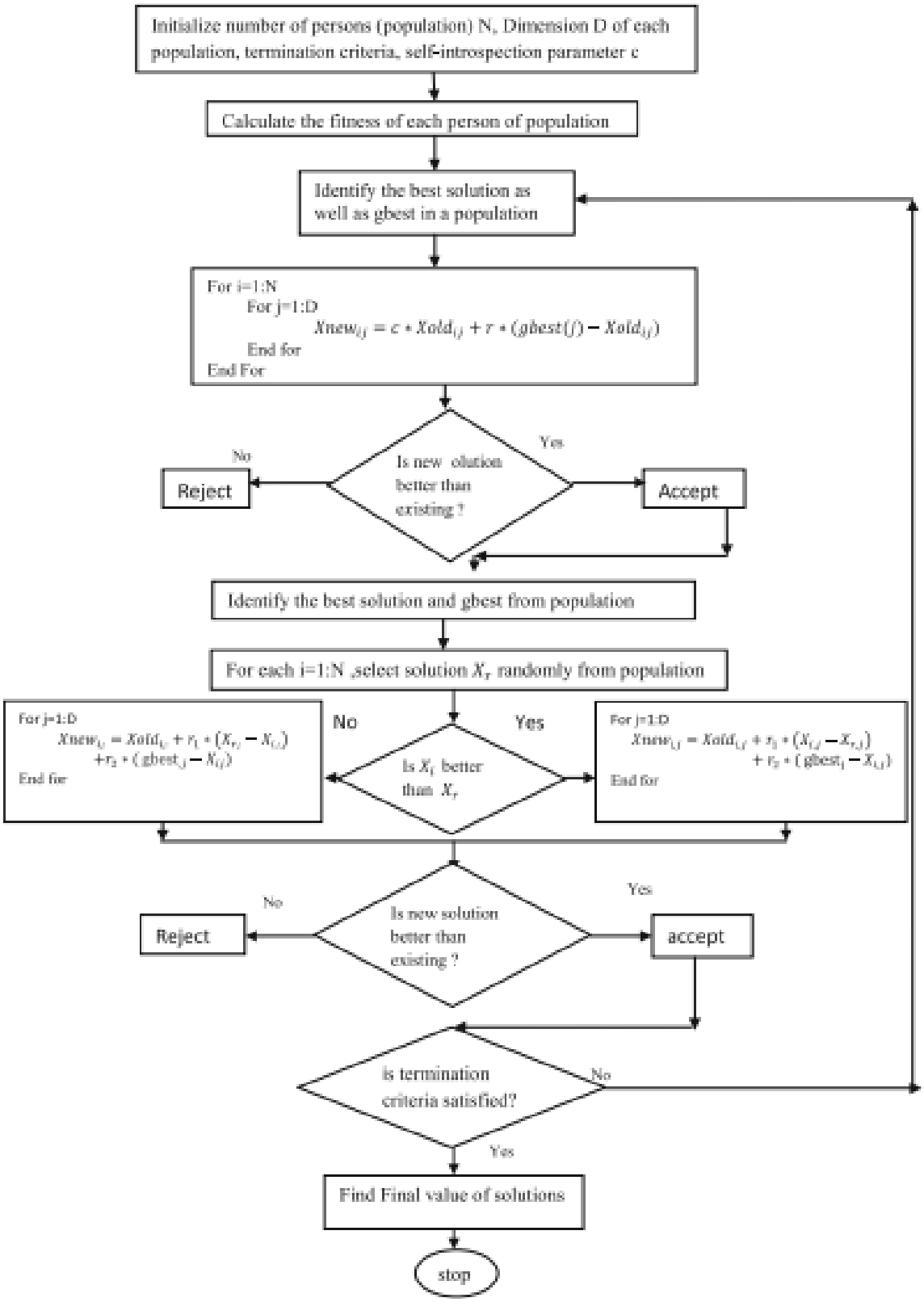

Figure 2.11: Flow chart of SGO Algorithm

As this optimization technic was developed and published in 2016, there has been lot of study been carried out using the SGO algorithm, (Das et al., 2020) utilized the SGO to optimized 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 a 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

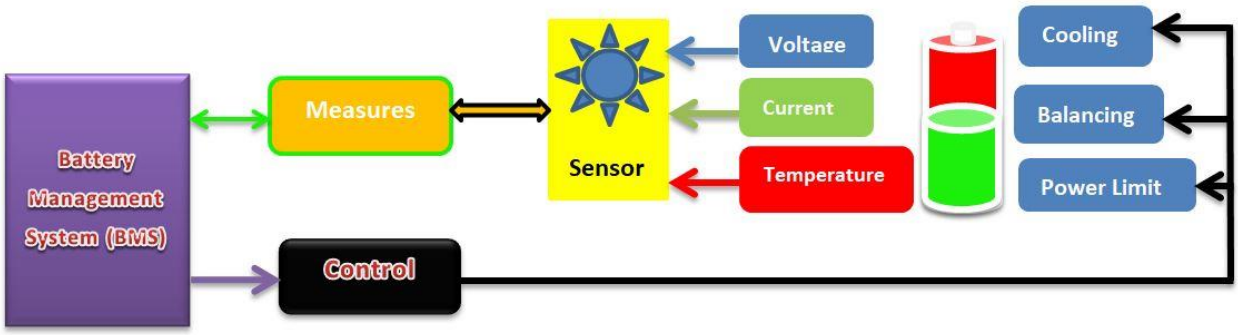

Figure 3.1: Block diagram of a BMS

The above figure presents the block diagram of the BMS, a sensor receives battery parameter (which is voltage, current and temperature) into the BMS, and this now compared the initial state of charge (SOC) of the battery and then performs cooling, balancing and power limiting controls. The system is a close loop system with a feedback mechanism.

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

We consider three particles (Voltage, Current and Temperature) this are associated with the actually 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 wanders through in the solution area and recalls the best objective function value (SOC), which has already been discovered; the fitness value is saved and known.

3.2. 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 phase. We present three objective function consists of the battery charging time, energy loss and the battery temperature change.

The constraints considered during the charging process notwithstanding to find the optimal current so as to minimize the time required to move the state of charge (SOC) from a low level SOC to it desired level with a short time.

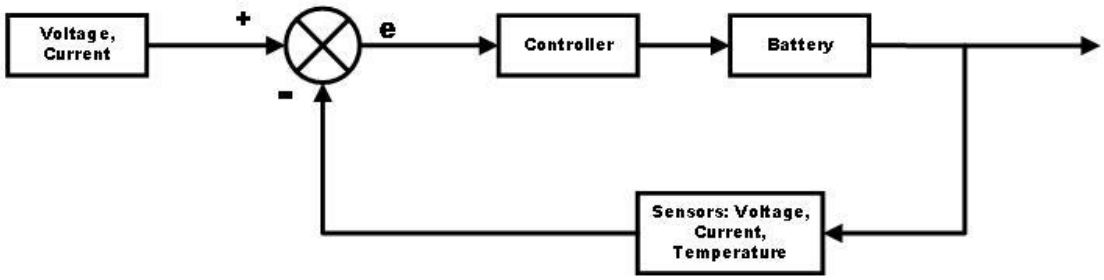

Figure 3.2: Demonstration of the control strategy flow

3.2.1 Problem Formulation

3.2.2.1 Optimization Model Construction and Solution

To formulate the problem of battery charging, some key 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 key 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 larger energy loss results to thermal run away this mean that the battery eventually will experience a drop in it charging efficiency. The battery charging time and energy loss are critical issues when optimizing the battery, 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 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:

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

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

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

Table 3.1: Parameter definitions one

$\mathfrak{C}_{C_T}$ *and* $\mathfrak{C}_{E_{\emptyset l}}$	Cost function.
T_{st}	Is the sampling time 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;

$$\begin{cases} D_1 * \dot{T}_{in} = i^2 * R + \mathfrak{B}_1 * (T_{sh} - T_{in}) \\ D_1 * \dot{T}_{sh} = \mathfrak{B}_1 * (T_{sh} - T_{in}) + \mathfrak{B}_2 * (T_{amb} - T_{sh} \end{cases} \tag{3.4}$$

By adopting $Q = i^2 * R$

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

$$\begin{cases} T_{in}(\mathfrak{B}+1) = \left(1 - T_s * \frac{\mathfrak{B}_1}{D_1}\right) * T_{in}(\mathfrak{B}) + T_s * \frac{\mathfrak{B}_1}{D_1} * T_{sh}(\mathfrak{B}) + \frac{T_s}{D_1} * i^2(\mathfrak{B}) * R \\ T_{in}(\mathfrak{B}+1) = T_s * \frac{\mathfrak{B}_1}{D_2} * T_{in}(\mathfrak{B}) + \left(1 - T_s * (\frac{\mathfrak{B}_1+\mathfrak{B}_2}{D_2}\right) * T_{sh}(\mathfrak{B}) + \mathfrak{B}_2 * T_s * \frac{T_{amb}}{D_2} \end{cases} \quad (3.5)$$

From the above equation (3.5)

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

Now the temperature rise index can be formulated as

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

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 $\mathfrak{C}_{TR}$ $becomes$;

$$\mathfrak{C}_{T_{rise}} = T_s * (\sum_{\mathfrak{B}=0}^{\mathfrak{B}_{tf}} \tilde{T}_{in}(\mathfrak{B}) + \sum_{\mathfrak{B}=0}^{\mathfrak{B}_{tf}} \tilde{T}_{sh}(\mathfrak{B})) \quad (3.6)$$

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

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

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

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

T_s Is the sampling time period of the battery, it is process in one seconds.

3.2.2.2 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 achieve during optimal charging process.

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

$$\begin{cases} SOC(\mathfrak{B}) = SOC(\mathfrak{B}-1) - \frac{T_s}{C_n} * i(\mathfrak{B}-1) \\ V_1(\mathfrak{B}) = a_1 * V_1(\mathfrak{B}-1) - b_1 * i(\mathfrak{B}-1) \\ V_2(\mathfrak{B}) = a_2 * V_2(\mathfrak{B}-1) - b_2 * i(\mathfrak{B}-1) \\ A_1 * \tilde{T}_{in}(\mathfrak{B}) + B_1 * T_{sh}(\mathfrak{B}) + C * R(\mathfrak{B}) * i^2(\mathfrak{B}) \\ A_2 * \tilde{T}_{in}(\mathfrak{B}) + B_2 * \tilde{T}_{sh}(\mathfrak{B}) \end{cases} \tag{3.10}$$

$$V(\mathfrak{B}) = V_1(k) + V_2(\mathfrak{B}) + i(\mathfrak{B}) * R(\mathfrak{B}) + U_{ocv} \tag{3.11}$$

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

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

Table 3.2 Parameter definitions two.

S_0	initial SOC state during battery charging process
S_{t_f}	final SOC state during 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 constant increase of the battery voltage until its

approaches V_{max} $bound$. At this point the circuitry switching, the CC is transferred to CV to continues 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 $i_{CV}(\mathfrak{B})$ $is\ thus$ calculated, the objective function $\mathfrak{C}_{charge_cV}$is then calculated based on the charging profile.

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

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

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

Subject to:

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

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

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

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

Table 3.3 Parameter definitions three

$\mathfrak{B}_{cc}$	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 temperature weights the interior temperature and the surface temperature.

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

3.3 PERFORMANCE ARCHITECTURE

Some parameters of the battery defers 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 the complicated optimization problem. SGO algorithm is employed in this work to solve the

nonlinear, time-varying, complicated battery optimal charging problem. The optimization process undergoes three phases which are the searching phase, the improving phase, and 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 new solution and the calculation of new fitness is initiated by apply greedy selection. This will select the initial charging profile by comparing. The acquiring phase will find new solution then calculate the new fitness, apply greedy selection then lastly memorize the best solution. It is convenient and simple to adopt this optimization algorithm for battery optimal charging strategy since there are no algorithm specific parameters that need to be adjusted by 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 in discussed in section 3.2 and to obtain the suitable charge current profile for battery optimal charging.

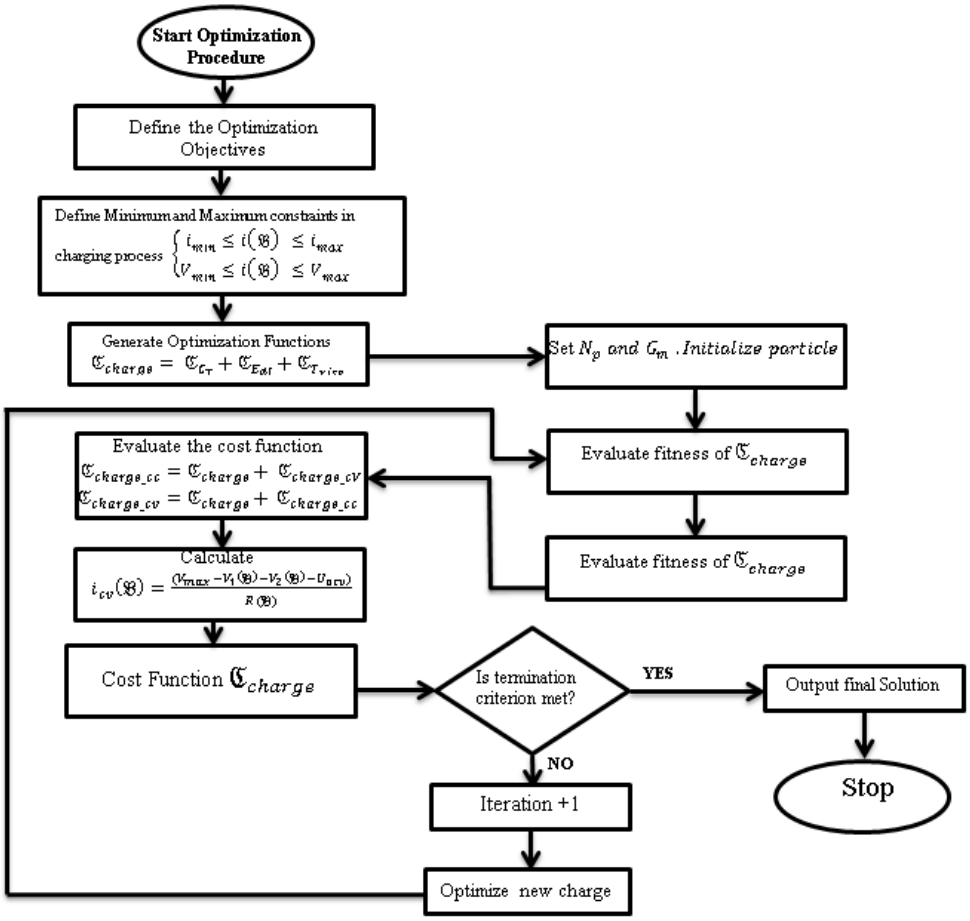

Figure 3.3: Flowchart of implementing the Social group optimization Algorithm methods for battery optimal charging strategy

3.3.1: Flowchart Execution Explanation

Step 1: Define the optimization objectives, define minimum and maximum constraints in charging process 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 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 to 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 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, terminate the CV stage. When the termination criteria have been satisfied, terminate the whole optimization process.

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

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

3.3.2 Simulink Implementation

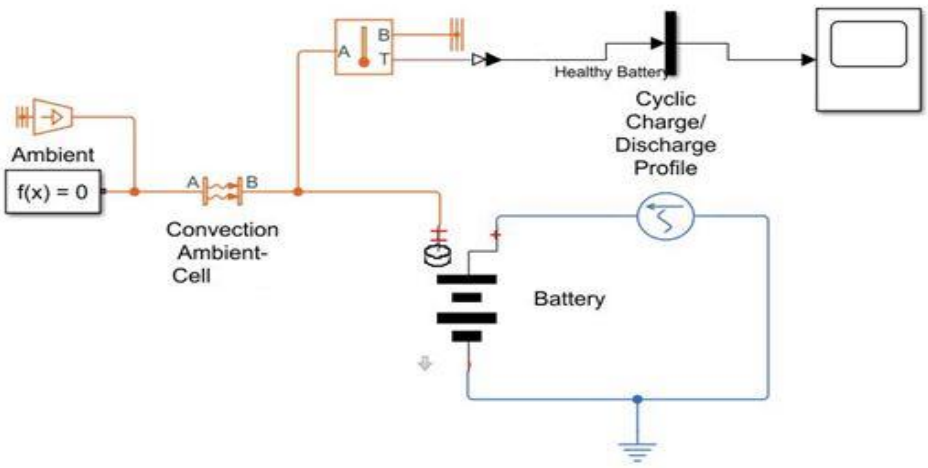

Figure 3.4: Battery Pack Schematic

CHAPTER FOUR

RESULT AND DISCUSSION

4.1. Experimental Setup

The experiment was carried out with MATLAB Simulink to optimize the battery state of charge, however it is true that the state of charge (SOC) cannot be measured, it is given in terms of its percentage, it refers to the amount of charge capacity remaining, given in milliamp hours, mAh.

$$SOC = \frac{\text{Capacity Remainig}}{\text{Total capacity of battery pack}} \times 100 \qquad (4.1)$$

From the above equation we can determine the state of charge of a battery cell.

