LIFE SPAN PREDICTION OF LITHIUM ION BATTERY USING OPTIMIZATION TECHNIQUE

A PROJECT REPORT

Submitted by

SABARINATHAN P	**(20BEE4073)**
SUJEETHVISHNU V	**(20BEE4098)**
VIJAYABALAN S	**(20BEE4106)**
YESVANTH B	**(20BEE4108)**

in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

in

ELECTRICAL AND ELECTRONICS ENGINEERING

M. KUMARASAMY COLLEGE OF ENGINEERING, KARUR

ANNA UNIVERSITY: CHENNAI 60025

NOVEMBER 2023

M.KUMARASAMY COLLEGE OF ENGINEERING

(Autonomous Institution affiliated to Anna University, Chennai)

BONAFIDE CERTIFICATE

Certified that this project report **"LIFE SPAN PREDICTION OF LITHIUM ION BATTERY USING OPTIMIZATION TECHNIQUE"** is the bonafide work of **"SABARINATHAN P (20BEE4073), SUJEETHVISHNU V (20BEE4098), VIJAYABALAN S (20BEE4106), YESVANTH B (20BEE4108)"** who carried out the project work during the academicyear 2023-2024 under my supervision. Certified further, that to the best of my knowledge thework reported herein does not form part of any other project report or dissertation on the basisof which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE

Dr. J. UMA, M.E., Ph. D.,

HEAD OF THE DEPARTMENT,

Department of Electrical and
Electronics Engineering,

M. Kumarasamy College of Engineering,

Thalavapalayam, Karur - 639113.

SIGNATURE

Dr. K. SUNDARARAJU, M.E., Ph.D.,

SUPERVISOR,

Department of Electrical and
Electronics Engineering,

M. Kumarasamy College of Engineering,

Thalavapalayam, Karur - 639113.

This Project Work 1 (18EEP401L) has been submitted for the End Semester Project Viva voce Examination held on _____________

INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION

We affirm that the Project report titled **"LIFE SPAN PREDICTION OF LITHIUM ION BATTERY USING OPTIMIZATION TECHNIQUE"** being submitted in partial fulfillment for the award of **Bachelor of Engineering** in **Electrical and Electronics Engineering**, is the original work carried out by us. It has not formed the part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

		Signature
SABARINATHAN P	(20BEE4073)	__________________
SUJEETHVISHNU V	(20BEE4098)	__________________
VIJAYABALAN S	(20BEE4106)	__________________
YESVANTH B	(20BEE4108)	__________________

I certify that the declaration made above by the candidates is true to the best of my knowledge.

Dr. K. SUNDARARAJU, M.E., Ph.D.,

(Supervisor)

ACKNOWLEDGEMENT

Our sincere thanks to **Thiru.M.Kumarasamy, Chairman and Dr.K.Ramakrishnan, B.E, Secretary** of **M.Kumarasamy College of Engineering** for providing extra ordinary infrastructure, which helped us to complete the project in time.

It is a great privilege for us to express our gratitude to our esteemed **Principal Dr.B.S.Murugan, M.Tech., Ph.D.,** for providing us right ambiance for carrying out the projectwork.

We would like to thank **Dr.J.Uma, M.E, Ph.D., Professor and Head, Department of Electrical and Electronics Engineering,** for her unwavering moral support throughout the evolution of the project.

We offer our whole hearted thanks to our project guide **Dr.K.Sundararaju, M.E., Ph.D., Professor, Department of Electrical and Electronics Engineering,** for her constant encouragement, kind co-operation, valuable suggestions and support rendered in making our project a success.

We would like to thank our project coordinator **Mr.N.Selvam, M.E., Assistant Professor, Department of Electrical and Electronics Engineering** for his kind cooperation and culminating in the successful completion of project work.

We glad to thank all the **Faculty Members** of **Department of Electrical and Electronics Engineering** for extending a warm helping hand and valuable suggestions throughout the project.

Words are boundless to thank **Our Parents and Friends** for their constantencouragement to complete this project successful.

VISION AND MISSION OF THE INSTITUTION

VISION

To emerge as a leader among the top institutions in the field of technical education.

MISSION

- Produce smart technocrats with empirical knowledge who can surmount the global challenges.
- Create a diverse, fully-engaged, learner-centric campus environment to provide quality education to the students.
- Maintain mutually beneficial partnerships with our alumni, industry and professional associations.

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

VISION

To produce smart and dynamic professionals with profound theoretical and practical knowledge comparable with the best in the field.

MISSION

- Produce hi-tech professionals in the field of Electrical and Electronics Engineering by inculcating core knowledge.
- Produce highly competent professionals with thrust on research.
- Provide personalized training to the students for enriching their skills.

PROGRAMME EDUCATIONAL OBJECTIVES (PEOs)

PEO1: Graduates will have flourishing career in the core areas of Electrical Engineering and allied disciplines.

PEO2: Graduates will pursue higher studies and succeed in academic/research careers.

PEO3: Graduates will be a successful entrepreneur in creating jobs related to Electrical and Electronics Engineering /allied disciplines.

PEO4: Graduates will practice ethics and have habit of continuous learning for their success in the chosen career.

PROGRAMME OUTCOMES (POs)

After the successful completion of the B.E. Electrical and Electronics Engineering degree programme, the students will be able to:

- **PO1: Engineering Knowledge:** Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

- **PO2: Problem Analysis:** Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

- **PO3: Design/Development of Solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

- **PO4: Conduct Investigations of Complex Problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
- **PO5: Modern Tool Usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
- **PO6: The Engineer and Society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
- **PO7: Environment and Sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
- **PO8: Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
- **PO9: Individual and Team Work:** Function effectively as an individual, andas a member or leader in diverse teams, and in multidisciplinary settings.
- **PO10: Communication:** Communicate effectively on complex engineering activities with the engineering community, such as, being able to comprehendand write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

- **PO11: Project Management and Finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

- **PO12: Life-Long Learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOME (PSOs)

The following are the Program Specific Outcomes of Engineering Students:

PSO1: Apply the basic concepts of mathematics and science to analyze and design circuits, controls, Electrical machines and drives to solve complex problems.

PSO2: Apply relevant models, resources and emerging tools and techniques to provide solutions to power and energy related issues & challenges.

PSO3: Design, Develop and implement methods and concepts to facilitate solutions for electrical and electronics engineering related real world problems.