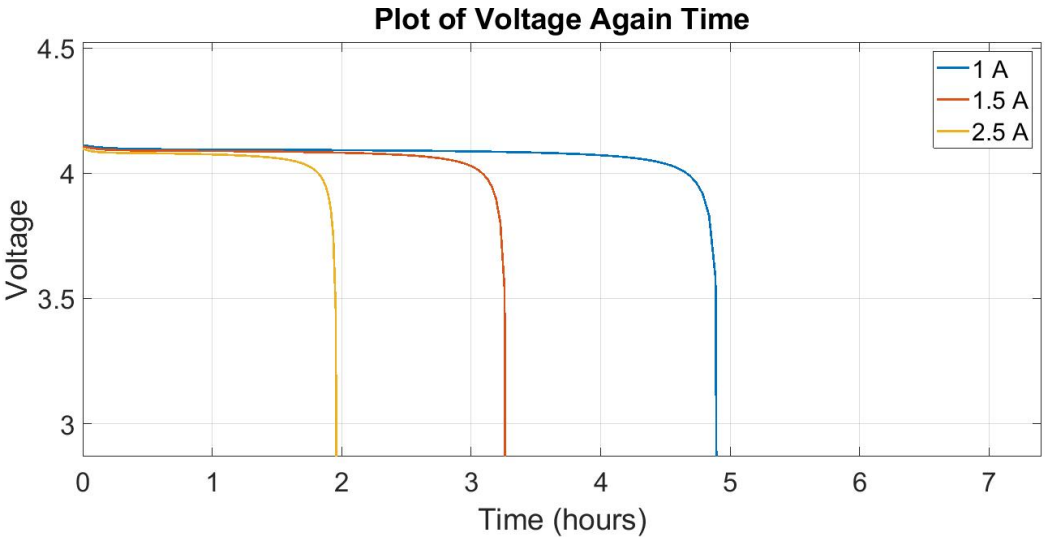

Figure 12: Effect of temperature on nominal current discharge characteristics

Figure 4.1 above shows the voltage profile with respect to the current in Ampere, it is clear to see that for the battery to attain optimum voltage at 4.2V it charges for 2hrs with a charging current of 2.5A and also with a charging current of 1.5A the battery will charge at 3hr20min, for a charging current of 1A the charging time of the battery is 4hr58min.

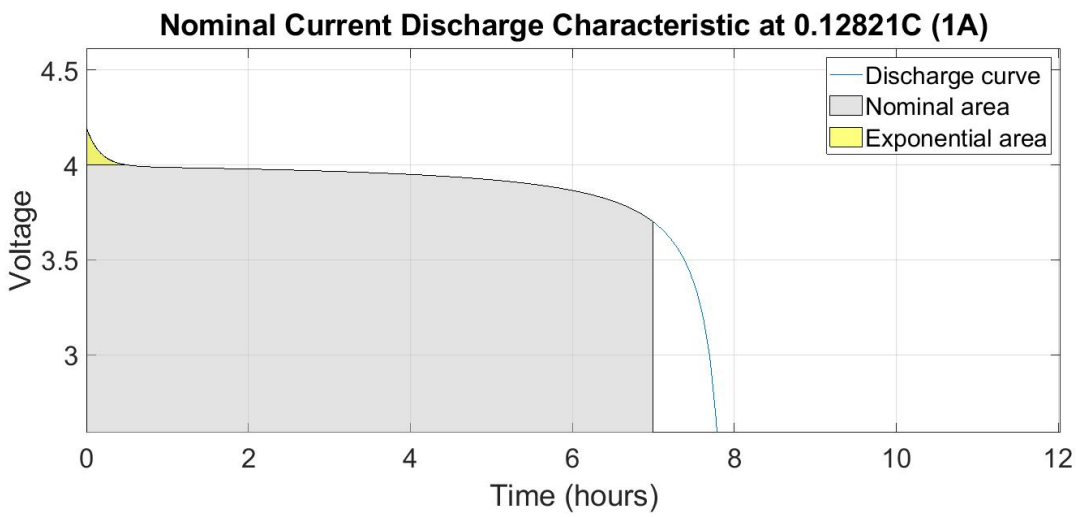

Figure 4.2: Discharge characteristics

Figure 4.2 present the discharging curves of the battery at 1A, 1.5A and 2.5A. The curves show that the battery was charged almost at its full capacity (7800mAh) using the proposed technique.

Using the proposed technique, the charging time of the battery was decreased without affecting its life cycle and charge capacity. Simulation was performed using MATLAB Simulink to validate the proposed technique.

4.2. Simulation Validation

The simulation was carried out using MATLAB

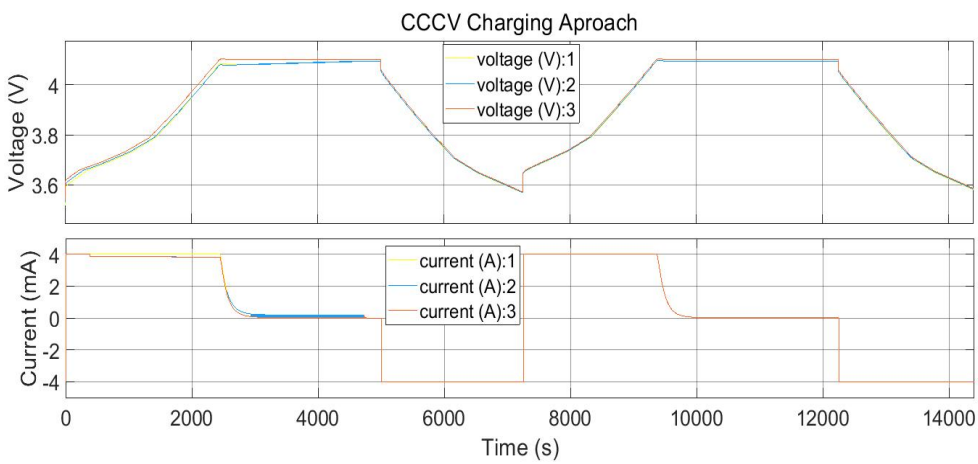

Figure 4.3: A Plot to Show the relationship between voltage and Current

In figure 4.3 the battery voltage rose from 3.6V to it optimum voltage 4.2V during charging ,the battery charges fast at the beginning until it reaches its absorption stage and then charge slow during it float stage, it then stop charging when I = 0. It utilizes the constant current (CC) approach to discharge, this discharge process occurs when SOC = 99% and charges when SOC is 30%.

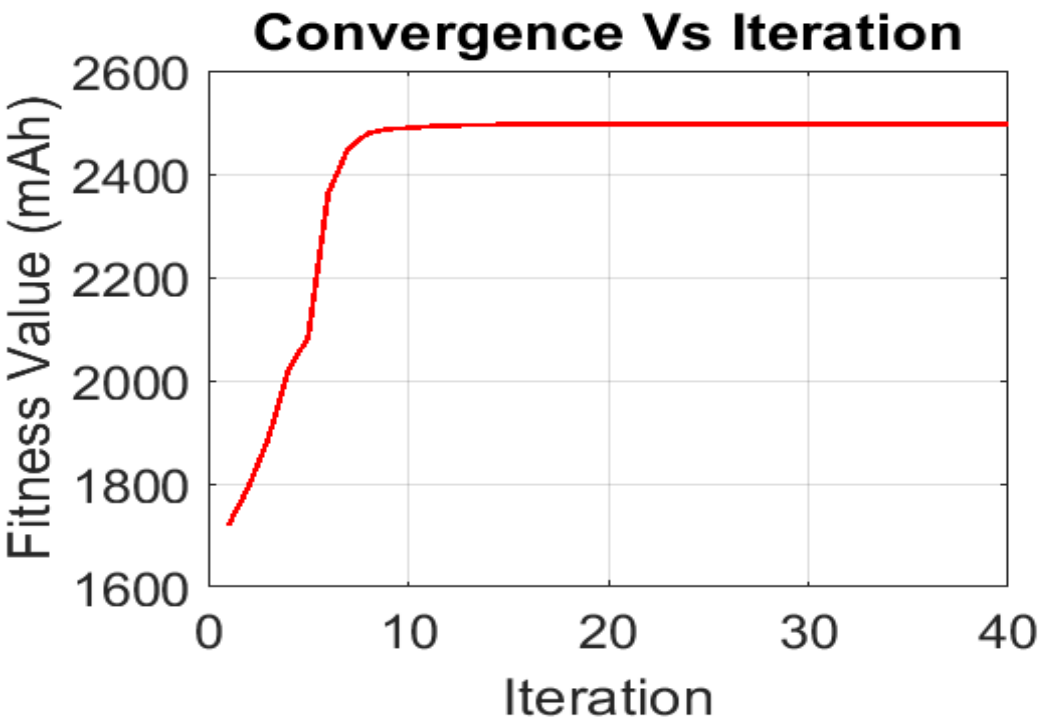

Figure 4.413: A Plot to Show the fitness value charging of Current after 40 Iteration.

As shown in figure 4.4 above, the best fitness value is no longer updated after 40 iterations, which means the convergence of the SGO algorithm has been reached. The best value reached from the plot above is 2500mAh which is 2.5A; this signifies an optimal charging current. It demonstrated that the proposed searching algorithm can obtain a global optimization solution with fast convergence performance.

Table 4.1 Comparison of the charging techniques

Method	**Charging Time/s**	**Charging Efficiency (%)**

PSO based method	3024	93.10
Proposed Technique (SGO)	2500	95.51
Improvement	524	2.41

The charge capacity of the proposed technique is 7800 with a discharge capacity of 7450

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

$$= \frac{\mathbf{7450}}{\mathbf{7800}} \times \mathbf{100} = \mathbf{2.41}\%$$

The evaluation of the performance of the charging pattern was carried out by comparative simulated experiment of PSO technique; this utilized the CC-CV method and the obtained charging pattern is as show in table 4.1 above. Using the proposed technique, the charging time of the battery was decreased without affecting its life cycle and charge capacity. By adopting this method, the decrease in the charging time is 524 seconds. The performance of SGO is dependent on the system accuracy; the advantages of the proposed method over the previous technique are that it is easy to implement and that all battery states are considered during the charging process, allowing maximum protection of the battery from overvoltage, overcharging and overheating conditions. The result shows an almost 9min decrease in the charging time without affecting the capacity and the life cycle which is most significant for the battery life.

CHAPTER FIVE

CONCLUSION

This thesis presents an approach for optimizing the battery management system in a Nano-satellite; this was achieved by the utilization of an optimization technique. The Social Group Optimization technique was chosen and the objective functions were derived. The proposed technique was programmed in MATLAB. The methodology was implemented using a single cell lithium-ion battery. The result revealed a 95.51% reduction in the charging time compared to the conventional way of charging. The experimental result shows that the proposed charging technique for charging a battery is faster and safer than conventional techniques.

5.1 Summary of Contributions

A methodology for optimizing the BMS performance has been demonstrated. The BMS accounts for state of charge of battery cells; this has been implemented in MATLAB environment. Intensive literature review has been done on considering other Approach for Battery Management System (BMS); this thesis presented a SGO algorithm which is used as an approach to optimize the charging current so as to minimize the charging time.

5.2 Future Work

Real time implementation of the proposed method will be carried out in the laboratory; the state of charge will be performed for different battery types .The incorporation of a real time battery monitoring system based on computer visualization will be performed.

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Zou, C., Hu, X., Wei, Z., Wik, T., & Egardt, B. (2018). Electrochemical Estimation and Control for Lithium-Ion Battery Health-Aware Fast Charging. *IEEE Transactions on Industrial Electronics*, *65*(8), 6635–6645. https://doi.org/10.1109/TIE.2017.2772154

Appendix

CODE BY EDET DAVID KOKOETTE

MSC SYSTEM ENGINEERING

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African University of Science and Technology FCT Abuja

```
% 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

% Objective function is $\boldsymbol{i_{cv}} = \frac{(\boldsymbol{V_{\max}} - \mathbf{V_1} - \mathbf{V_2} + \boldsymbol{V_{ocv}})}{\boldsymbol{R}}$

% Constrain $\mathbf{LB} = [-\mathbf{0.9}\ \ \mathbf{2.5}], \mathbf{Ub} = [\mathbf{3}\ \ \mathbf{4.2}]$

% 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

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 parater. c∈(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);
```

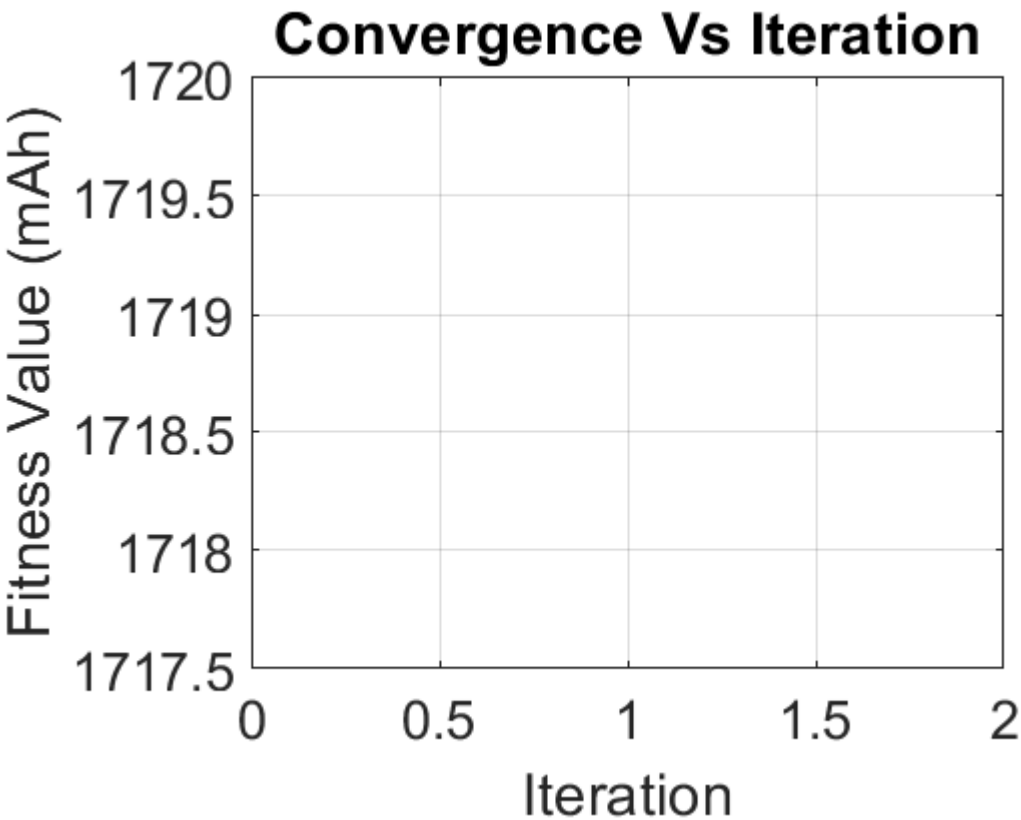
```
    if fx(i,:) > fp
        Inew = X + rand(size(X)).*(X-Xp) + rand (size(X)).*(gbest - X);
    else
        Inew = X-rand(size(X)).*(X-Xp) + rand(size(X)).*(gbest - X);
    end
```

```
    % check the bounds to variied 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 greedy selection
      fnew = fun(Inew);
      if fnew > fx(i,:)
         pos(i,:) = Inew;
         fx(i,:) = fnew;
      end
```

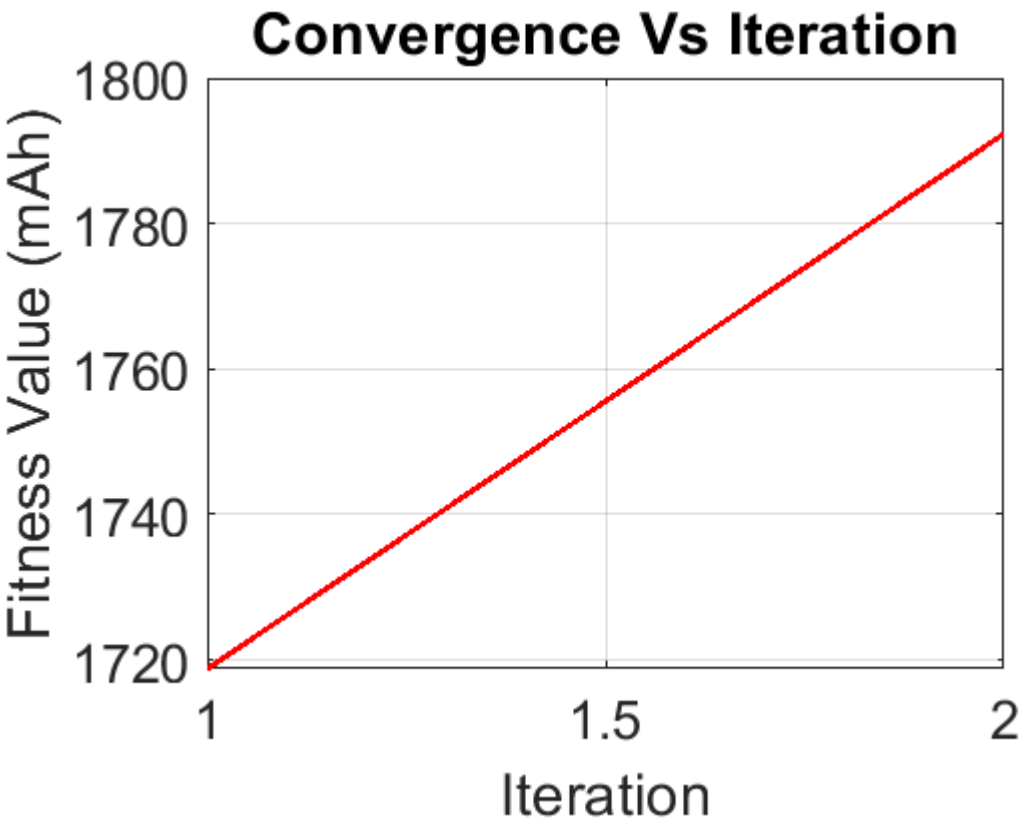
MEMORIZE THE BEST CHARGING CURRENT

```
[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;
```

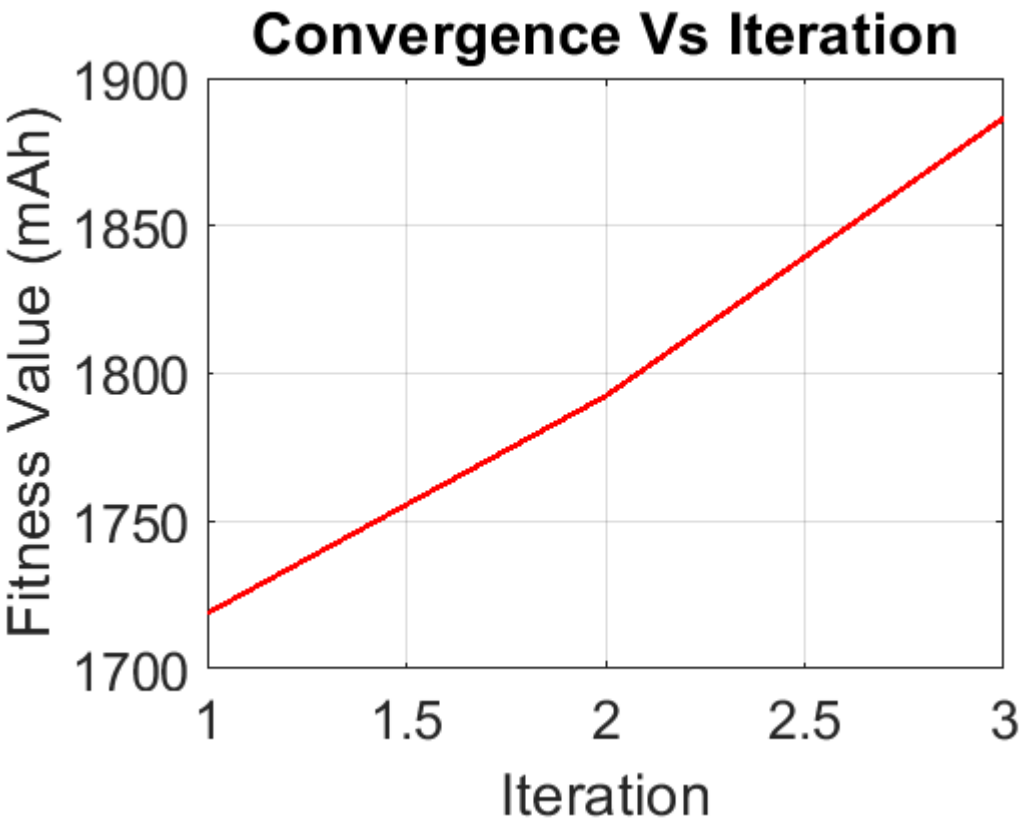
```
Xnew =

    1.8039    3.9381   45.0000

Iteration = 1
Best Cost = 2.4762
```



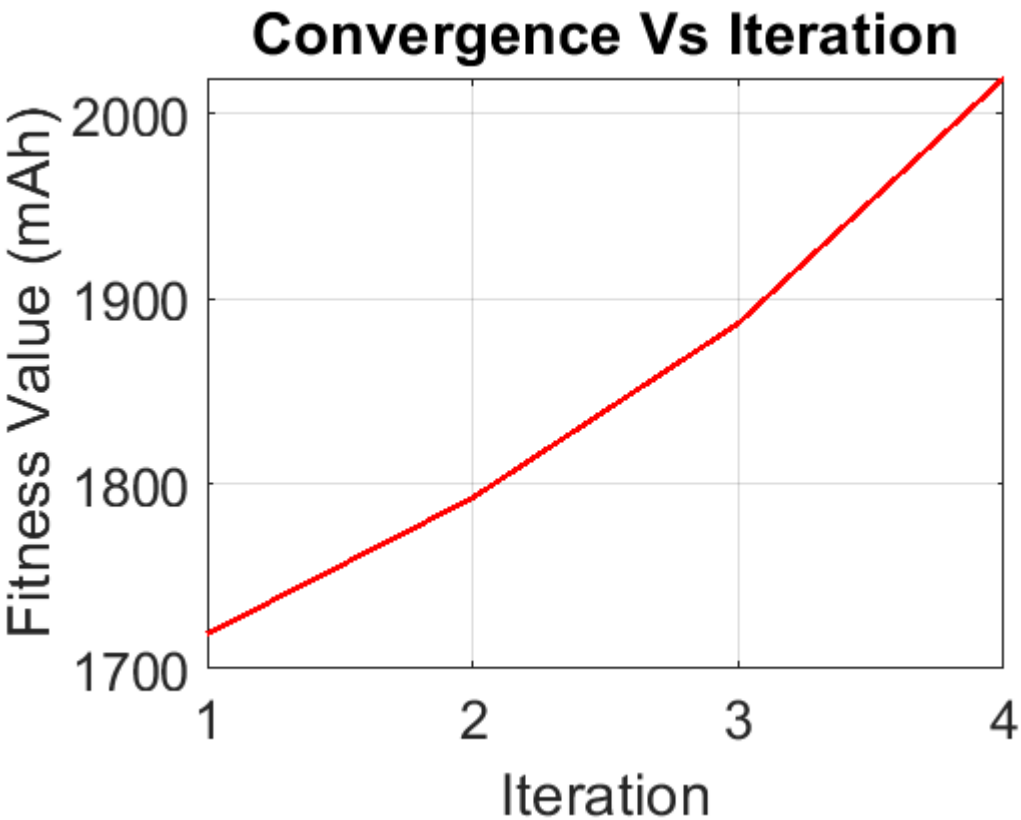

```
Xnew =

    1.7967    3.9144   45.0000

Iteration = 2
Best Cost = 1.7875
```



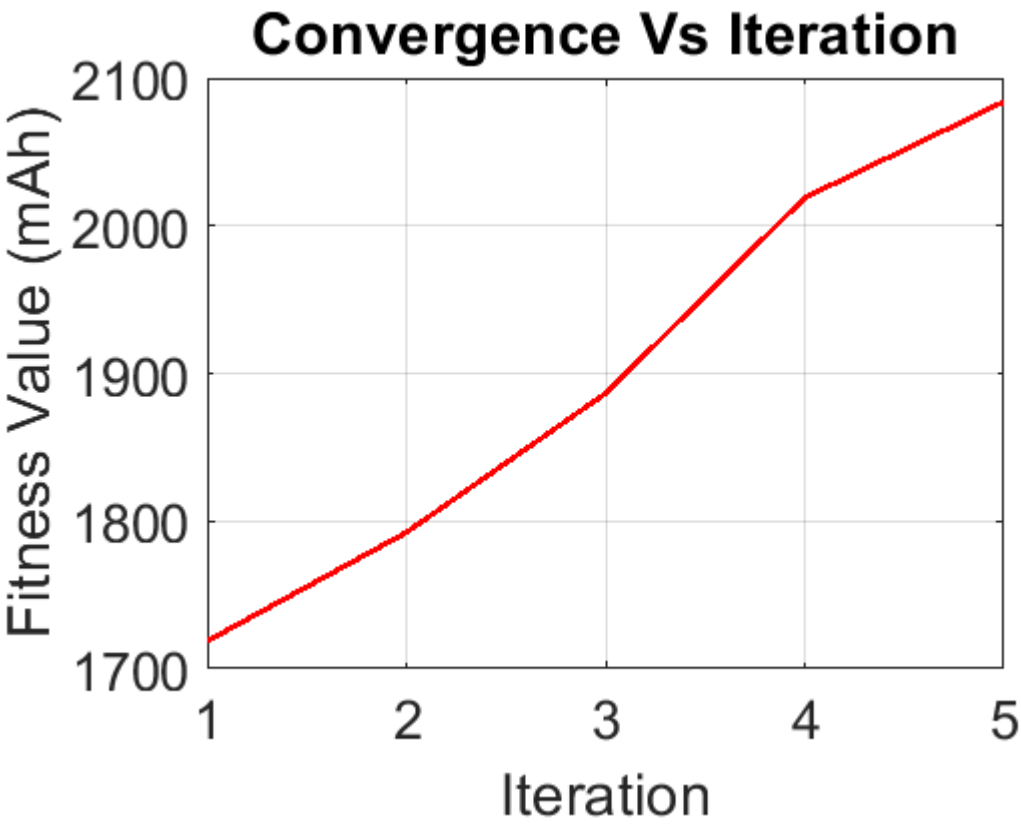

```
Xnew =

    1.7890    4.0002   45.0000

Iteration = 3
Best Cost = 1.7881
```



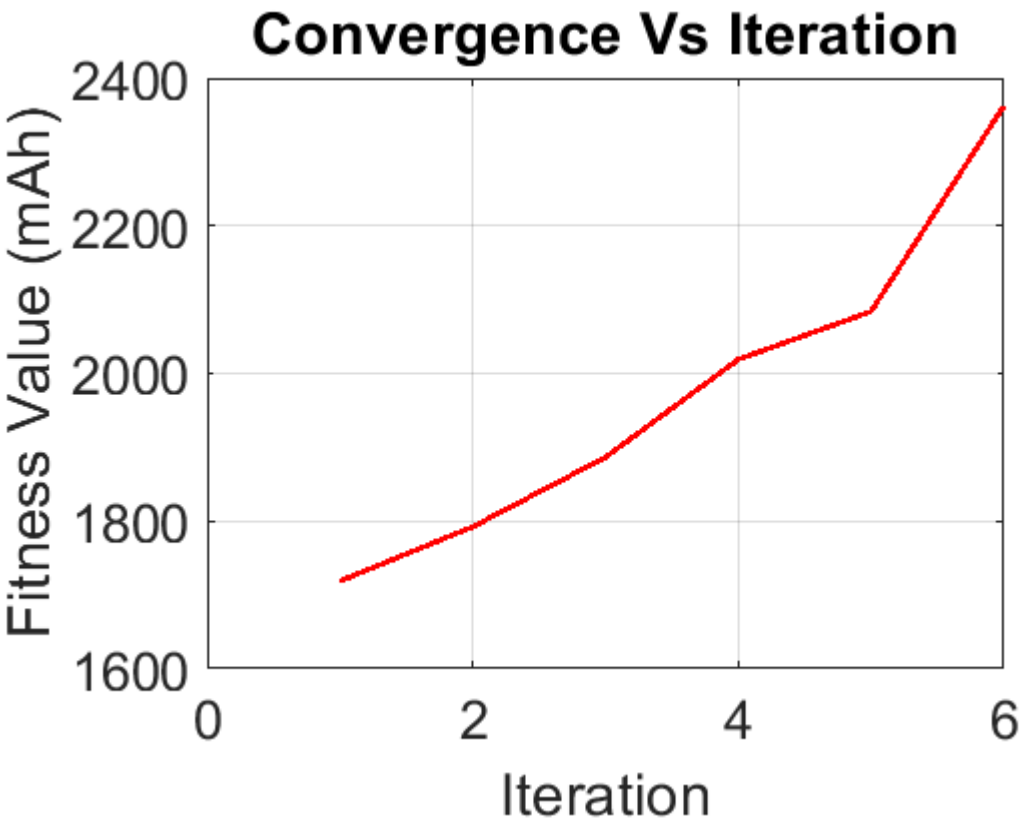

```
Xnew =

    1.7830    4.1131   45.0000

Iteration = 4
Best Cost = 1.7881
```



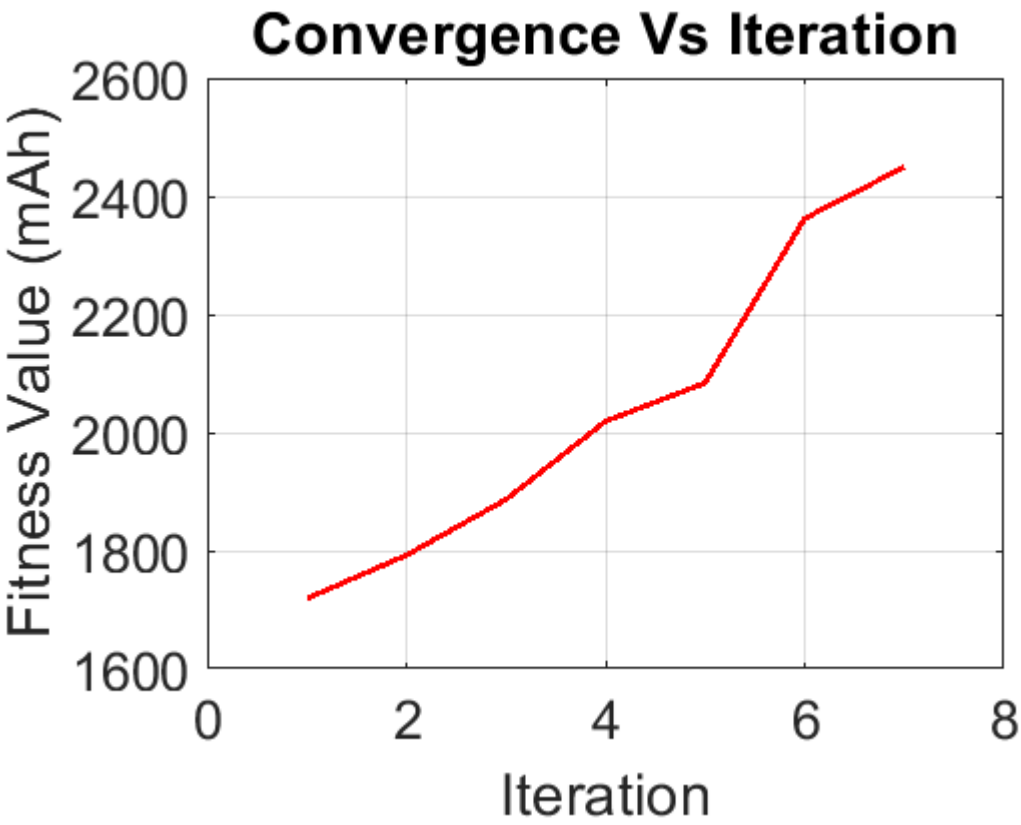

```
Xnew =

    1.7808    4.1310   45.0000

Iteration = 5
Best Cost = 1.7877
```



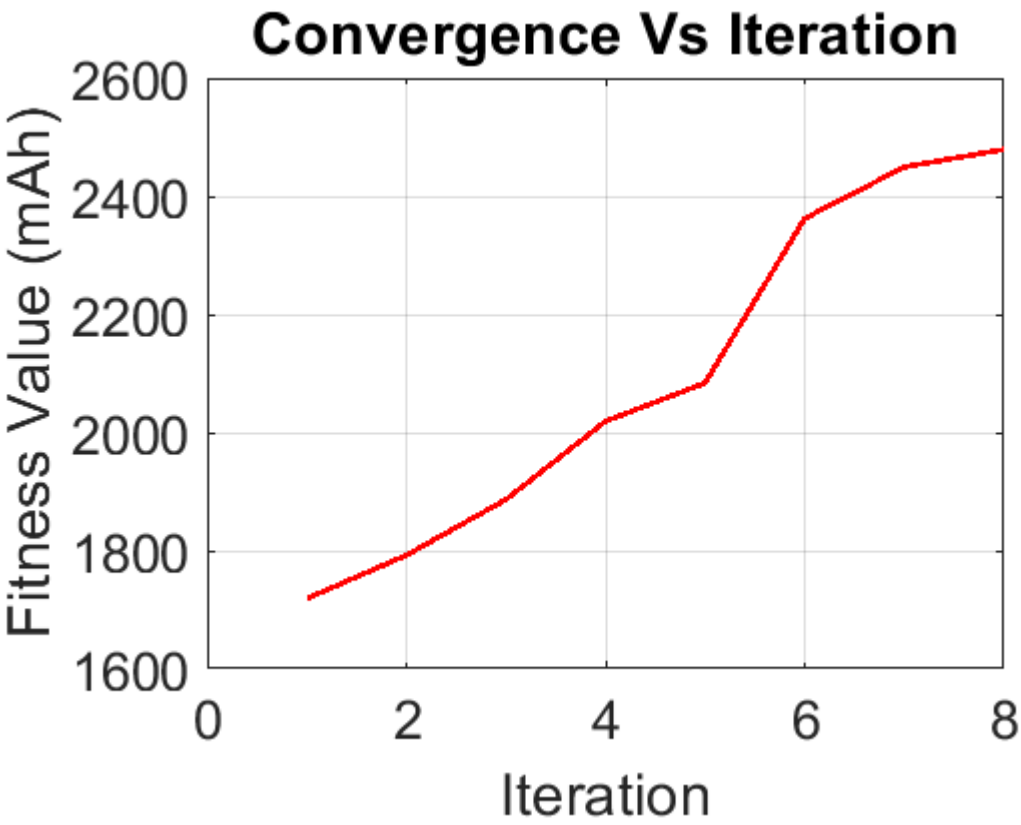

```
Xnew =

    1.7424    4.1461   45.0000

Iteration = 6
Best Cost = 1.7835
```



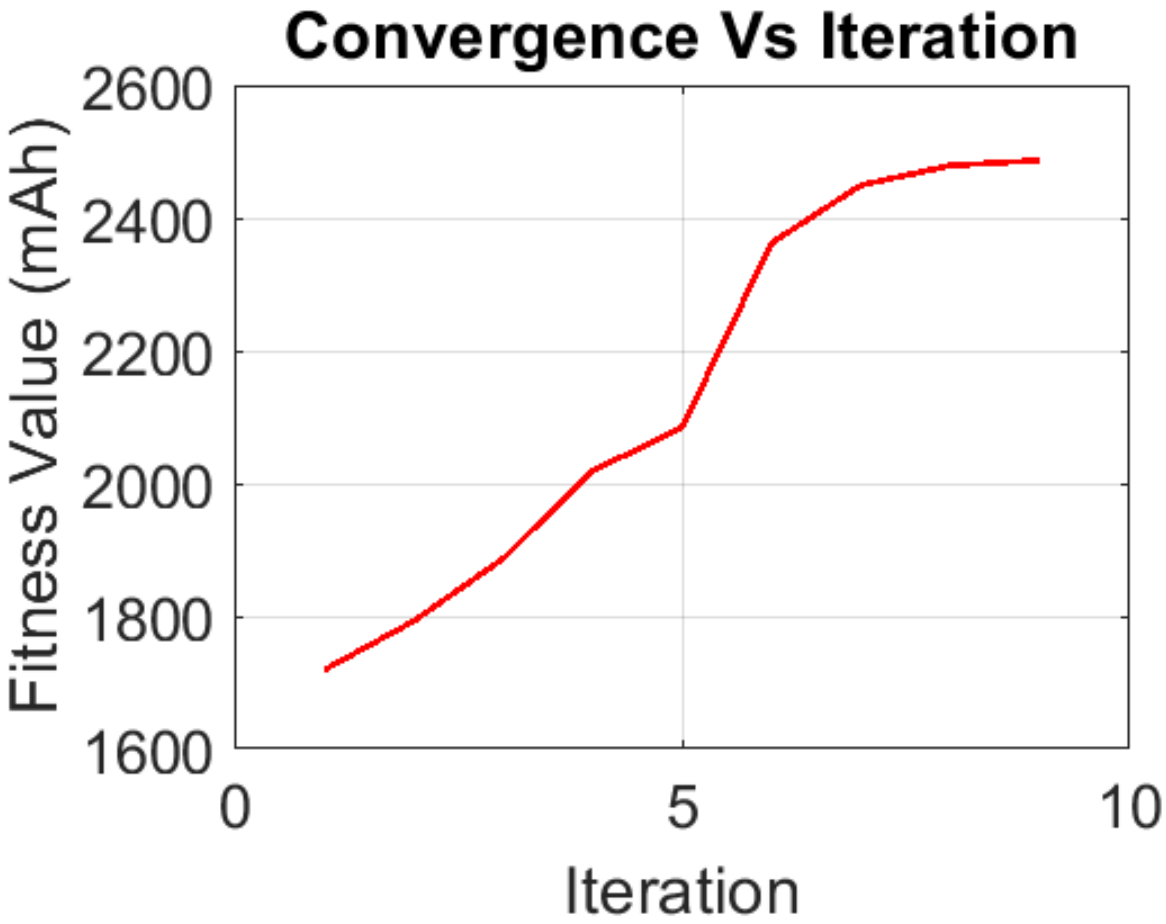

```
Xnew =

    1.7401    4.1511   45.0000

Iteration = 7
Best Cost = 1.7687
```