Abstract (key words)	POs mapping
Grey Wolf Optimization method, SOC, SOT, SOH, Battery Management System, Electric Vehicle	PO1, PO2, PO3, PO4, PO5, PO6, PO7, PO8, PO9, PO10, PO11, PO12, PSO1, PSO2, PSO3

ABSTRACT

Now-a-days lithium-ion batteries play a vital role. This project aims to develop an efficient methodology for identifying the parameters of a lithium-ion battery model through the use of optimization technique. Parameter identification of lithium-ion batteries using optimization methods is a process of determining the unknown parameters of a battery model using experimental data. This is a challenging task because lithium-ion battery models are highly nonlinear and contain many parameters. Optimization methods are used to solve this problem by finding the set of parameters that minimizes the error between the model output and the experimental data. When performing parameter identification of a lithium-ion battery using the Grey Wolf Algorithm (GWO) or any other optimization method, it's important to define clear objectives that guide the process and help achieve meaningful results. Some specific objectives of a parameter identification of Lithium-ion battery using Grey wolf optimization method Identify the parameters of a lithium-ion battery model that can be used to estimate its state of charge (SOC), state of temperature (SOT), state of health (SOH), voltage, current and remaining useful life (RUL). Identify parameters that describe the battery's ability to deliver power at different discharge rates. These parameters are used to find the battery life and performance of the battery.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATION

S.NO	EXPANSION	ABREVIATION
1	State of Charge	SOC
2	State of Temperature	SOT
3	State of Health	SOH
4	Lithium Cobalt Oxide	LCO
5	Intrinsic Mode Function	IMF
6	Battery Management System	BMS

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

A battery can change chemical energy to electricity by putting certain chemicals in contact with each other in a specific way. Electrons, which are small parts of an atoms, will travel from one kind of chemical to another under the right circumstances. When electrons flow, this makes an electrical current that can power something. What a battery does is put the right chemicals in the right relationships, and then puts a wall between them. Only when the two sides of a battery are connected by a wire or another conductor can the electrons flow. Many approaches for cycle life test optimization have been proposed, which are mainly based on two types of technology, i.e., accelerated aging test (ADT) technology and RUL prediction. ADT is the standard method for test optimization, which uses high-level test-stress conditions to accelerate the performance degradation process of the products until they reach their EOL.

Then, the aging models that consider the physical mechanisms estimate the lifespan at a standard stress-level by inputting the test data at high-level stress. For ADT-based optimization, although the high-level stress tests are accelerated, a longer time–cost (approximately 2 to 5 months) is still unavoidable owing to the prolonged life of the Li-ion battery.

Additionally, the estimation error of the ADT model is a major obstacle because the aging model cannot cover all possible degradation factors, such as the lithium deposition of the negative electrode, state-of-charge rang, discharge C-rate, and working temperature. The core of this type of optimization method is designing an appropriate prediction method with highly accuracy in company application scenarios.

However there are two challenges including data difference caused by formulation variation and insufficient information on global degradation trend implying in limited data caused by test optimization. Because of the degradation law differences, it is difficult to find a highly generalized model suitable for an accurate RUL estimation of each formulation. On the other hand, constructing a specific model for each one might be a feasible solution although it has higher cost-effectiveness.

Besides, to obtain the maximum possibility of optimization, the test is ended early at a preset threshold, which significantly shortens the data length compared to the common life cycle test. The short-term test data of the target battery with lower quantity and quality are insufficient for effectively developing the specific prediction model and giving accurate RUL estimation results. Additionally, the degradation law inconsistency aggravates this obstacle. It is difficult for the model to learn more degradation patterns and the global degradation law from limited data of the target battery. Regarding RUL prediction of Li-ion battery, the acknowledged methods mainly include physics-based methods, data-driven methods, and hybrids of the former two methods.

The physical-based methods require mathematically physical models to accurately describe the electrochemical degradation process. However, a universal physics-based model could not cover all the possible information of all formulations and provide accurate results. In contrast, it is time-consuming and different to fit specific models well for each formulation with limited data. In addition, the difference between the formulations cannot be entirely and accurately represented in the model.

The abundant historical test data of other formulations might be utilized to augment the data volume and help to make up for the lost information. However, determining how to mine and utilize the data with highly individual differences is a huge challenge. Predicting the lifespan of a lithium-ion battery involves a combination of empirical testing, physical models, and machine learning techniques. Optimization techniques can also be utilized to enhance battery performance and extend its lifespan. Here's an overview of the approaches commonly used.

Lithium-ion batteries have become the preferred energy storage solution due to their high energy density, lightweight nature, and rechargeable capabilities. However, their lifespan is influenced by multiple factors, including chemical composition, temperature, depth of discharge, charging rates and usage patterns. Over time, these batteries degrade, resulting in reduced capacity and performance. The prediction and optimization of lithium-ion battery lifespan involve a multidisciplinary approach, combining empirical data, physical models, and advanced computational techniques. The primary goal is to estimate the remaining useful life of a battery and develop strategies to prolong its longevity by minimizing degradation.

1.2 LITERATURE SURVERY

1. A comparison of lead-acid and lithium-based battery behavior and capacity fade in off-grid renewable charging applications.

Author: krieger, Elena M., Cannarella, John, et Arnold, Craig B

Year: 2013

The effects of variable charging rates and incomplete charging in off-grid renewable energy applications are studied by comparing battery degradation rates and mechanisms in lead-acid, LCO (lithium cobalt oxide), LCO-NMC (LCO-lithium nickel manganese cobalt oxide composite), and LFP (lithium iron phosphate) cells charged with wind-based charging protocols. Poor pulse charge acceptance, particularly for long pulses, contributes to incomplete charging and rapid degradation of lead-acid cells due to apparent high rates of sulphation and resistance growth. Partial charging and pulse charging, common lead-acid stressors in off-grid applications, are found to have little if any effect on degradation in the lithium-based cells when compared to constant current charging. These cells all last much longer than the lead-acid cells; the LFP batteries show the greatest longevity, with minimal capacity fade observed after over 1000 cycles. Pulse charge acceptance is found to depend on pulse length in lead-acid and LFP cells, but not in LCO and LCO-NMC cells. Excellent power performance and consistent voltage and power behavior during cycling suggest that LFP batteries are well-suited to withstand the stresses associated with off-grid renewable energy storage and have the potential to reduce system lifetime costs.

2. Lithium-Ion Battery Remaining Useful Life Prediction Based on Hybrid Model

Author: Xuliang, TangHeng Wan, Weiwen Wang, Mengxu Gu, Linfeng Wang and Linfeng Gan

Year: 2023

Accurate prediction of the remaining useful life (RUL) is a key function for ensuring the safety and stability of lithium-ion batteries. To solve the capacity regeneration and model adaptability under different working conditions, a hybrid RUL prediction model based on complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and a bi-directional gated recurrent unit (BiGRU) is proposed. CEEMDAN is used to divide the capacity into intrinsic mode functions (IMFs) to reduce the impact of capacity regeneration. In addition, an improved grey wolf optimizer (IGOW) is proposed to maintain the reliability of the BiGRU network. The diversity of the initial population in the GWO algorithm was improved using chaotic tent mapping. An improved control factor and dynamic population weight are adopted to accelerate the convergence speed of the algorithm. Finally, capacity and RUL prediction experiments are conducted to verify the battery prediction performance under different training data and working conditions. The results indicate that the proposed method can achieve an MAE of less than 4% with only 30% of the training set, which is verified using the CALCE and NASA battery data.

3. A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendation

Author: Hannan, M.A, Lipu. M.H.Hussain and Mohamed. A

Year: 2017

Lithium-ion power batteries have been widely used in transportation due to their advantages of long life, high specific power, and energy. However, the safety problems caused by the inaccurate estimation and prediction of battery health state have attracted wide attention in academic circles. In this paper, the degradation mechanism and main definitions of state of health (SOH) were described by summarizing domestic and foreign literatures. The estimation and prediction methods of lithium-ion power battery SOH were discussed from three aspects: model-based methods, data-driven methods, and fusion technology methods. This review summarizes the advantages and disadvantages of the current mainstream SOH estimation and prediction methods. This paper believes that more innovative feature parameter extraction methods, multi-algorithm coupling, combined with cloud platform and other technologies will be the development trend of SOH estimation and prediction in the future, which provides a reference for health state estimation and prediction of lithium-ion power battery.