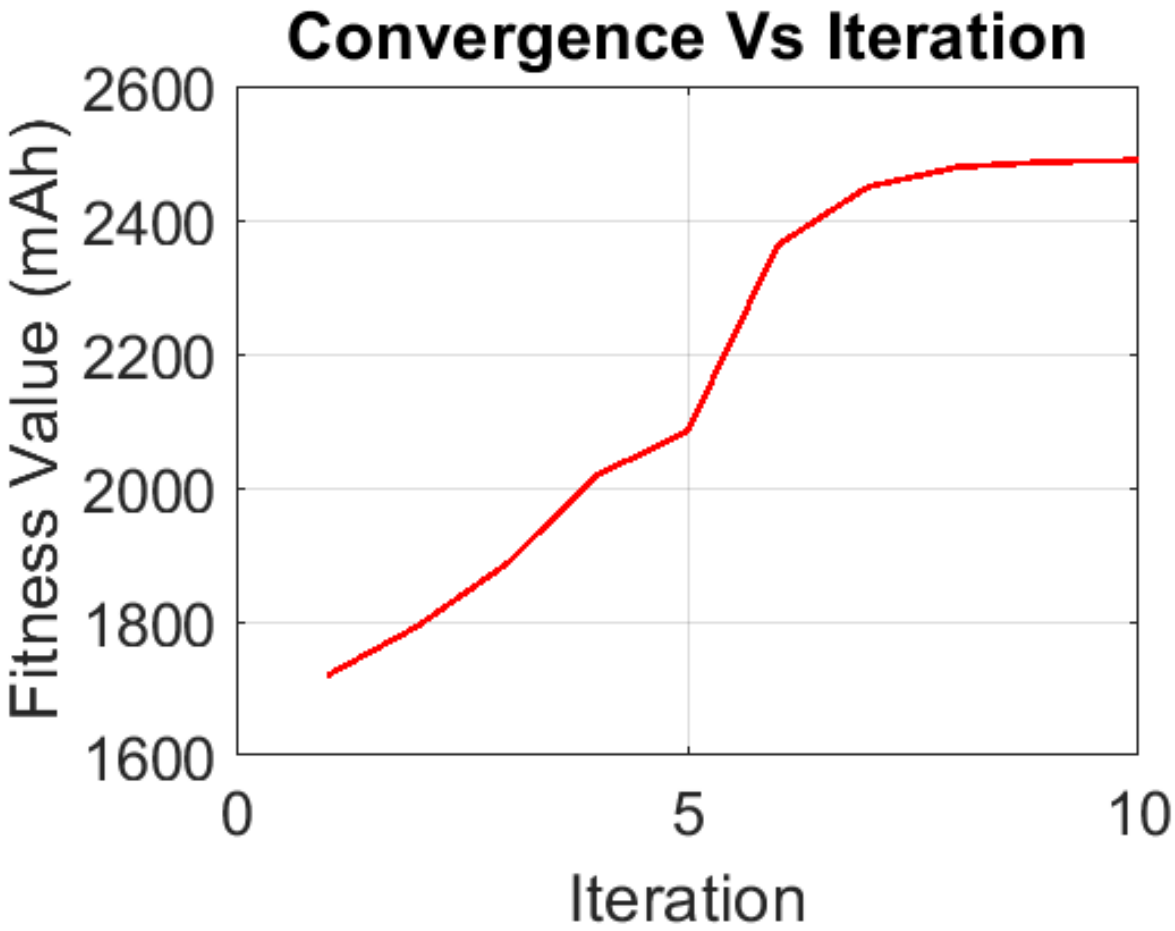

```
Xnew =

    1.7380    4.1524   45.0000

Iteration = 8
Best Cost = 1.7524
```



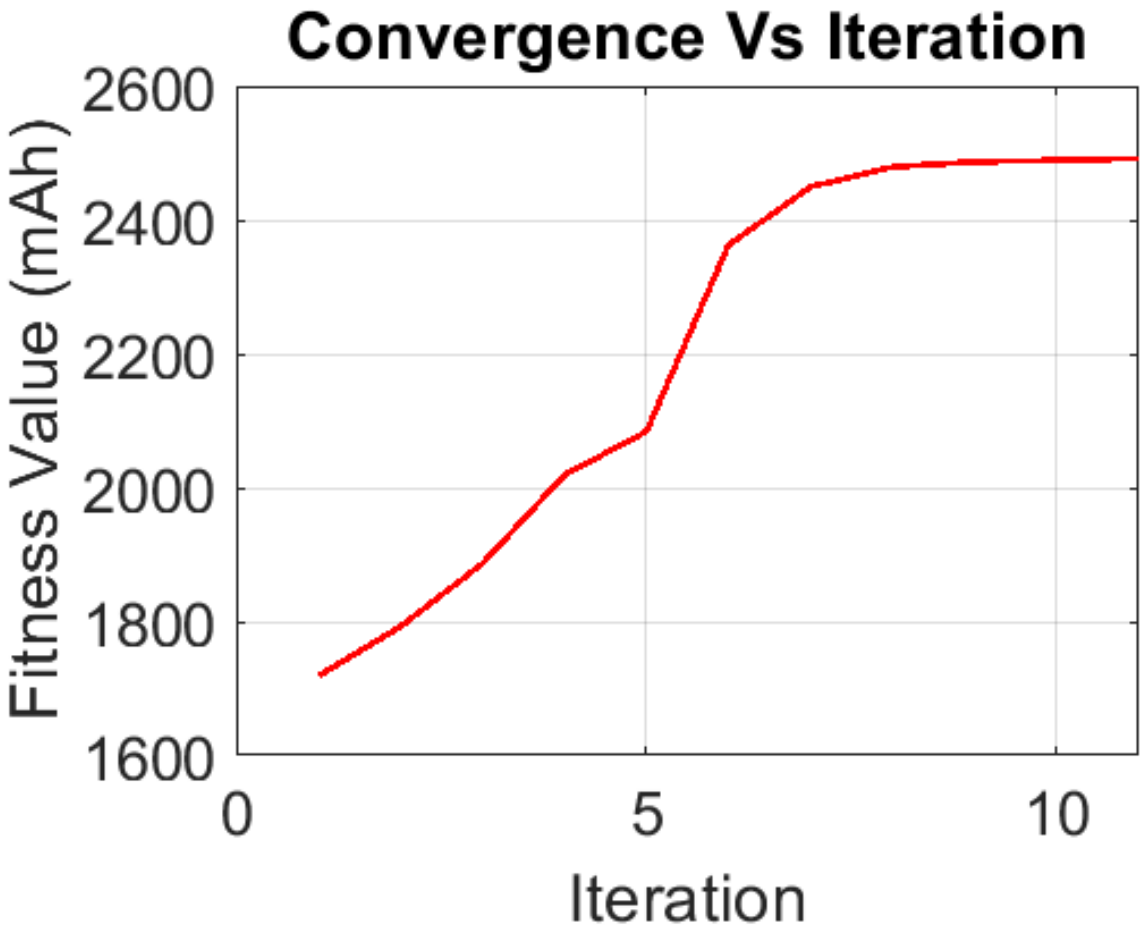

```
Xnew =

    1.7328    4.1811   45.0000

Iteration = 9
Best Cost = 1.7449
```



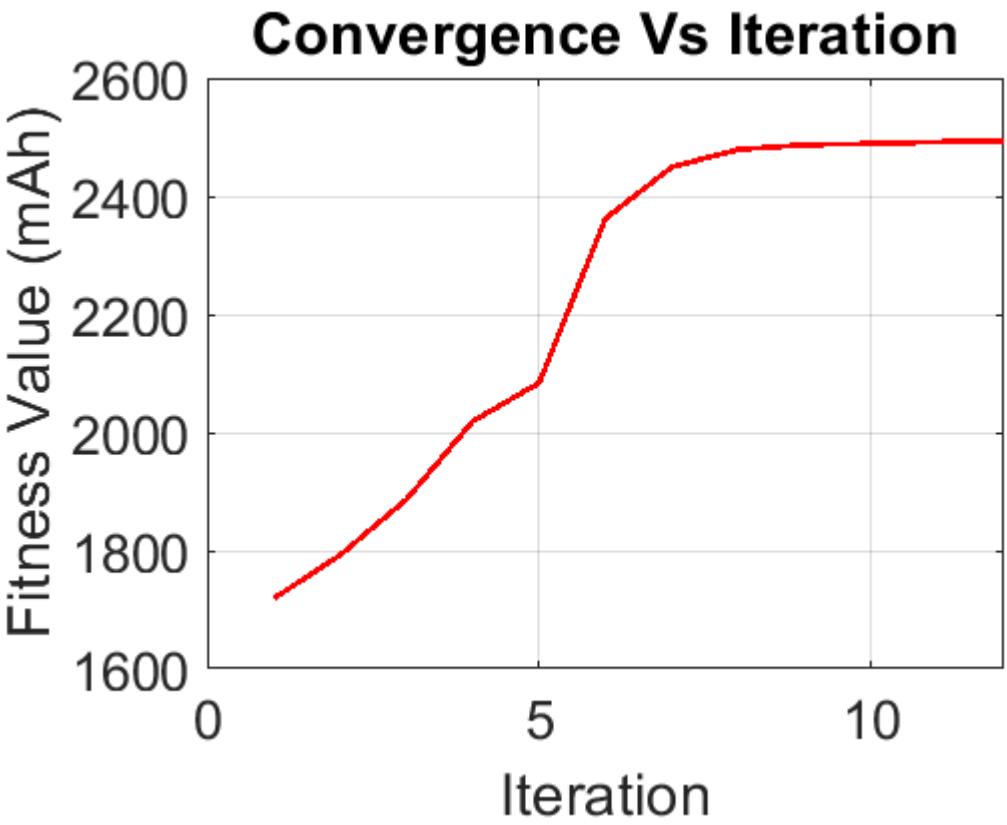

```
Xnew =

    1.7261    4.1933   45.0000

Iteration = 10
Best Cost = 1.7424
```



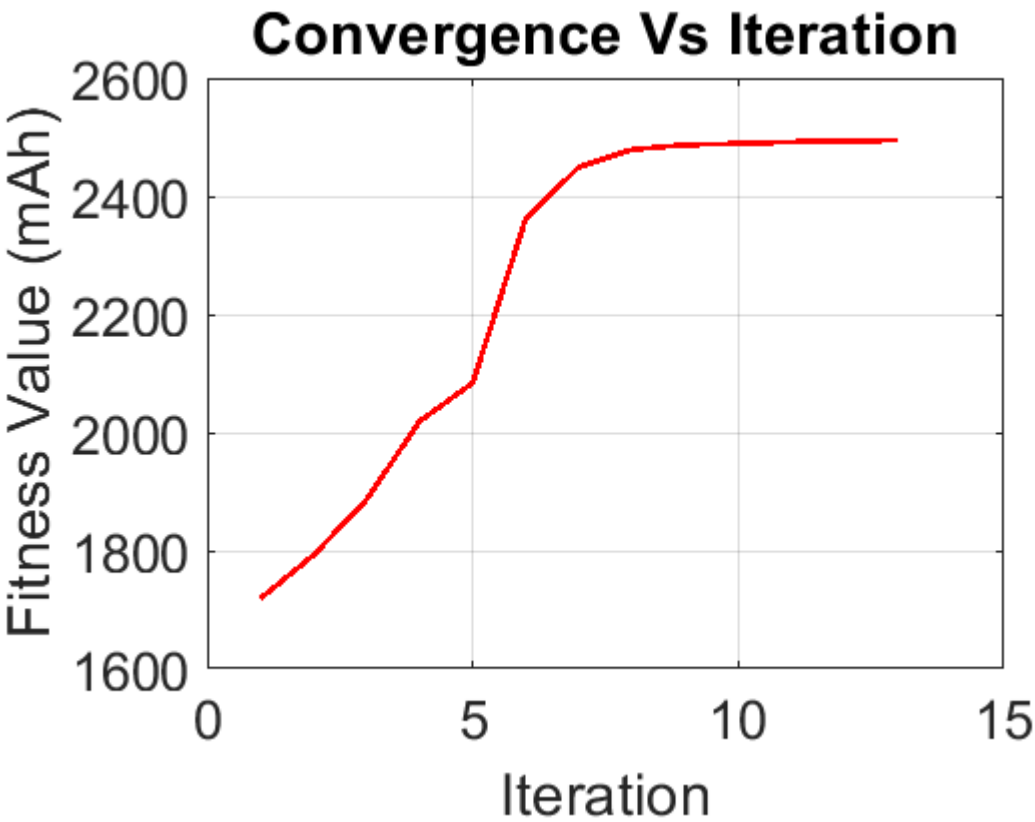

```
Xnew =

    1.7188    4.1954   45.0000

Iteration = 11
Best Cost = 1.7278
```



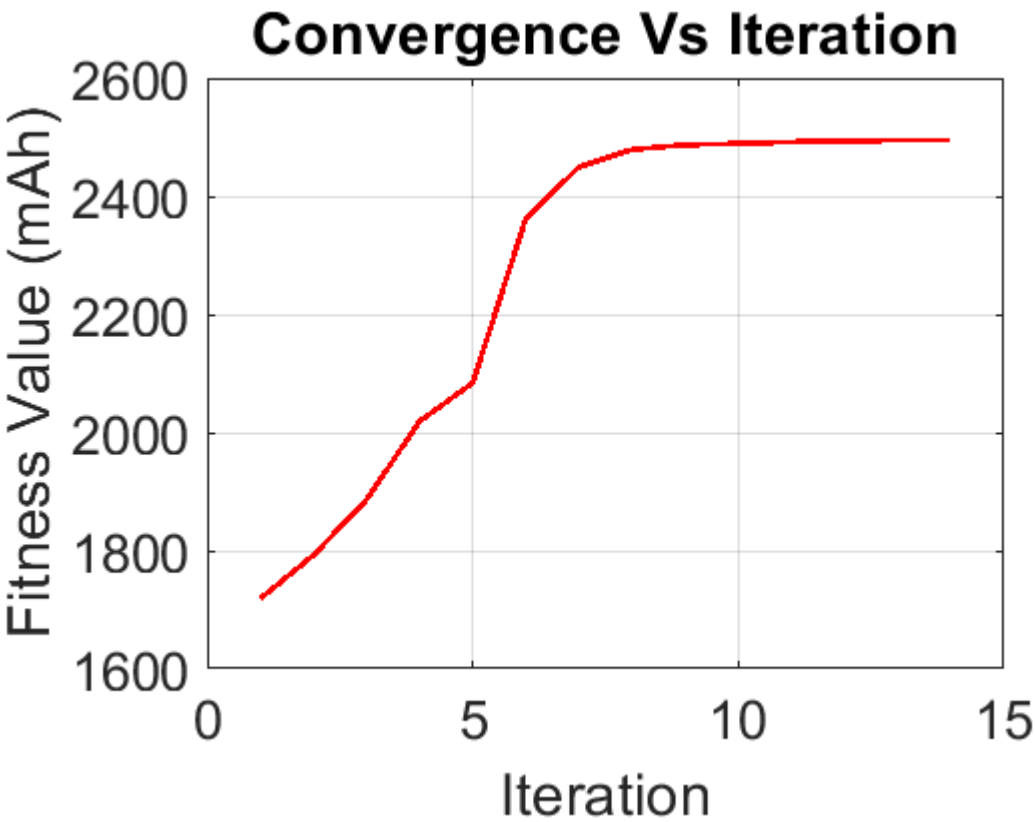

```
Xnew =

    1.7150    4.1986   45.0000

Iteration = 12
Best Cost = 1.7261
```



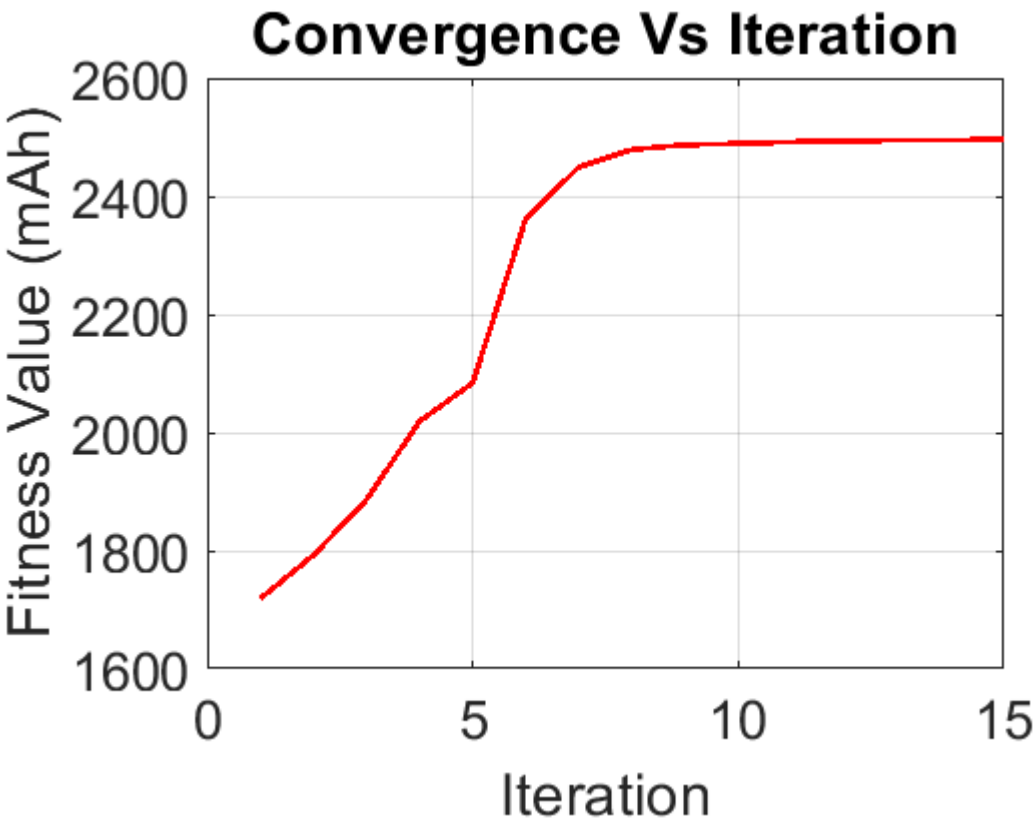

```
Xnew =

    1.7113    4.2000   45.0007


Xnew =

    1.7113    4.2000   45.0000

Iteration = 13
Best Cost = 1.715
```



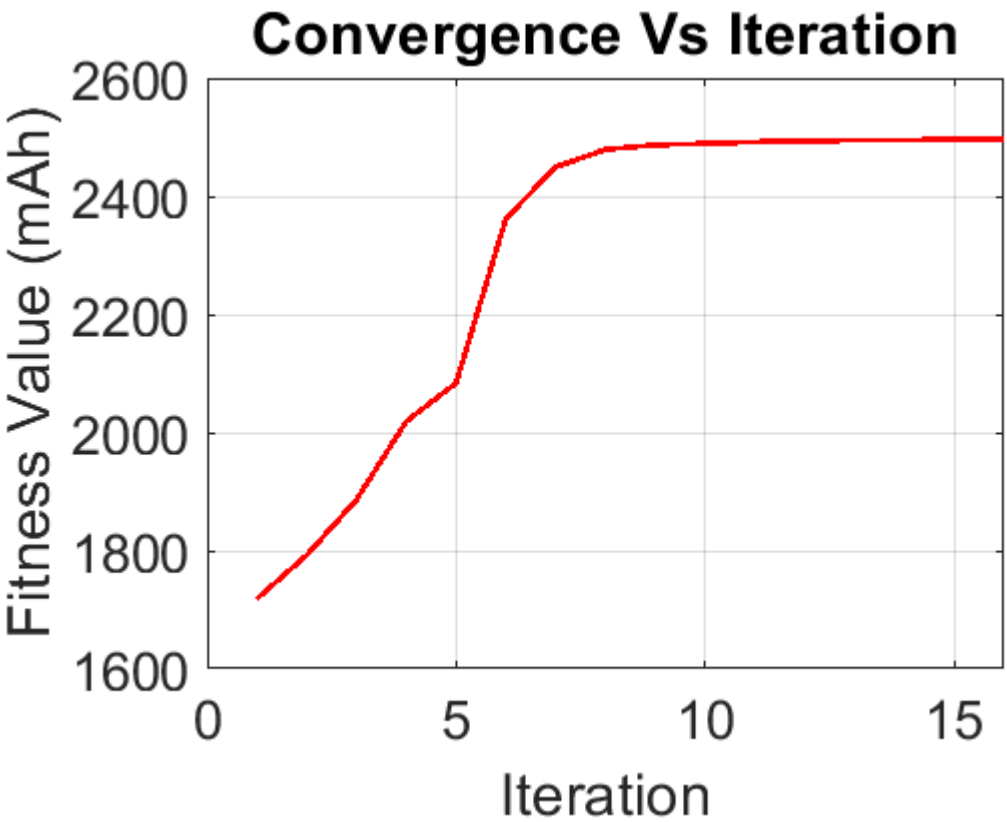

```
Xnew =

    1.7150    4.2000   45.0000


Xnew =

    1.7150    4.2000   45.0000

Iteration = 14
Best Cost = 1.7143
```



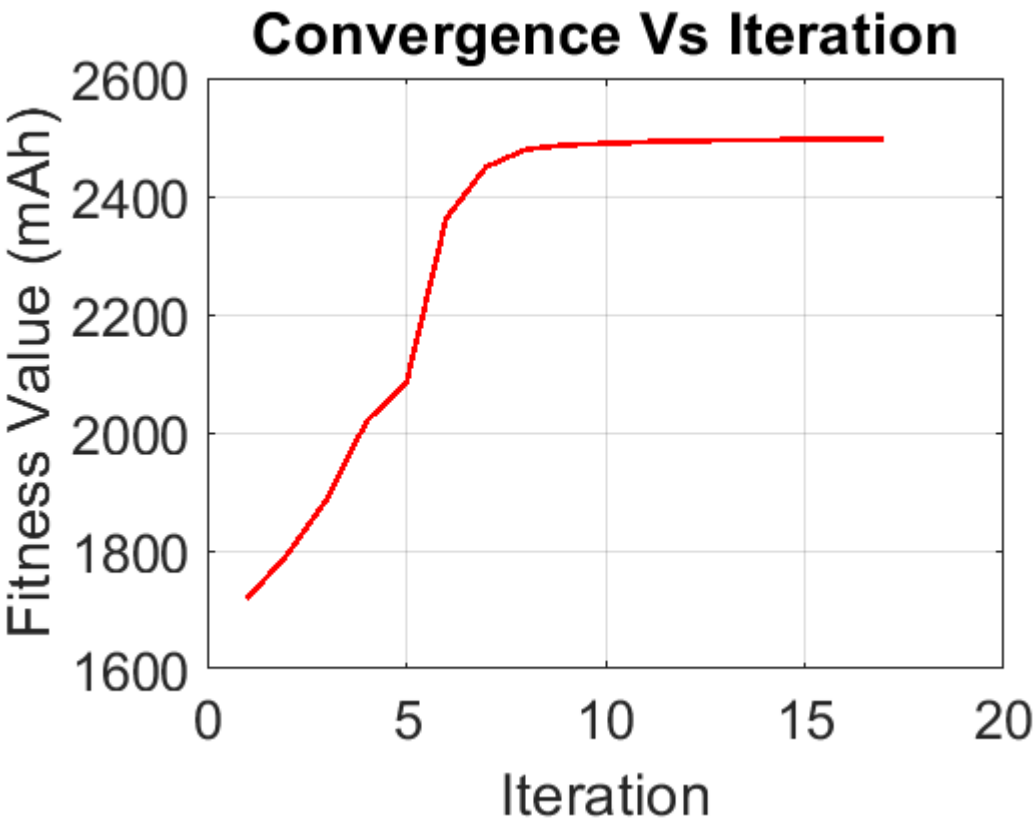

```
Xnew =

    1.7178    4.2000   45.0000

Iteration = 15
Best Cost = 1.7162
```



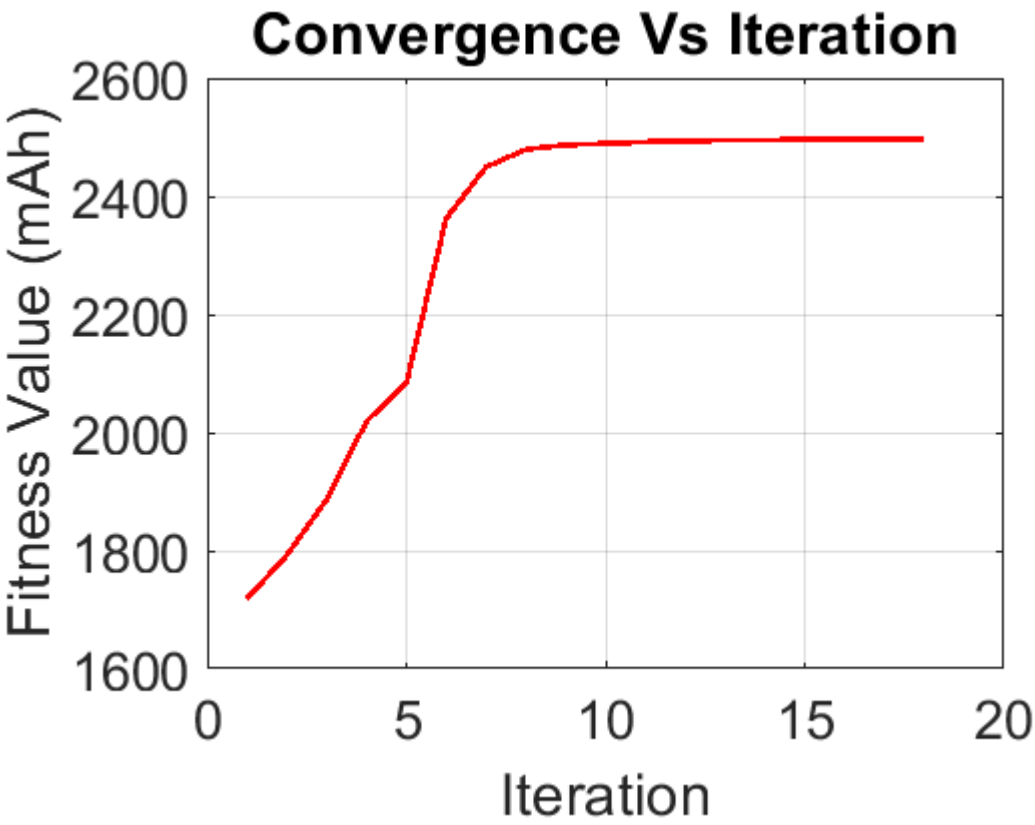

```
Xnew =

    1.7199    4.2000   45.0000


Xnew =

    1.7199    4.2000   45.0000

Iteration = 16
Best Cost = 1.719
```



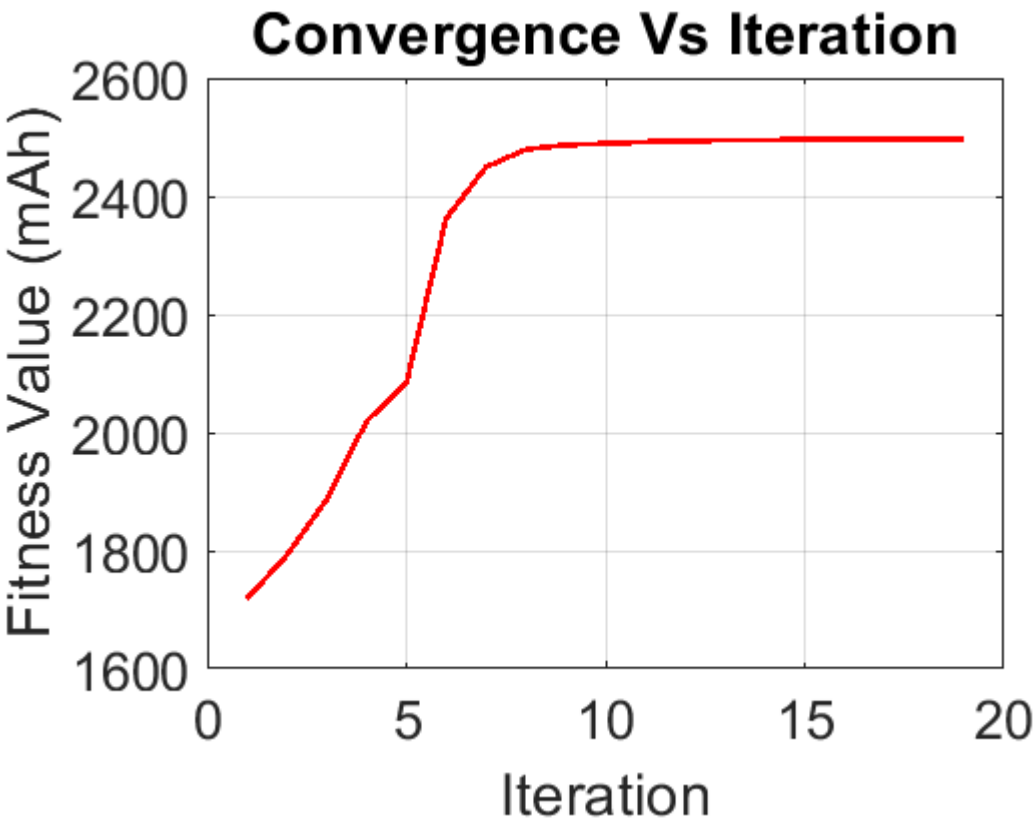

```
Xnew =

    1.7200    4.2000   45.0001


Xnew =

    1.7200    4.2000   45.0000

Iteration = 17
Best Cost = 1.719
```



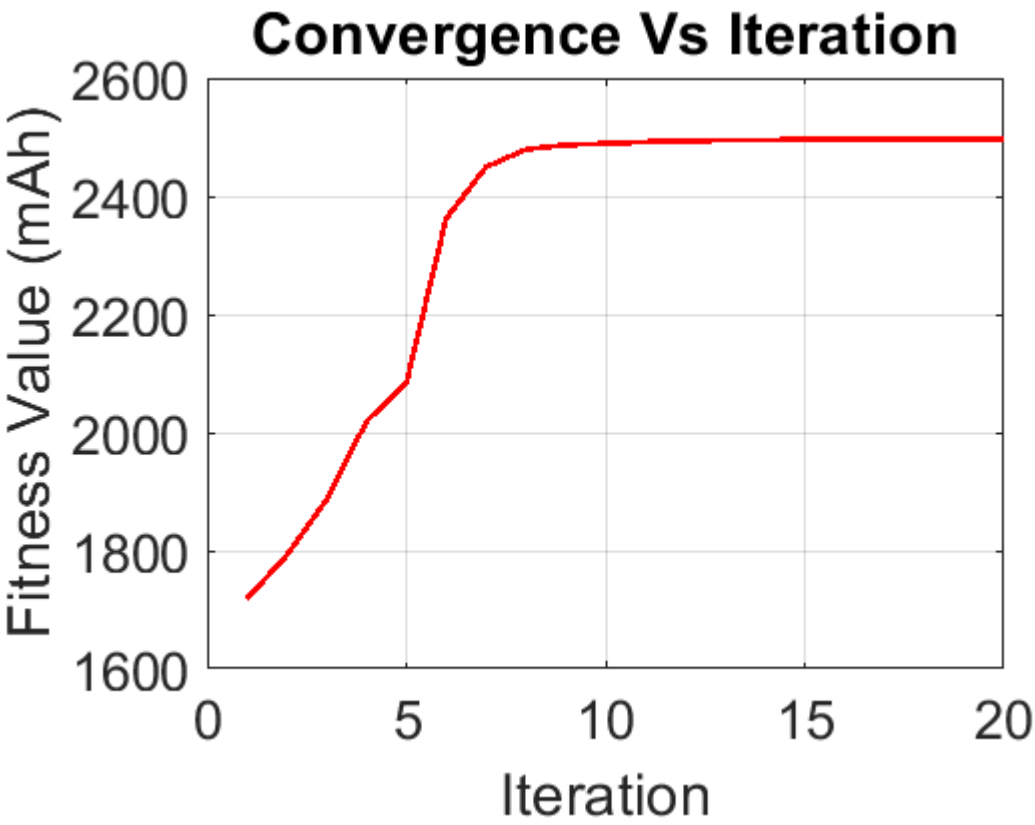

```
Xnew =

    1.7219    4.2000   45.0000


Xnew =

    1.7219    4.2000   45.0000

Iteration = 18
Best Cost = 1.7198
```



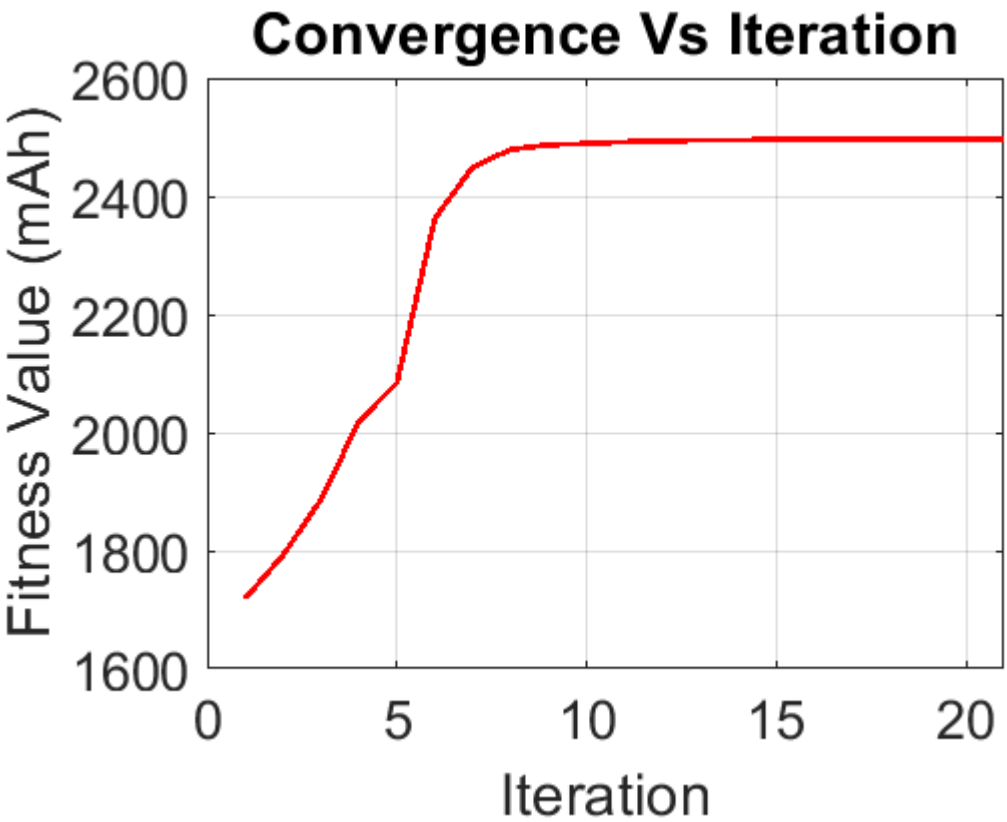

```
Xnew =

    1.7226    4.2000   45.0000


Xnew =

    1.7226    4.2000   45.0000

Iteration = 19
Best Cost = 1.7202
```