4. Critical review of state of health estimation methods of Li-ion batteries for real applications

Author: Maitane Berecibar, Igor Villarreal, Iñigo Gandiaga and N. Omar

Year: 2015

Lithium-ion battery packs in hybrid and electric vehicles, as well as in other traction applications, are always equipped with a Battery Management System (BMS). The BMS consists of hardware and software for battery management including, among others, algorithms determining battery states. The accurate and reliable State of Health (SOH) estimation is a challenging issue and it is a core factor of a battery energy storage system. In this paper, battery SOH monitoring methods are reviewed. To this end, different scientific and technical literature is studied and the respective approaches are classified in specific groups. The groups are organized in terms of the way the method is carried out: Experimental Techniques or Adaptive Models. Not only strengths and weaknesses for the use in online BMS applications are reviewed but also their accuracy and precision is studied. At the end of the document a potential, new and promising via in order to develop a methodology to estimate the SOH in real applications is detailed.

5. Remaining useful life prediction and state of health diagnosis for lithium-ion batteries based on improved grey wolf optimization algorithm-deep extreme learning machine algorithm

Author: Zhou, Yifei; Wang, Shunli; Xie, Yanxing; Shen, Xianfeng; Fernandez, Carlos

Year: 2023

The prediction of SOH for Lithium-ion battery systems determines the safety of Electric vehicles and stationary energy storage devices powered by LIBs. State of health diagnosis and remaining useful life prediction also rely significantly on excellent algorithms and effective indicators extraction. Since the data obtained from the aging experiment of Lithium-ion batteries is rich in electrochemical and dynamic information, useful health indicators can be extracted for SOH and RUL prediction of machine learning. This paper presents a method for predicting SOH and RUL based on a data-driven model of deep extreme learning machine based on improved Grey Wolf optimization algorithm.

CHAPTER 2
BATTERIES

2.1 INTRODUTION

A battery can be defined as an electrochemical device (consisting of one or more electrochemical cells) which can be charged with an electric current and discharged whenever required. Batteries are usually devices that are made up of multiple electrochemical cells that are connected to external inputs and outputs. Batteries are widely employed in order to power small electric devices such as mobile phones, remotes, and flashlights. Historically, the ‘term’ battery has always been used in order to refer to the combination of two or more electrochemical cells. However, the modern definition of the term ‘battery’ is believed to accommodate devices that only feature a single cell.

2.2 BATTERY TYPES:

Batteries nowadays are one of the most important components of electronic appliances and are used in almost every portable electronic device. From Drones to phones, and tablets to automobile EVs, one common electronic component you find is the battery. Batteries are broadly classified into two categories, namely primary batteries and secondary batteries.

Primary batteries can only be charged once. When these batteries are completely discharged, they become useless and must be discarded. The most common reason why primary batteries cannot be recharged is that the electrochemical reaction that takes place inside of them is irreversible in nature. It is important to note that primary batteries are also referred to as use-and-throw batteries.

On the other hand, secondary batteries are the batteries than can be charged and reused for many charging-discharging cycle.

2.3 PRIMARY BATTERY TYPES:

2.3.1 Alkaline Batteries:

This type of battery drives the energy by a reaction of zinc metal and manganese oxide and we named it an alkaline battery because instead of using an acidic electrolyte, we use an alkaline electrolyte like potassium hydroxide (KOH).

Figure 2.3.1 Alkaline battery

2.3.2 Aluminum Air Batteries:

This is the highest energy density battery and produces energy from the reaction of oxygen with aluminum. Once the aluminum is consumed and all aluminum gets reacted with air oxygen, we can't use this battery further and we need to dispose of it after a single use.

2.3.3 Dry Cells:

This is another type of primary battery and most of us used it in our toys and TV remote control but these batteries are now getting replaced by alkaline batteries because of their high lifetime and energy density over the dry cells. The dry cell is named after its electrolyte type as we use the dry electrolyte in it instead of liquid or wet electrolyte.

Figure 2.3.3 Dry cells

2.4 SECONDARY BATTERY TYPES

2.4.1 Li – Ion battery

This kind of battery uses Lithium metal so named Li-Ion battery. These batteries are composed of cells and lithium ions from the negative electrode move to the positive electrode and when we charge, the ions move back to their place; this cycle occurs in each charging and discharging process. A lithium-ion cell consists of a cathode, an anode, separator, and electrolyte. The anode and cathode materials are deposited onto copper and aluminium foil current collectors, respectively. The electrolyte enables the movement of lithium ions between the electrodes while the separator fits between the anode and cathode preventing shorting between the two electrodes but permitting ion

Figure 2.4.1 Li-ion battery

transfer. During the discharge reaction, lithium ions move from the anode and insert into the voids between layers of cathode crystals (the process named intercalation). The power density of Li-ion batteries is 126 Wh/Kg.

2.4.2 Li-PO battery:

The Li-Po battery lithium polymer battery and we named polymer battery because they use polymer electrolyte instead of liquid electrolyte. The high conductivity gel polymer form of electrolyte is used. These batteries carry high energy density compared to their weight. These are mostly used in drones due to their lightweight and high density of energy. It has a Power density of 185 Wh/Kg.

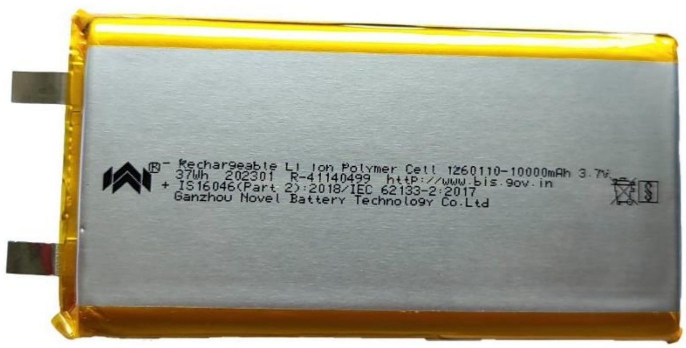

Figure 2.4.2 Li-PO battery

2.4.3 Ni-MH battery

Ni-MH (nickel metal hydride) battery uses nickel oxide hydroxide and they are quite similar to Nikel cadmium NiCd battery but here they use a hydrogen-absorbing alloy instead of cadmium and have a lower impact on the environment compared to others. The power density of these batteries is 100 Wh/Kg. Nickel Metal Hydride batteries offer a high energy density, low self-discharge rate, and good cycle life. They are also more environmentally friendly than other rechargeable battery chemistries.

Figure 2.4.3-Ni-MH battery

2.4.4 Lead acid battery

The chemical reactions that occur in secondary cells are reversible. The reactants that generate an electric current in these batteries (via chemical reactions) can be regenerated by passing a current through the battery (recharging).The chemical process of extracting current from a secondary battery (forward reaction) is called discharging The method of regenerating active material is called charging. The lead acid battery has electrodes submerged in sulfuric acid electrolytes.