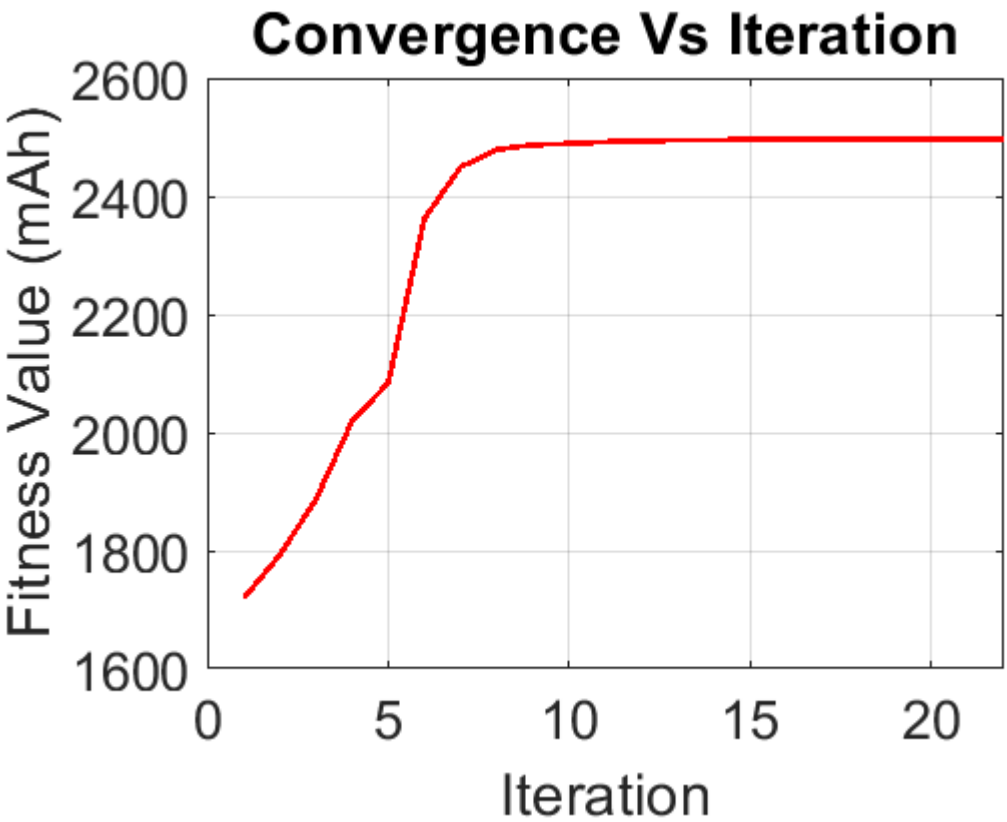

```
Xnew =

    1.7226    4.2000   45.0000


Xnew =

    1.7226    4.2000   45.0000

Iteration = 20
Best Cost = 1.7216
```



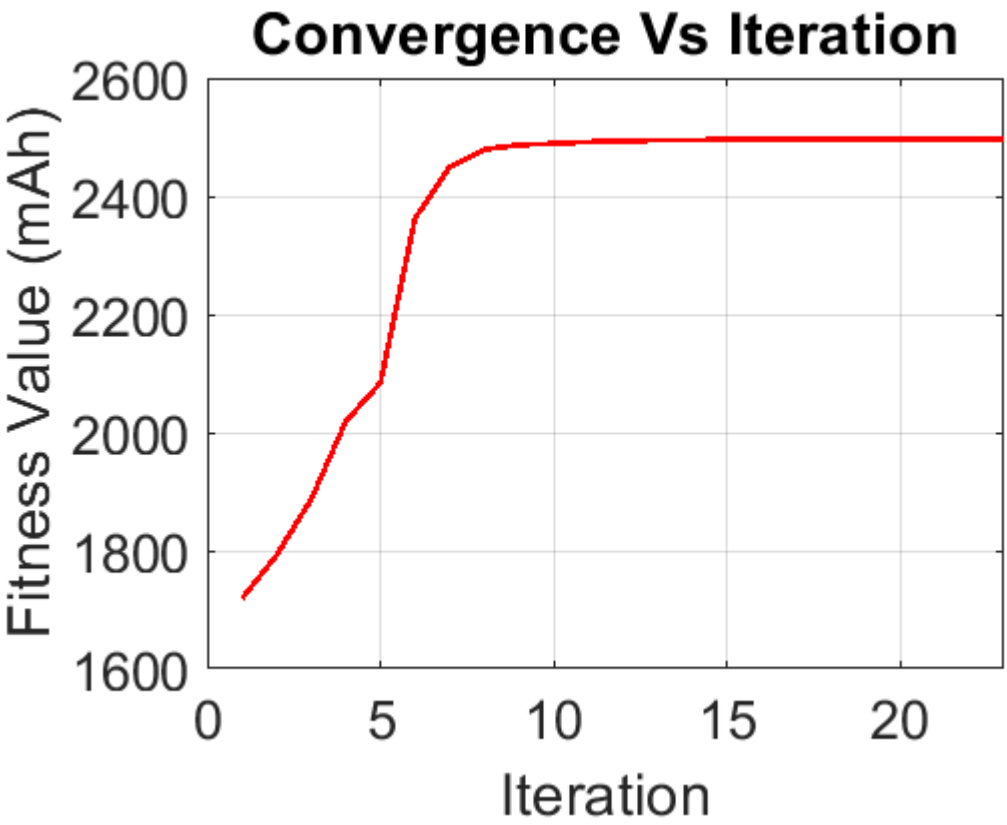

```
Xnew =

    1.7226    4.2000   45.0000


Xnew =

    1.7226    4.2000   45.0000

Iteration = 21
Best Cost = 1.7225
```



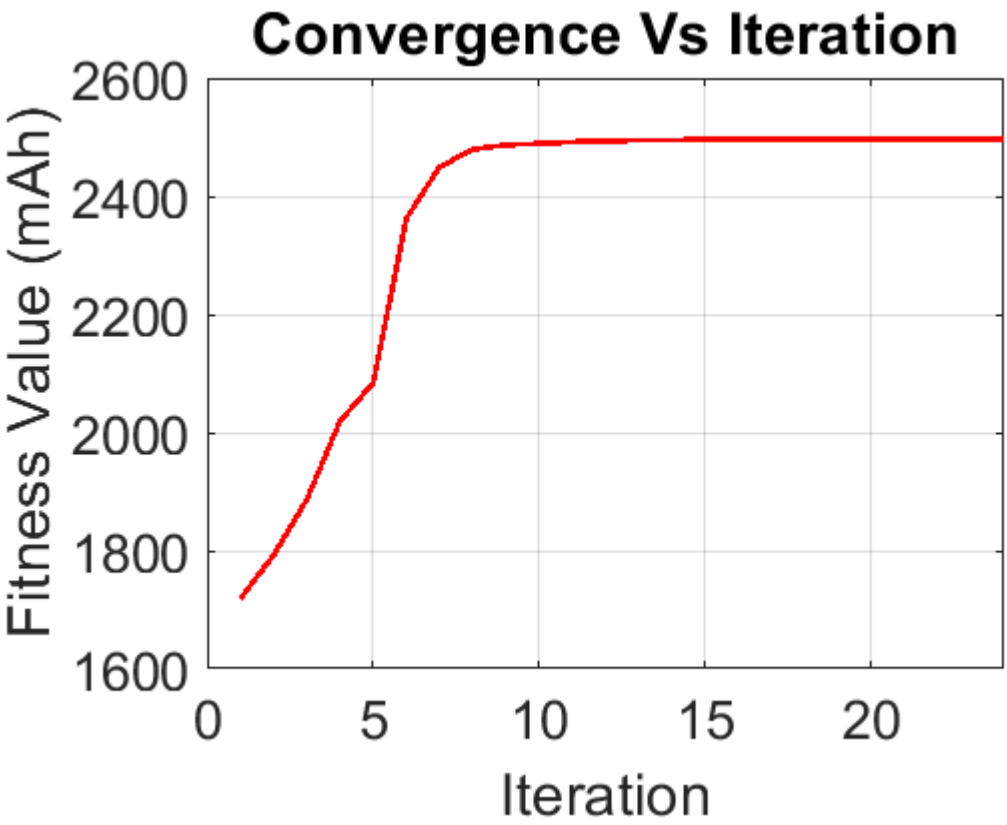

```
Xnew =

    1.7227    4.2000   45.0000


Xnew =

    1.7227    4.2000   45.0000

Iteration = 22
Best Cost = 1.7226
```



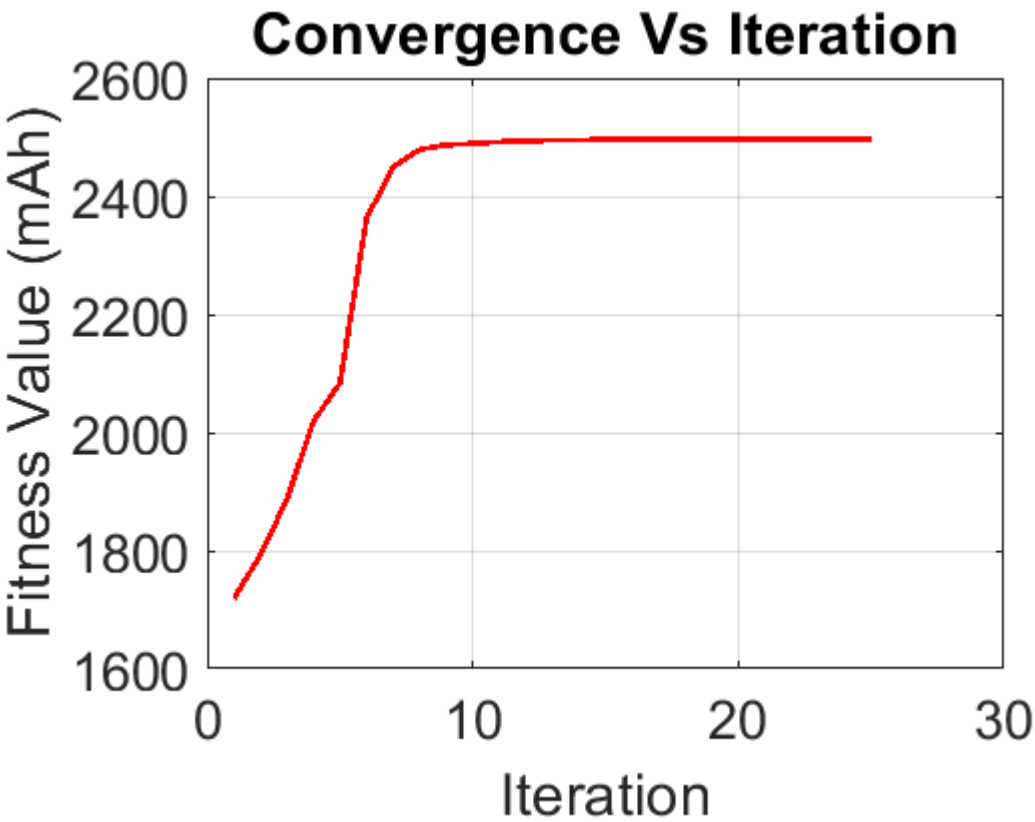

```
Xnew =

    1.7229    4.2000   45.0000


Xnew =

    1.7229    4.2000   45.0000

Iteration = 23
Best Cost = 1.7227
```



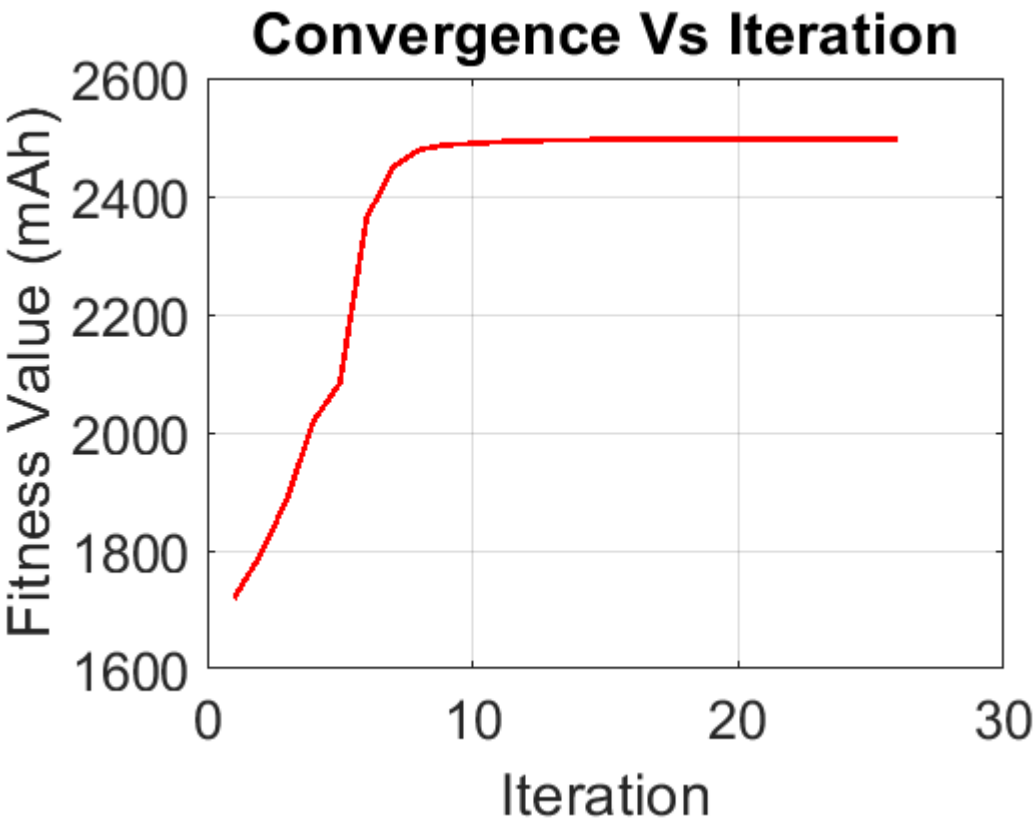

```
Xnew =

    1.7229    4.2000   45.0000


Xnew =

    1.7229    4.2000   45.0000

Iteration = 24
Best Cost = 1.7222
```



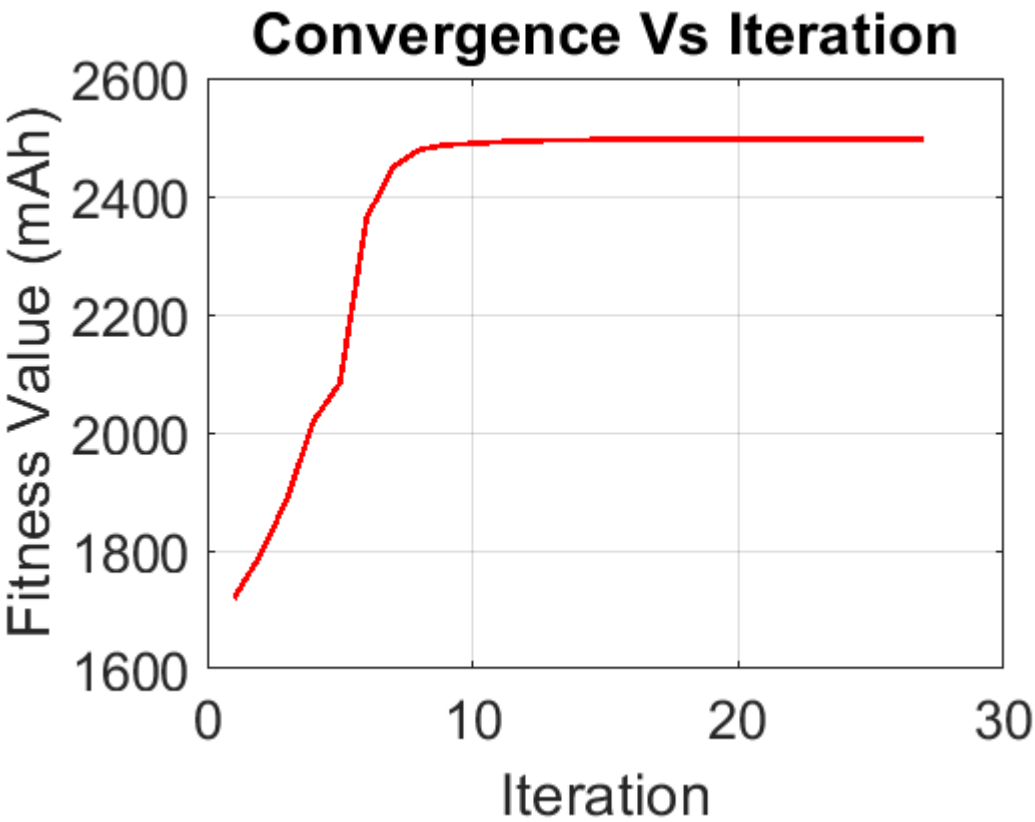

```
Xnew =

    1.7229    4.2000   45.0000


Xnew =

    1.7229    4.2000   45.0000

Iteration = 25
Best Cost = 1.7222
```



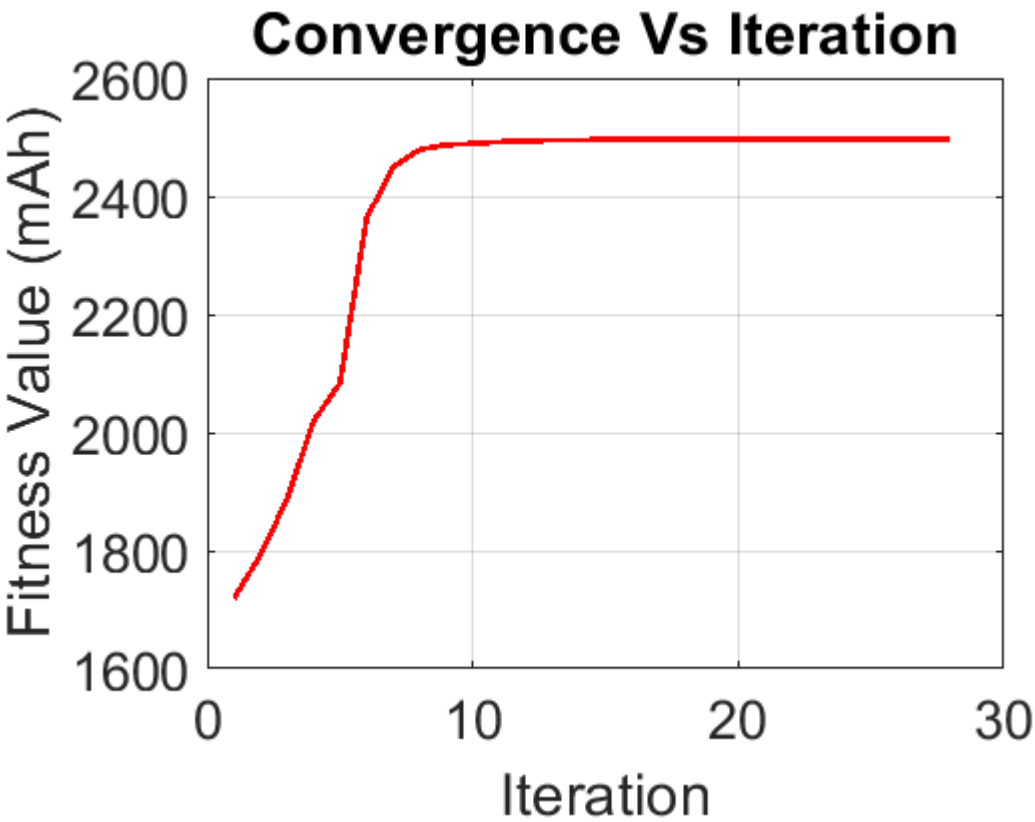

```
Xnew =

    1.7229    4.2000   45.0000


Xnew =

    1.7229    4.2000   45.0000

Iteration = 26
Best Cost = 1.7226
```



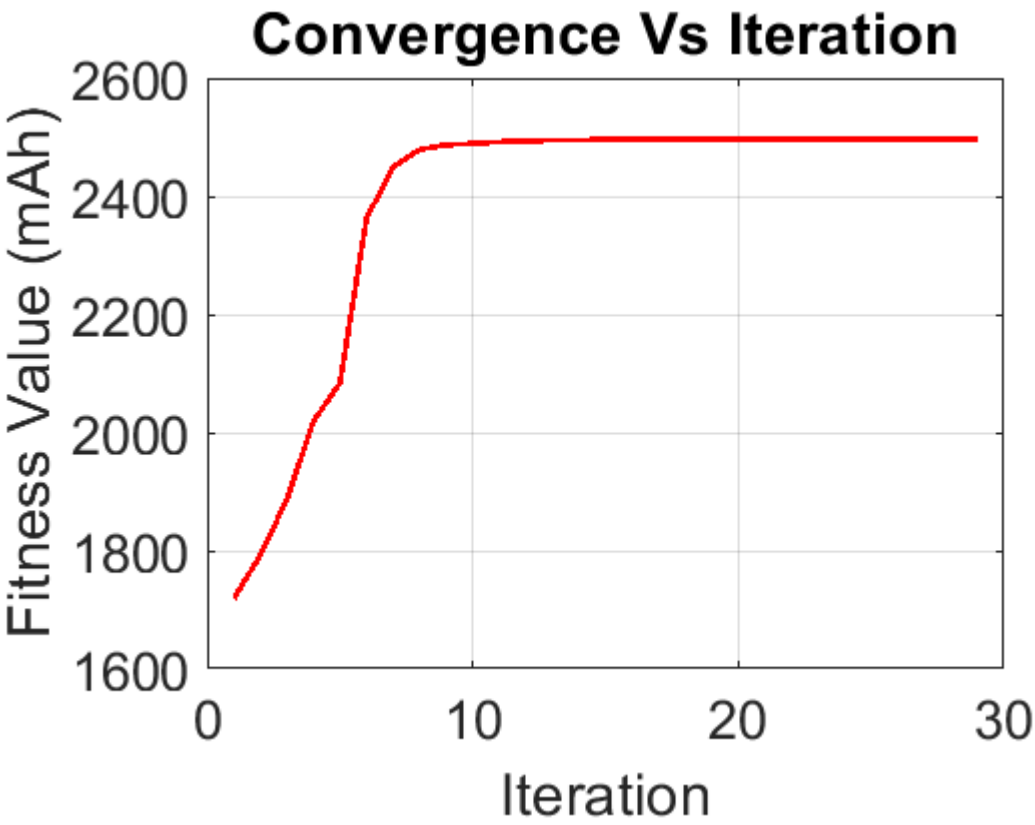

```
Xnew =

    1.7230    4.2000   45.0000


Xnew =

    1.7230    4.2000   45.0000

Iteration = 27
Best Cost = 1.7228
```



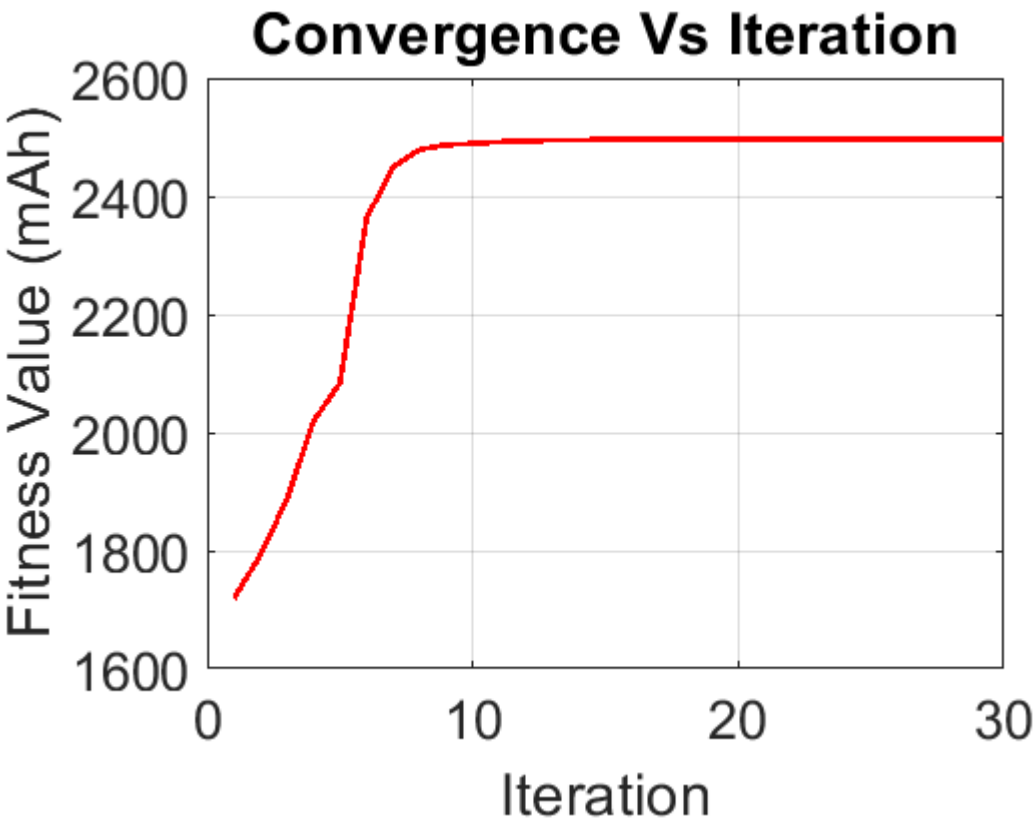

```
Xnew =

    1.7230    4.2000   45.0000


Xnew =

    1.7230    4.2000   45.0000

Iteration = 28
Best Cost = 1.7229
```



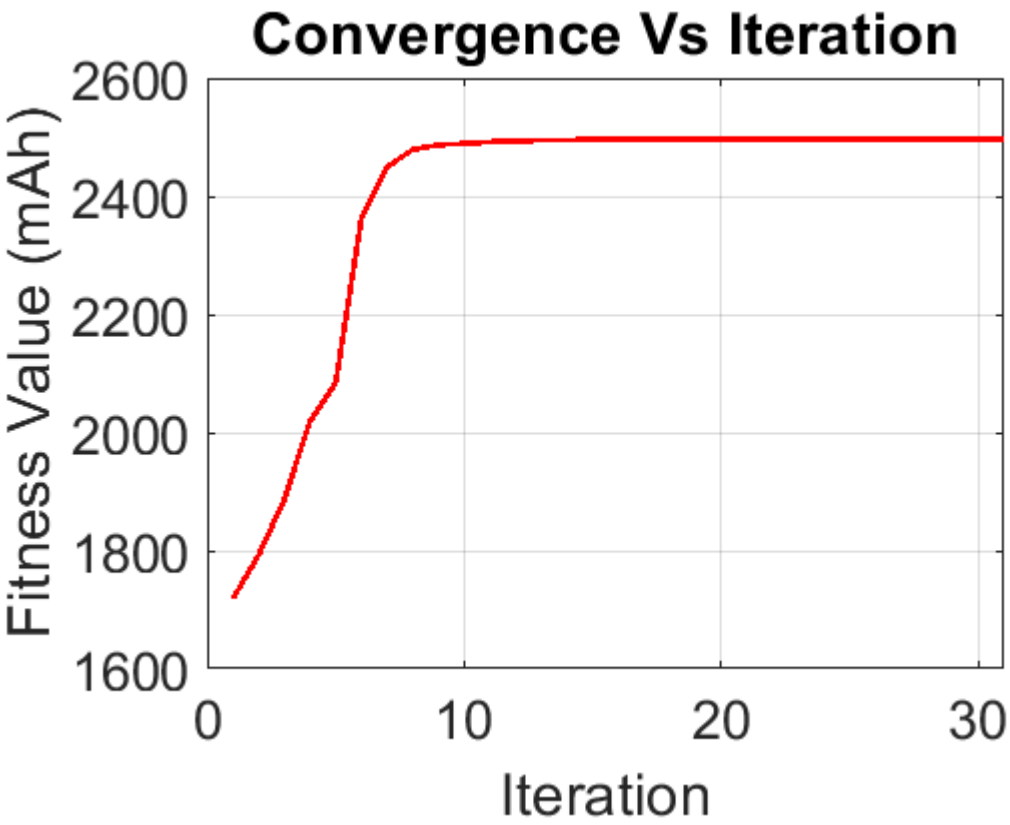

```
Xnew =

    1.7230    4.2000   45.0000


Xnew =

    1.7230    4.2000   45.0000

Iteration = 29
Best Cost = 1.7229
```



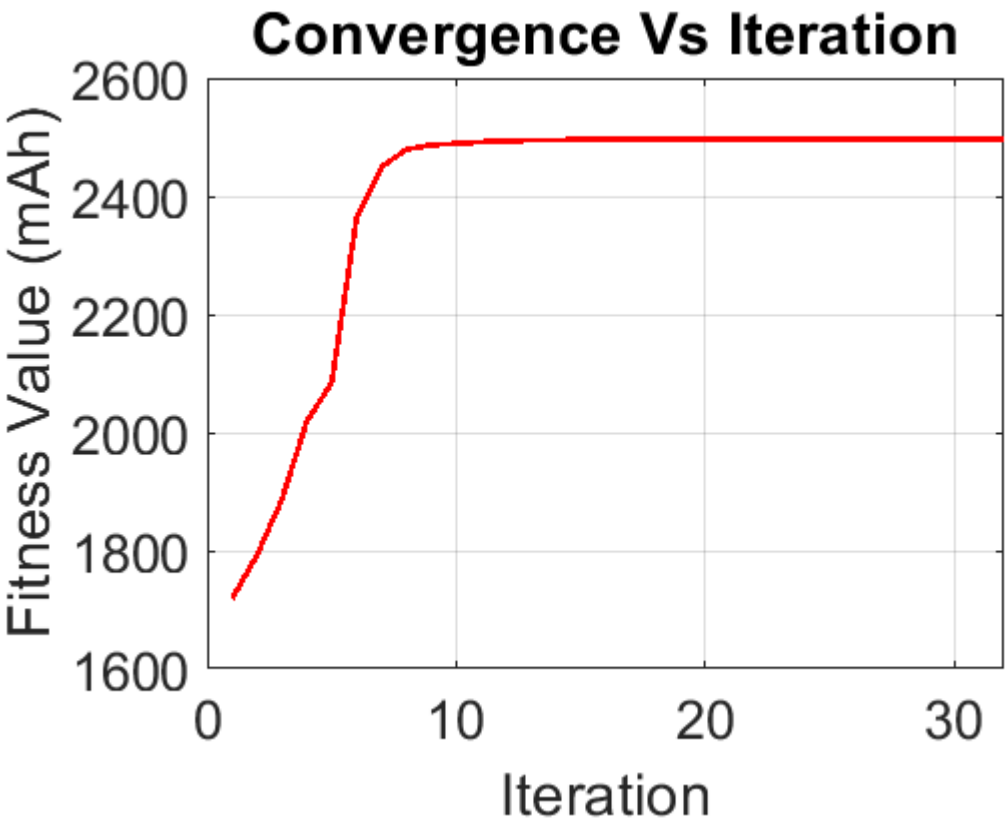

```
Xnew =

    1.7230    4.2000   45.0000

Iteration = 30
Best Cost = 1.7229
```



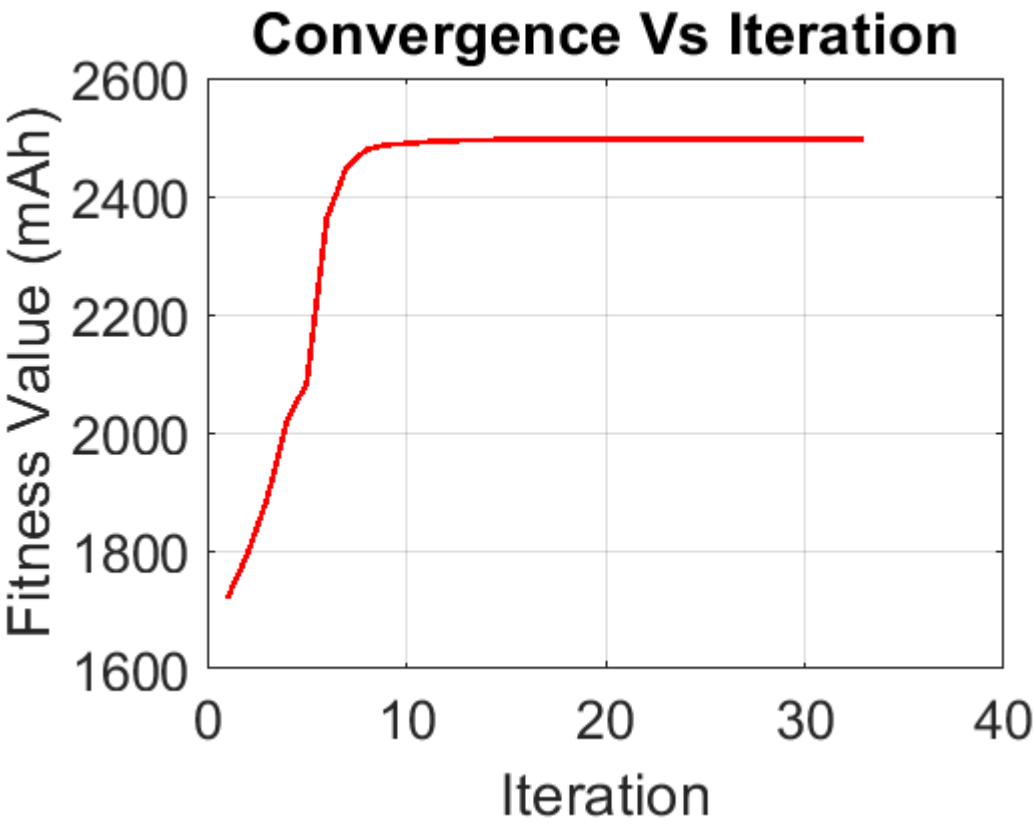

```
Xnew =

    1.7230    4.2000   45.0000


Xnew =

    1.7230    4.2000   45.0000

Iteration = 31
Best Cost = 1.723
```



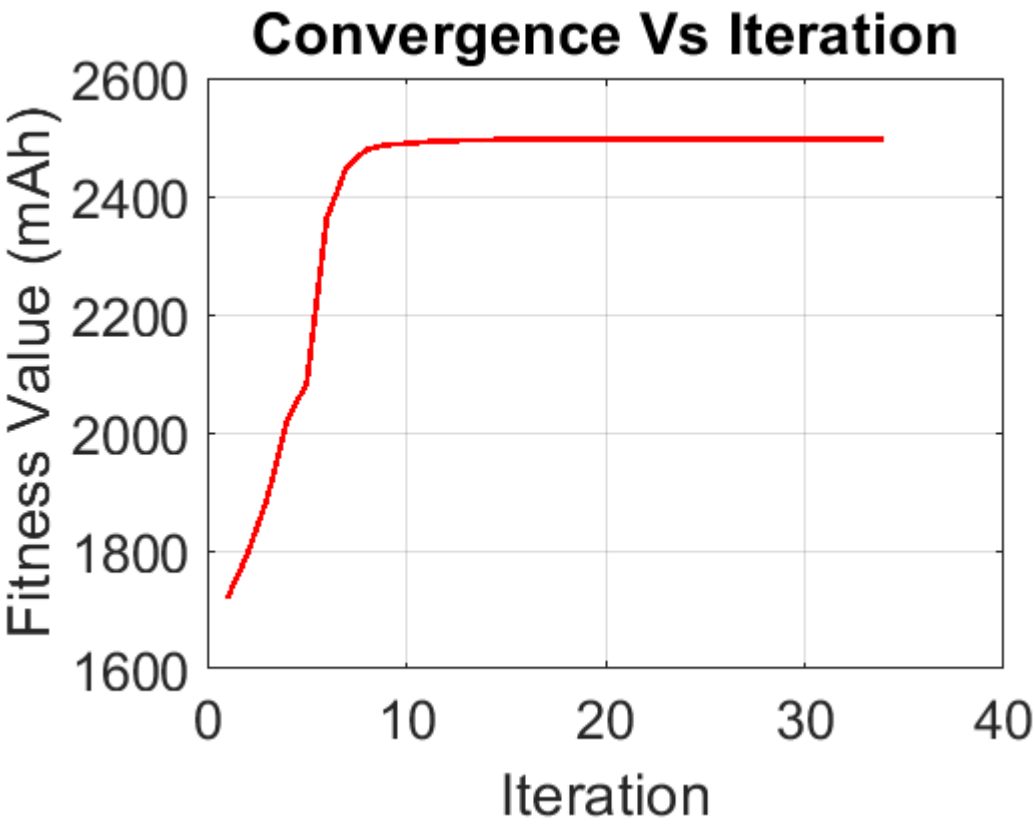

```
Xnew =

    1.7230    4.2000   45.0000


Xnew =

    1.7230    4.2000   45.0000

Iteration = 32
Best Cost = 1.723
```