Figure 2.4.4 Lead acid battery

CHAPTER 3

EXISTING SYSTEM

3.1 INTRODCTION

In existing method the lead-acid batteries are the most used for PV off-grid applications due to their affordable prices for large installed capacities. The total battery price is the highest in the system's net present cost (NPC); hence, the accurate estimation of battery life is one of the most critical problems in the optimization process of standalone systems. The authors in suggested continuous and ON/OFF control methods to minimize the cost of a stand-alone PV-battery diesel system taking into account only the diesel generator (DG) fuel consumption cost.

A battery management system for a PV-battery diesel micro-grid is proposed in to reduce DG operating hours, controlling battery charge and discharge processes and reducing PV power output fluctuations. In many OM were proposed to operate a PV-battery system considering the grid scheduled blackouts problem in order to decrease the total cost of the consumed energy from the grid. Lately, an economic model predictive control (MPC) was used in to create an optimal power distribution framework for a PV-battery system taking into consideration the battery life and the problem of grid failures. Compared to the previously mentioned studies, this paper proposes a predictive optimization novel approach to extend lead acid battery lifetime. Based on a given power predictive data, it decides, on a future horizon of specified length, the number of PVs (nPV) connected to the system (PV's mode ON).

Knowing that the lifetime of a battery depends on its depth of charge (DOC), discharge cycles and on the time between two recharges, the idea developed in this paper is to determine the nPV to be put into service, over a given time horizon, to satisfy the users' needs, while minimizing the degradation of the battery. In the first section, a third order equivalent electrical circuit model of the battery is presented which allows to calculate the current and SOC of the battery.

Due to the difference between the input power provided by the source (solar panels) and the output power consumed by the load, the batteries storage system is used as a backup to deliver the power required by the load. Power and energy management strategy leads to maximize the utility of RE sources. To find the degradation of battery used by an implementation of genetic algorithm (GA) which is a heuristic search algorithm used for solving optimization problems. It is a kind of stochastic optimization approach that finds a solution by randomly searching the solution space.

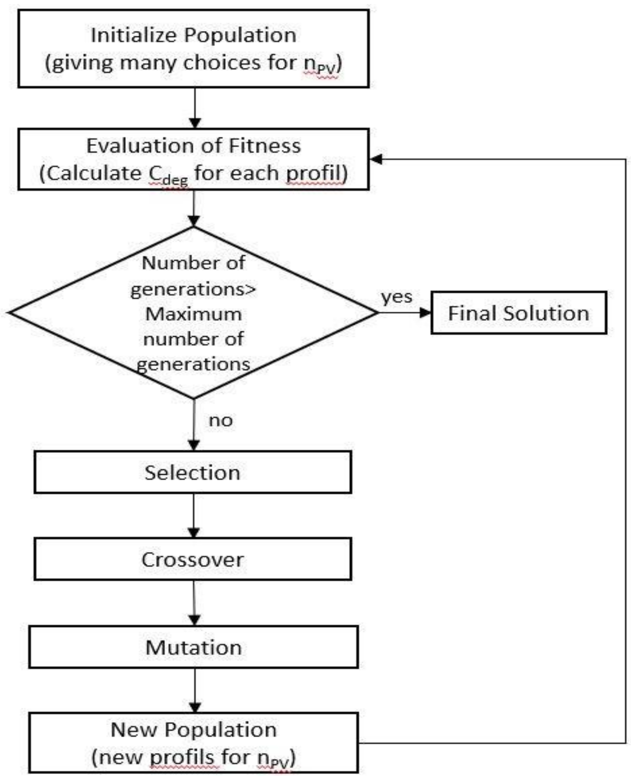

Figure 3.1 Simple genetic algorithm Flow chart

3.2 BLOCK DIAGRAM OF BATTERY LIFETIME OPTIMIZATION

The general procedure for GA can be summarized in the flowchart of fig 3.2. Individuals are chosen using a fitness-based selection method. The selection operator is composed of ranking and selection progress, which means that in the following generation, more copies of the individuals that match the optimization issue better will be generated. The tournament selection (TS) method is used here, in which a tournament is held between two solutions, with the better solution being chosen and placed in the mating pool.

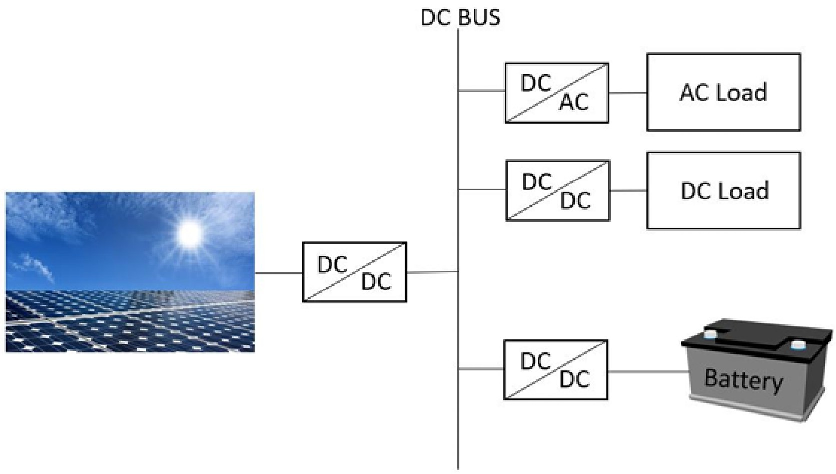

Figure 3.2 Block diagram of Battery Lifetime Optimization

Two more options are considered, and a new slot in the mating pool is created. It is carried out in such a way that each solution can be used in exactly two tournaments. Following the selection, the individuals will be recombined (crossover). This process consists of cutting two existing individuals at one or more positions and exchanging the portions following the cut to create two new individuals from two existing individuals picked by the operator of selection. As a result, the new individuals can inherit some genetic material from both parents. This can usually be accomplished in one of four ways: one-point crossover, two point crossover, cycle crossover, and uniform cross-over.The method employed is Simulated Binary Crossover (SBX), which uses two parent solutions to produce two off-springs.

CHAPTER 4
PROPOSED SYSTEM

4.1 INTRODUCTION

Due to its availability and the good conversion factor, solar energy technology has advanced at an exponential rate in the last few years. As a renewable energy source, generation from solar energy eliminates pollution caused by traditional energy industries by lowering air novice emissions. Moreover, electricity generation from this resource is quite viable for a variety of uses. In particular, the rapid development of solar energy instruments gives a complete kit of tools that can be directly applied into the field of Electric Vehicles (EV). Several studies have suggested that photovoltaic cells can be used to cover EVs' surfaces to store a significant amount of electricity in the storage system. This would increase EVs' autonomy, which will in turn increase the use of EVs. Some additional benefits are also associated to solar-powered Electric Vehicles. First, the load peaks may be reduced so that the grid management is easier. Second, a decrement of the costs of charging the EVs would also be perceived by the drivers.

4.2 EQUIVALENT CIRCUIT OF BATTERY MODEL

To comprehend the dynamic behavior of lithium-ion batteries, a thorough battery model must be chosen. Various lithium-ion battery models were displayed and compared in terms of their complexity and accuracy; the more advantageous choice was a network-based battery model with single and double RC branches and lumped parameters. The single-order RC model, the one-time constant model of the lithium-ion battery, is the most frequently used. This model mainly consists of three parts, which are as follows: a battery voltage source, which is called battery open-circuit voltage ($Vocv$), internal ohmic resistance (Ro), and a resistance and capacitance branch, which describes the battery's transient behavior while being charged and discharged (Rtr,Ctr)

and is called the charge dynamics of the battery. (Vtr) and ($ICtr$) are the voltage across and the current of the transient capacitance (Ctr) and ($Ibatt$) is the battery's terminal current.

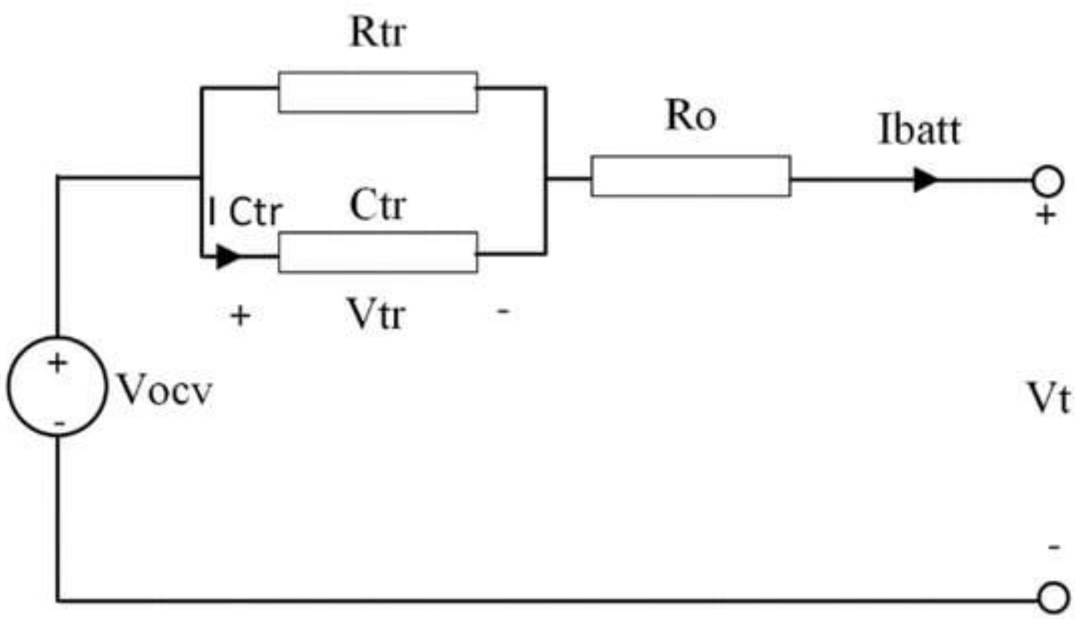

Figure 4.2 Equivalent circuit of Battery Model

4.3 GREY WOLF ALGORITHM

Grey wolf optimizer (GWO) is a population-based meta-heuristics algorithm that simulates the leadership hierarchy and hunting mechanism of grey wolves in nature, and it's proposed by Seyedali Mirjalili et al. in 2014. Grey wolves are considered apex predators, which are at the top of the food chain Grey wolves prefer to live in groups (packs), each group contain 5-12 individuals on average. All the individuals in the group have a very strict social dominance hierarchy as demonstrated in the accompanying figure. The inspiration for this algorithm is the behavior of the grey wolf, which hunts large prey in packs and relies on cooperation among individual wolves. There are two interesting aspects of this behavior social hierarchy and hunting mechanism.

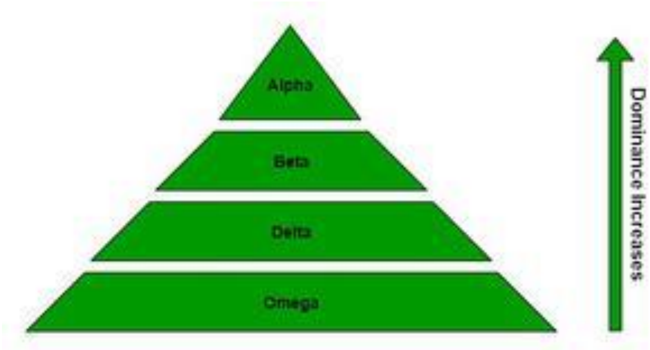

Figure 4.2 Social dominance hierarchy of Grey wolf

4.4 ADVANTAGES:

Grey wolf optimization (GWO) is a relatively new optimization algorithm that has been shown to have several advantages over other popular algorithms such as particle swarm optimization (PSO) and genetic algorithm (GA). These advantages include:

Fewer parameters: GWO has only a few parameters to tune, which makes it easier to use than other algorithms.

Simple principles: GWO is based on the social hierarchy and hunting behavior of grey wolves, which makes it easy to understand and implement.

Fast convergence speed: GWO has been shown to converge to the optimal solution faster than other algorithms, especially for complex problems with many dimensions. Good exploration and exploitation capabilities: GWO has a good balance between exploration and exploitation, which helps it to avoid getting trapped in local optima.

Robustness: GWO is relatively robust to noise and disturbances, which makes it suitable for a wide range of applications.

In addition to these general advantages, GWO has also been shown to be particularly effective for certain types of problems, such as:

Feature selection: GWO can be used to select the most important features from a dataset, which can improve the performance of machine learning models.

Parameter optimization: GWO can be used to optimize the parameters of machine learning models, such as the hyper-parameters of a neural network.

Path planning: GWO can be used to find the shortest or most efficient path between two points, which has applications in robotics and navigation.

Engineering design: GWO can be used to design engineering systems, such as antennas and filters.

Overall, GWO is a powerful and versatile optimization algorithm that has several advantages over other popular algorithms. It is particularly well-suited for complex problems with many dimensions, as well as for problems such as feature selection, parameter optimization, path planning, and engineering design.

Here are some examples of how GWO has been used successfully in the real world. GWO has been used to optimize the parameters of a solar cell design, resulting in a significant increase in efficiency. GWO has been used to design a new type of antenna that is smaller and more efficient than traditional antennas. GWO has been used to develop a new algorithm for path planning in robots, which has resulted in a significant improvement in performance. GWO has been used to select the most important features from a medical dataset, which has improved the accuracy of a machine learning model for diagnosing cancer. These are just a few examples of the many potential applications of GWO. As research into GWO continues, we can expect to see it used in even more innovative and exciting ways in the future.

CHAPTER 5

SOFTWARE IMPLEMENTATION

MATLAB

Matlab, short for "Matrix Laboratory," is a high-level programming language and environment primarily designed for numerical computing, data analysis, and visualization. It is widely used in various fields, including engineering, science, finance, and academia, due to its extensive toolboxes, powerful mathematical functions, and ease of use.

5.1. INTRODUCTION:

Matlab was developed by MathWorks and first released in the late 1980s. It provides a convenient platform for performing a wide range of tasks related to data analysis, simulation, modelling, and algorithm development. Some key features of Matlab include:

Interactive Environment: Matlab provides an interactive environment where users can execute commands, perform calculations, and visualize data in real-time. This makes it suitable for rapid prototyping and experimentation.

Extensive Functionality: It offers a vast library of built-in functions and toolboxes for a wide range of applications, from linear algebra and signal processing to machine learning and image processing.