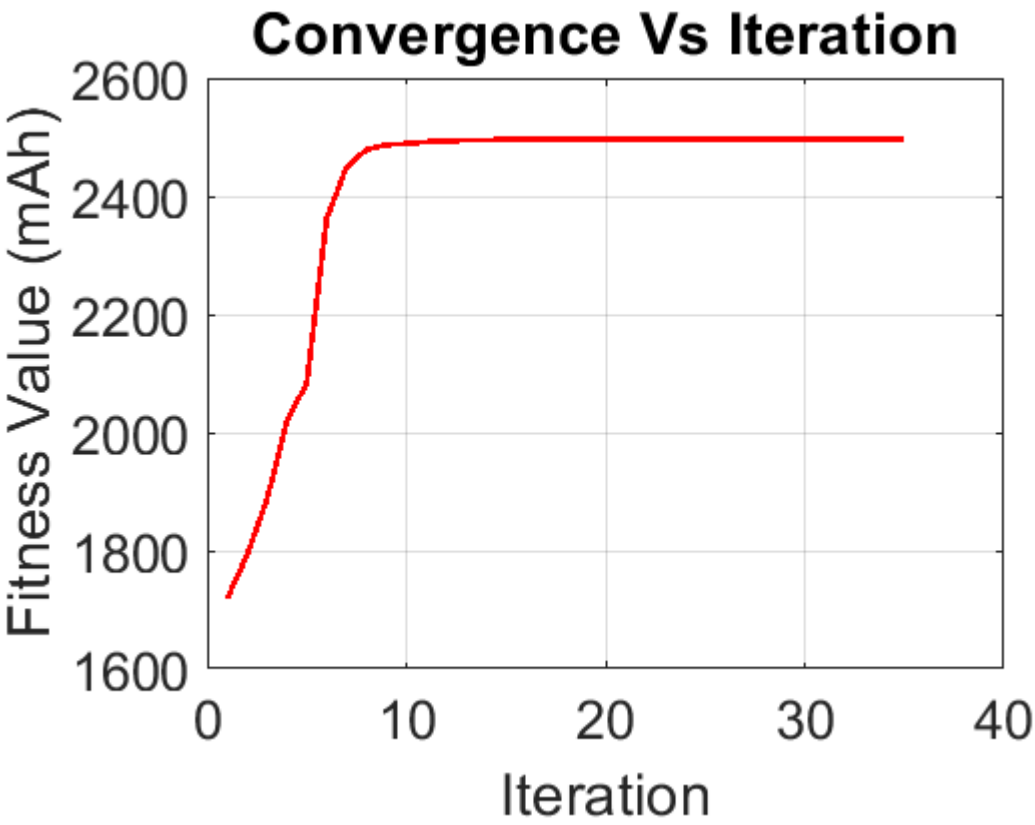

```
Xnew =

    1.7230    4.2000   45.0000


Xnew =

    1.7230    4.2000   45.0000

Iteration = 33
Best Cost = 1.723
```



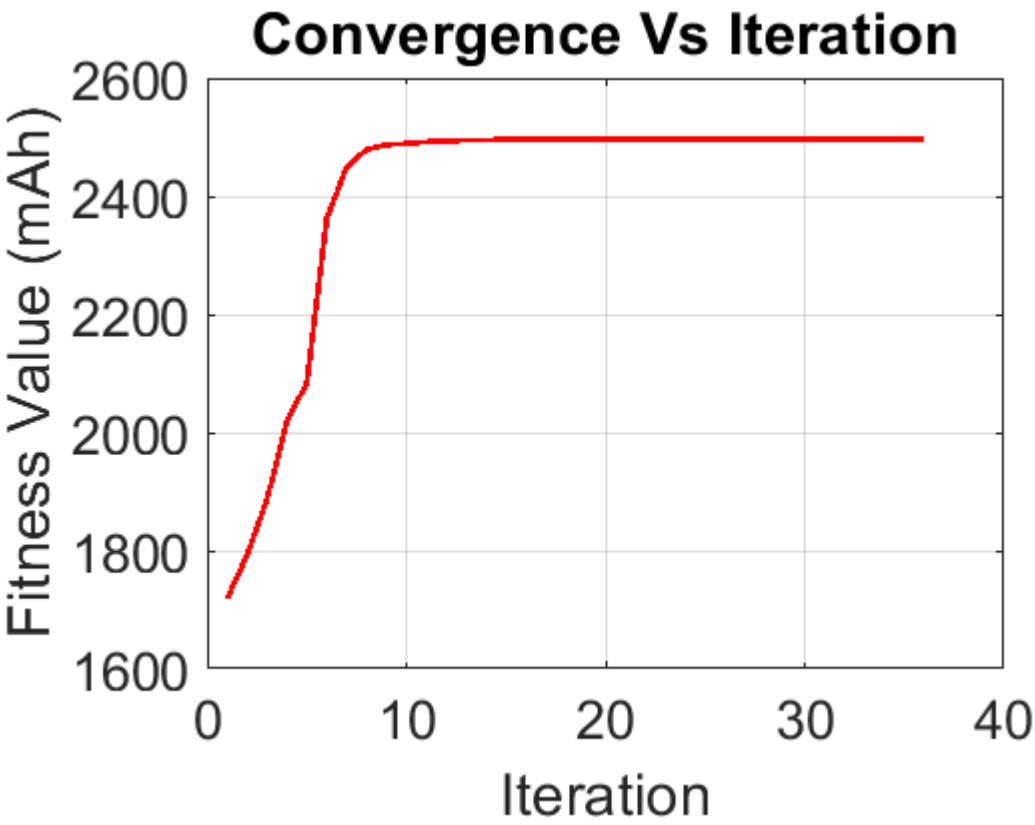

```
Xnew =

    1.7230    4.2000   45.0000

Iteration = 34
Best Cost = 1.723
```



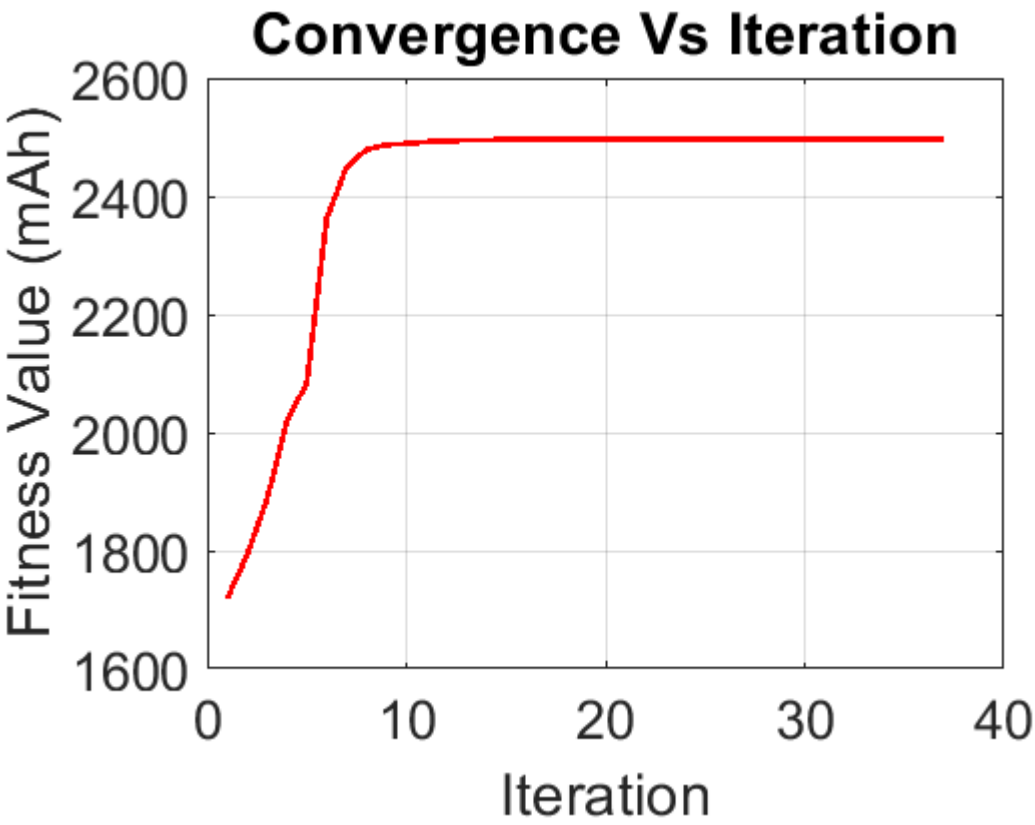

```
Xnew =

    1.7230    4.2000   45.0000

Iteration = 35
Best Cost = 1.723
```



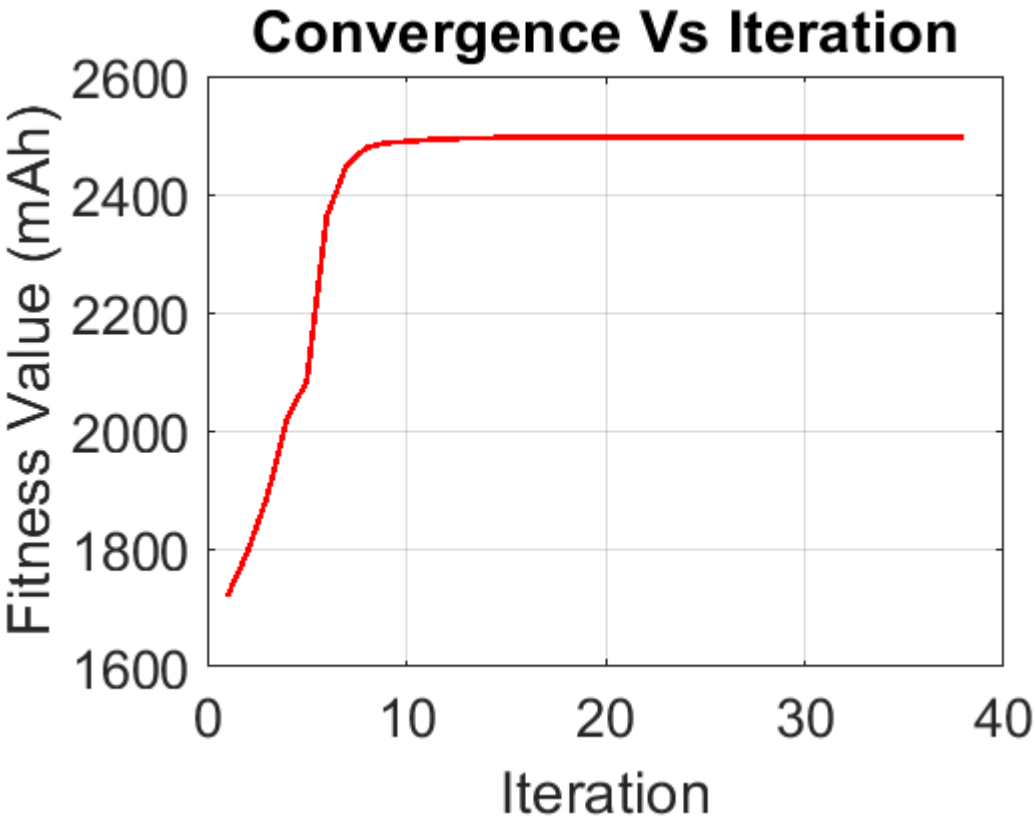

```
Xnew =

    1.7230    4.2000   45.0000

Iteration = 36
Best Cost = 1.723
```



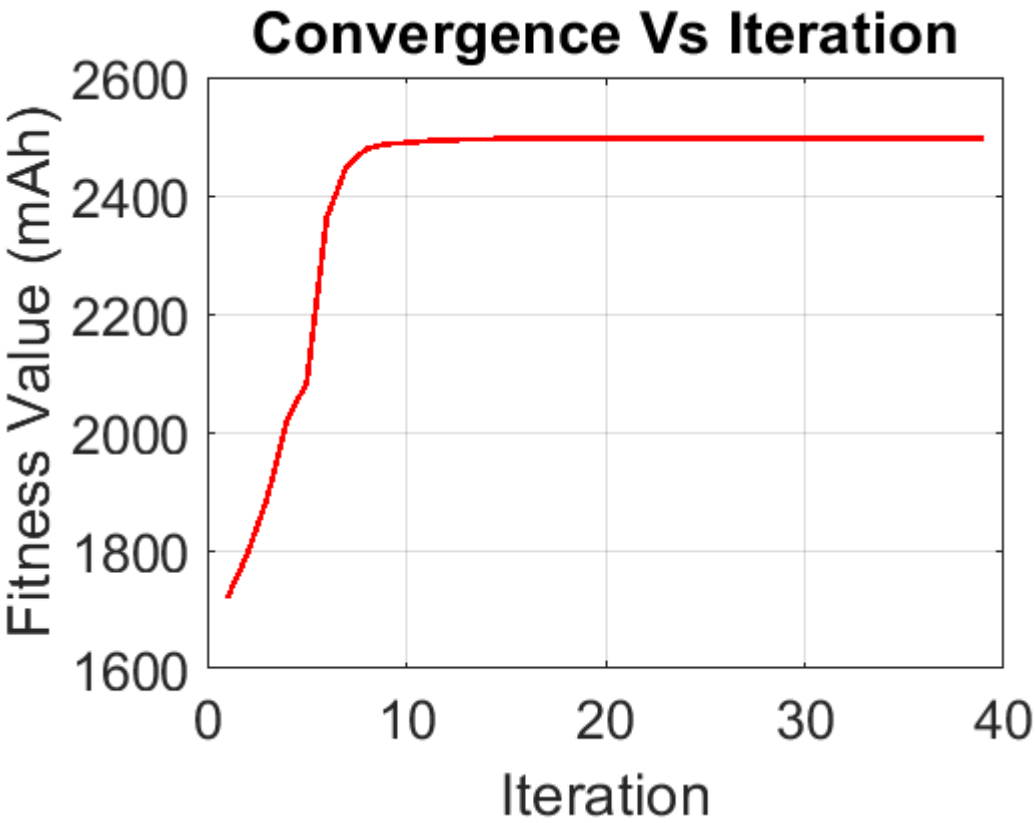

```
Xnew =

    1.7230    4.2000   45.0000

Iteration = 37
Best Cost = 1.723
```



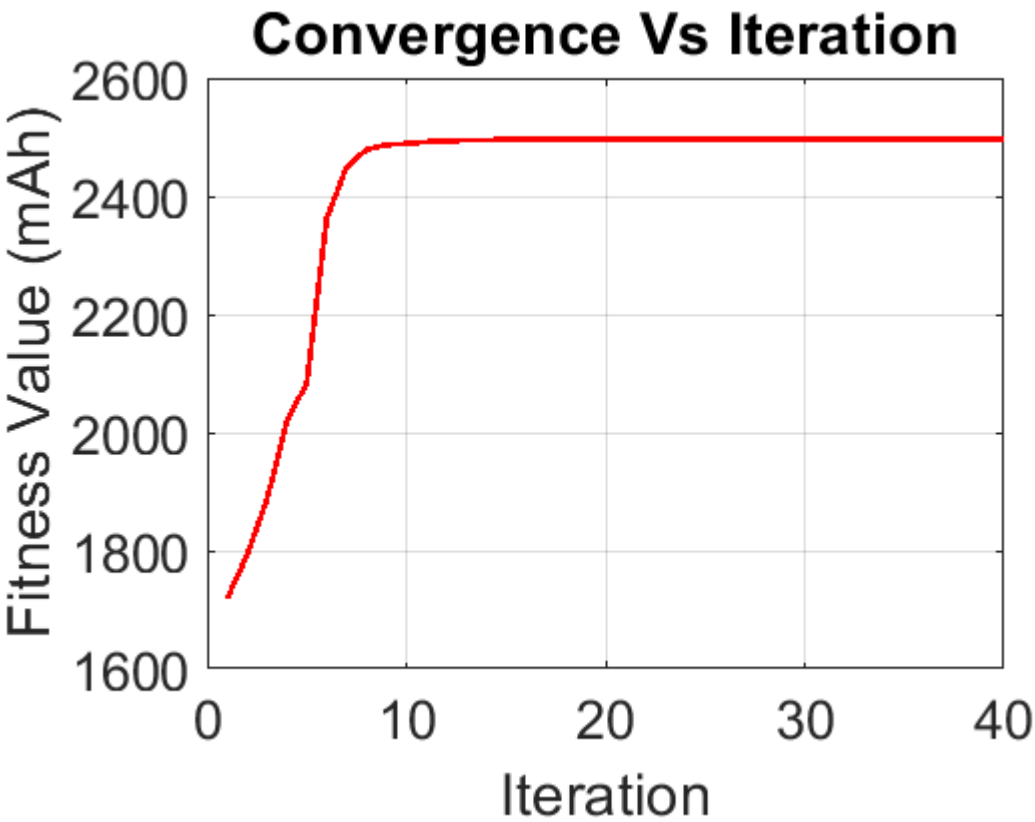

```
Iteration = 38
Best Cost = 1.723
```



```
Xnew =

    1.7230    4.2000   45.0000

Iteration = 39
Best Cost = 1.723
```




```
Xnew =

    1.7230    4.2000   45.0000

Iteration = 40
Best Cost = 1.723
```




```
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