Graphical User Interface (GUI): Matlab allows you to create user-friendly GUIs for your programs, enabling non-programmers to interact with your applications.

WORKING PROCESS:

- Command Window: Users can enter Matlab commands directly into the command window. This is where you can perform calculations, create variables, and test algorithms.

- Scripts and Functions: Matlab code is typically organized into scripts (sequences of Matlab commands stored in a .m file) and functions (reusable pieces of code with inputs and outputs).
- Data Visualization: Matlab offers various tools for data visualization, including 2D and 3D plots, graphs, charts, and image displays.
- Toolboxes: You can extend Matlab's capabilities by using specialized toolboxes for specific tasks. For instance, the Signal Processing Toolbox provides functions for signal analysis, while the Image Processing Toolbox is for image analysis and manipulation.
- Data Import/Export: Matlab supports the import and export of data in various formats, such as Excel, CSV, and HDF5, making it easy to work with external data sources.

5.2 GREY WOLF ALGORITHM PROCEDURE

The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. In addition, three main steps of hunting, searching for prey, encircling prey, and attacking prey, are implemented to perform optimization. In existing method used Genetic optimization technique and Schiffer model. Here used Grey wolf optimization techniques to measure the parameters of the battery. Linear programming is a widely used in optimization for several reasons, which can be: In operation research, complex real-life problems can be expressed as linear programming problems. Many algorithms in specific optimization problems operate by solving Linear Programming problems as sub-problems. Compared with traditional optimization algorithms such as PSO and GA, GWO has the advantages of fewer parameters, simple principles, and implementing easily.

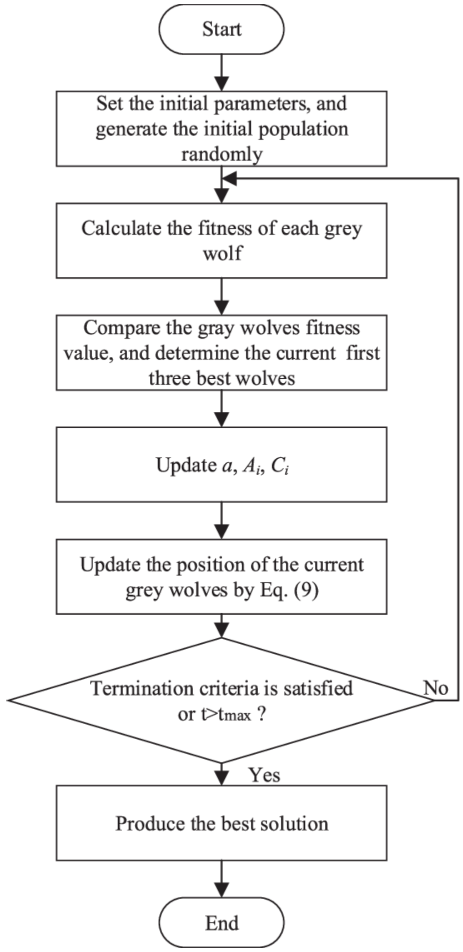

Figure 5.2 Grey wolf algorithm flow chart

Pseudocode of the GWO algorithm:

Step1: Randomly initialize the population of grey wolves Xi (i=1,2,…,n)

Step2: Initialize the value of a=2, A and C

Step3: Calculate the fitness of each member of the population Xα=member with the best fitness value Xβ=second best member (in terms of fitness value) Xδ=third best member (in terms of fitness value)

Step4: FOR t = 1 to Max_number_of_iterations: Update the position of all the omega wolves by eq. 4, 5 and 6 Update a, A, C (using eq. 3) a = 2(1-t/T) Calculate Fitness of all search agents Update Xα, Xβ, Xδ. END FOR Step5: return Xα

5.3 SIMULATION CODE:

```
SearchAgents_no=30; % Number of search agents
Function_name='F6'; % Name of the test function that can be from F1 to F23 (Table 1,2,3 in the paper)
Max_iteration=500; % Maximum numbef of iterations
% Load details of the selected benchmark function
[lb,ub,dim,fobj]=Get_Functions_details(Function_name);
[Best_score,Best_pos,GWO_cg_curve]=GWO(SearchAgents_no,Max_iteration,lb,ub,dim,fobj);
% This MATLAB program implements a simple battery charging algorithm using a PID controller
% Battery parameters
Capacity = 1000; % Battery capacity in mAh
Voltage =12;      % Battery voltage in volts
% Initialize PID controller parameters
Kp = 1;
Ki = 0.1;
Kd = 0.01;
% Setpoint (desired SOC)
setpoint = 80; % 80% state of charge
% Initialize variables
SOC = 50; % Initial state of charge in percentage
error = 0;
integral = 0;
% Time vector
time = 0:1:499; % Time range for simulation in seconds
```

```
% Battery charging simulation
for t = 1:length(time)
    % Calculate the errors
    error_prev = error;
    error = setpoint - SOC;

    % Calculate the integral term
    integral = integral + error;
    % Calculate the derivative term
    derivative = error - error_prev;

    % Calculate the control input (current) using PID controller
    current = Kp * error + Ki * integral + Kd * derivative;
    % Apply safety limits to the current
    current = max(min(current, 2), 0); % Limit charging current between 0 and 2
Amps
    % Update SOC based on the charging current
    SOC = SOC + (current * 0.1) / (Capacity/1000);
    % Calculate the battery voltage during charging
    battery_voltage = Voltage + 0.05 * (SOC - 50); % A simple linear model for
voltage variation
    % Save results for plotting
    SOC_data(t) = SOC;
    SOC_data1(t) = SOC+Best_score;
    current_data(t) = current;
    current_data1(t) = current+Best_score;
    voltage_data(t) = battery_voltage;
```

```
    voltage_data1(t) = battery_voltage-Best_score;
    SOH(t)= (voltage_data(t)/(12*100));
    SOH1(t)= (voltage_data1(t)/(12*100));
    SOT(t)= SOC_data(t)/ current_data(t);
    SOT1(t)= SOC_data1(t)/ current_data1(t);
End

subplot(1,2,1);
func_plot(Function_name);
title('Parameter space')
xlabel('x_1');
ylabel('x_2');
zlabel([Function_name,'( x_1 , x_2 )'])

%Draw objective space
subplot(1,2,2);
semilogy(GWO_cg_curve,'Color','r')
title('Objective space')
xlabel('Iteration');
ylabel('Best score obtained so far');

axis tight
grid on
box on
legend('GWO')

display(['The best solution obtained by GWO is : ', num2str(Best_pos)]);
```

```
display(['The best optimal value of the objective funciton found by GWO is : ', num2str(Best_score)]);

% Plot the results
figure(3);
%%semilogy(SOC_data,'Color','r')
plot(time, SOC_data,'r');
hold on;
plot(time, SOC_data1,'g');
xlabel('Time (s)');
ylabel('State of Charge (%)');
title('Battery Cell Charging using Controller');

figure(4);
% semilogy(current_data,'Color','r')
% grid on;
%    plot(time, current_data1);
plot(time, current_data,'r');
hold on;
plot(time, current_data1,'g');

xlabel('Time (s)');
ylabel('Current (A)');
title('Charging Current');

figure(5);
%plot(time, voltage_data
```

```
plot(time, voltage_data,'r');
hold on;
plot(time, voltage_data1,'g');
xlabel('Time (s)');


figure(6);

%plot(time, voltage_data
plot(time, SOH,'r');
hold on;
plot(time, SOH1,'g');
xlabel('Time (s)');
ylabel('Voltage (V)');
title('SOH');


figure(7);

%plot(time, voltage_data
plot(time, SOT,'r');
hold on;
plot(time, SOT1,'g');
xlabel('Time (s)');
ylabel('Voltage (V)');
title('SOT');
```

CHAPTER 6
RESULT AND DISCUSSION

6.1 VOLTAGE OUPUT GRAPH

The x-axis of the graph represents time, and the y-axis represents the battery voltage. The red line indicates the voltage varies without optimization techniques. The green line indicates the voltage varies with optimization. The difference between optimization and without optimization is the voltage increase slowly with respect to time. In this condition the voltage is efficient. Without optimization the voltage suddenly increases. It affects the battery life. Some time it may lead to the overcharging. The voltage graph shows in the figure 6.1

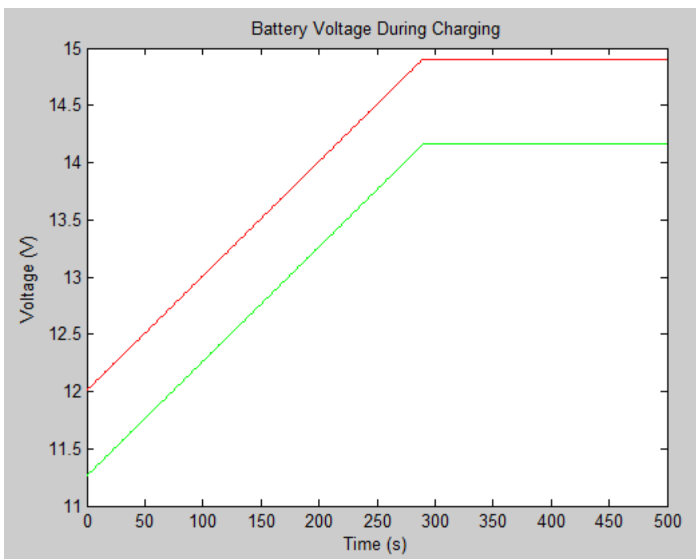

Figure 6.1 the graph shows the voltage with optimization and without optimization

6.2 CURRENT OUTPUT GRAPH

The x-axis of the graph represents time, and the y-axis represents the battery current. The red line indicates the current varies without optimization techniques.

The green line indicates the current varies with optimization.

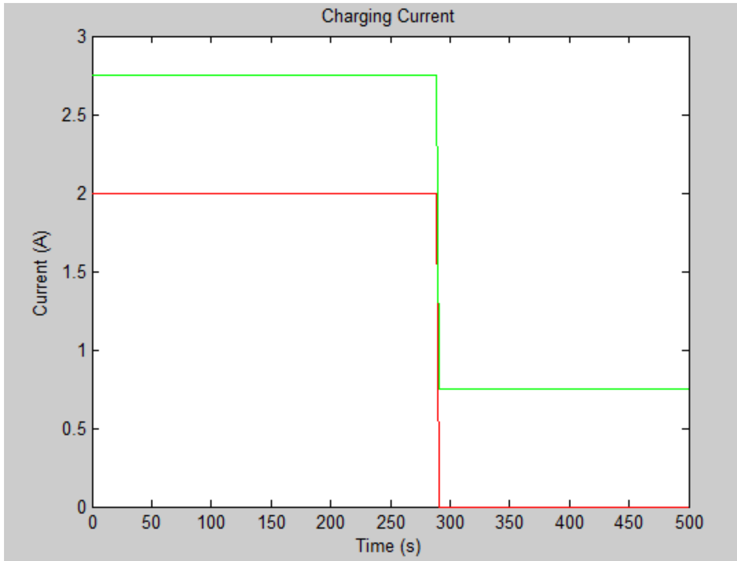

Figure 6.2 the graph shows the current with optimization and without optimization

The difference between optimization and without optimization is the current goes constant at some point the current decreases after some t\time period the current shows constant. In this condition the current is efficient. Without optimization the current reaches zero. It affects the battery life. The current graph shows in the figure 6.2.

6.3 SOC OUTPUT GRAPH

The x-axis of the graph represents time, and the y-axis represents the battery SOC. The red line indicates the SOC varies without optimization techniques. The green line indicates the SOC varies with optimization. The difference between the SOC with optimization and without optimization the SOC is increased. The charge time also increased. The SOC graph shows in the figure 6.3.

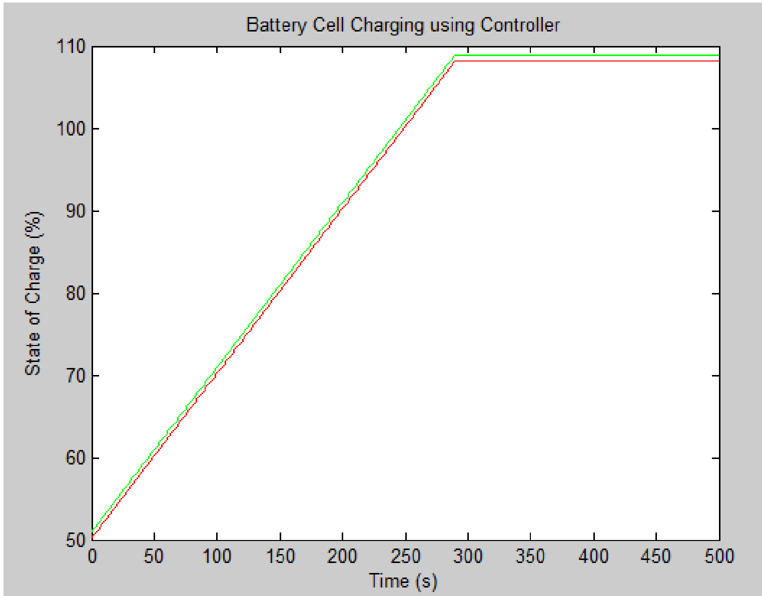

Figure 6.3 the graph shows SOC curve with optimization and without optimization

6.4 SOH OUTPUT GRAPH

The x-axis of the graph represents time, and the y-axis represents the battery voltage. The red line indicates the SOH varies without optimization techniques. The green line indicates the SOH varies with optimization.

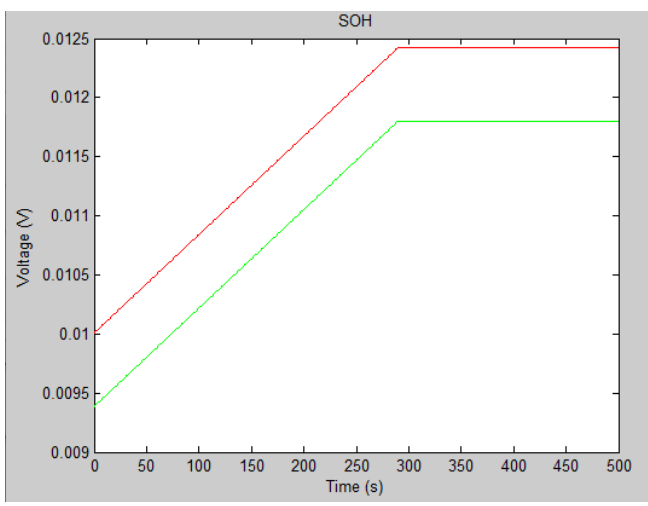

Figure 6.4 the graph shows SOH curve with optimization and without optimization

The difference between the SOH with optimization and without optimization the SOH is decreased in the optimization. The health of the battery is improved. The SOH graph shows in the figure 6.4.

6.5 SOT OUTPUT GRAPH

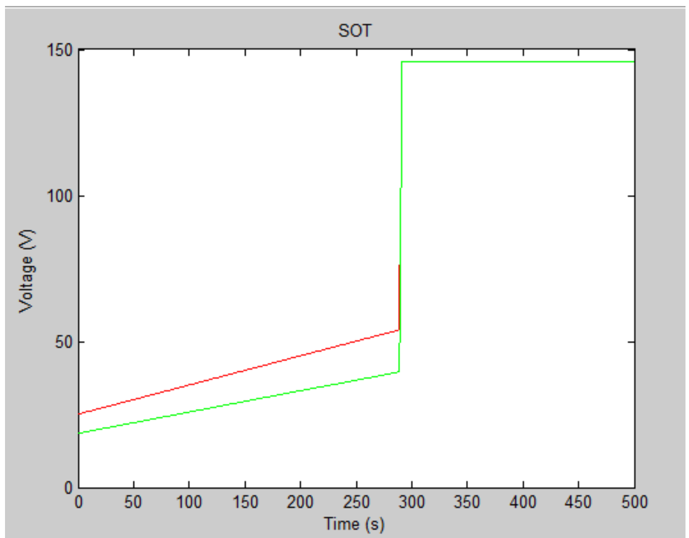

Figure 6.5 the graph shows SOT curve with optimization and without optimization

The State of Charge (SOC) of a lithium-ion battery is a measure of how much energy is remaining in the battery. It is typically expressed as a percentage, with 100% representing a fully charged battery and 0% representing a completely discharged battery. The x-axis of the graph represents time, and the y-axis represents the battery voltage. The red line indicates the SOT varies without optimization techniques. The green line indicates the SOT varies with optimization. Using optimization technique the temperature is decreased. The SOH graph shows in the figure 6.5.

By changing the parameters of battery capacity and voltage different state of charge, state of temperate and state of health graph is obtained. The dynamical value of battery is obtained on the basis of different iteration and time variation. Through the parameters of the battery the life span is predicted. The dynamic value obtained by using Grey Wolf algorithm is 0.547 on predefined capacity of battery is 1000 mAh and predefined voltage is 12V. On changing the iteration and time variation different dynamical value is obtained between 0 and 1. By calling the function of grey wolf optimization the dynamic value is obtained based on the predefined battery capacity and voltage.

CHAPTER 7
CONCLUSION

In conclusion, the study on the lifespan prediction of lithium ion battery using optimization techniques shows the battery optimal values and how the battery working in different condition. The Grey wolf optimization shows the battery lifecycle and also can be predicted with the help of SOC, SOH, SOT, current and voltage. The grey wolf method is simple and takes less time. Through the Grey wolf algorithm the output is efficient. GWO was confirmed by the results on multimodal functions. The results of the composite functions showed high local optima avoidance. Finally, the convergence analysis of GWO confirmed the convergence of this algorithm. In conclusion, the study on the lifespan prediction of lithium ion battery using optimization techniques shows the battery optimal values and how the battery working in different condition. The grey wolf algorithm plays a major role in the prediction of life span of the battery and its specifications.

REFERENCES

1]. “A comparison of lead-acid and lithium-based battery behavior and capacity fade in off-grid renewable charging applications” by krieger, Elena M., Cannarella, John, et Arnold, Craig B, 2013.

2]. C. Muro, R. Escobedo, L. Spector, and R. Coppinger, "Wolf-pack (Canis lupus) hunting strategies emerge from simple rules in computational simulations," Behavioural processes, vol. 88, pp. 192-197, 2011.

3]. “Critical review of state of health estimation methods of Li-ion batteries for real applications” by Maitane Berecibar, Igor Villarreal, Iñigo Gandiaga and N. Omar Year: 2015.

4]. “Lithium-Ion Battery Remaining Useful Life Prediction Based on Hybrid Model” by Xuliang, TangHeng Wan, Weiwen Wang, Mengxu Gu, Linfeng 2Wang and Linfeng Gan Year: 2023.

5]. “A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendation” by Hannan, M.A, Lipu. M.H.Hussain and Mohamed. A at 2017.

6]. KRIEGER, Elena M., CANNARELLA, John, et ARNOLD, Craig B. A comparison of lead-acid and lithium-based battery behavior and capacity fade in off-grid renewable charging applications. Energy, 2013, vol. 60, p. 492-500.

7]. DUFO-L´ OPEZ, Rodolfo, LUJANO-ROJAS, Juan M., et BERNAL AGUST´ IN, Jos´e L. Comparison of different lead–acid battery lifetime prediction models for use in simulation of stand-alone photovoltaic systems. Applied Energy, 2014, vol. 115, p. 242-253.

8]. NGUYEN, Minh Y., NGUYEN, Dinh Hung, et YOON, Yong Tae. A new battery energy storage charging/discharging scheme for wind power producers in real-time markets. Energies, 2012, vol. 5, no 12, p. 5439-5452. markets,” Energies, 2012.

9]. ALRAMLAWI, Mansour, GABASH, Aouss, et LI, Pu. Optimal operation strategy of a hybrid PV-battery system under grid scheduled blackouts. In 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe). IEEE, 2017. p. 1-5.

10].SCHIFFER, Julia, SAUER, Dirk Uwe, BINDNER, Henrik, et al. Model prediction for ranking lead-acid batteries according to expected lifetime in renewable energy systems and autonomous power-supply systems. Journal of Power sources, 2007, vol. 168, no 1, p. 66-78.

11].GOLCHHA, Ankita et QURESHI, Shahana Gajala. Enhanced NSGA II Algorithm for Solving Multi-objective Optimization Problems Using PBXCrossover and POM Mutation. International Journal of Computer Science and Information Technologies, 2015, vol. 6, no 1, p. 256-261.

12].Ma, G., Zhang, Y., Cheng, C., Zhou, B., and Yuan, Y., 2019, “Remaining Useful Life Prediction of Lithium-Ion Batteries Based on False Nearest Neighbors and a Hybrid Neural Network,” Appl. Energy, 253, p. 113626.

13].Wang, Y., Ni, Y., Li, N., Lu, S., Zhang, S., Feng, Z., and Wang, J., 2019, “A Method Based on Improved Ant Lion Optimization and Support Vector Regression for Remaining Useful Life Estimation of Lithium-Ion Batteries,” Energy Sci. Eng., 7(6), pp. 2797–2813.

14].Gao, D., and Huang, M., 2017, “Prediction of Remaining Useful Life of Lithium-Ion Battery Based on Multi-Kernel Support Vector Machine With Particle Swarm Optimization,” J. Power Electron, 17(5), pp. 1288–12.