MTech (Power Electronics and Systems) Sushaya Keisam 2026

CHARGING OPTIMIZATION, STUDY OF LIFE CYCLE AND SUSTAINABLE RECYCLING OF BATTERIES USED IN EVs

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CANDIDATE'S DECLARATION

I am Sushaya Keisam student of MTech Power Electronic System, hereby declare that the project entitled "**Charging Optimization, Study of Life Cycle and Sustainable Recycling of Batteries used in EVs**" which is submitted to the Department of Electrical Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology is original and not copied from any source without proper citation. This work has not previously formed the basis for the award for my Degree, Diploma Associateship, Fellowship, or any other similar title or recognition.

Place: New Delhi

Date: 10/12/2025

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CERTIFICATE

I hereby certify that the project titled "**Charging Optimization, Study of Life Cycle and Sustainable Recycling of Batteries used in EVs**" which is submitted by **Sushaya Keisam(24/PES/29),** student of the Department of Electrical Engineering, Delhi Technological University, in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of project work carried out by the student under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any degree or diploma to this university or elsewhere**.**

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Date- 12/05/2026

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ABSTRACT

This project examines the life cycle of recycled lithium in electric car batteries, focusing on the recycling process and its environmental impact at different stages of its life cycle. The goal is to gain insight into the environmental impacts of primarily lithium, but also other valuable materials in electric car batteries, and how their extraction, use and recycling are affected by political guidelines and regulations. Different techniques for recycling battery materials are investigated, such as pyrometallurgy, hydrometallurgy and direct recycling. These are then compared with regard to environmental impacts, efficiency and safety. The impact of policies and regulations on battery recycling is analysed, more specifically the guidelines given by the European Union within the framework of the Green Deal. Also, the proposed system integrates EV charging optimization using PSO with an objective to minimize energy cost while satisfying SOC constraints. The literature studies have contributed a lot of information as there is extensive research in the area, but as many of these articles have similar perspectives, there was a lack of more nuanced studies.

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CHAPTER 1

INTRODUCTION

1.1 Background

Society today is moving towards an electrified future, and the background to this work is to find out how the environment is affected by this. A major factor is the rapidly growing electrification of the automotive industry, i.e. the ongoing transition from combustion engines to electric motors. To drive this electrification of vehicles, such as cars, some kind of energy storage is needed: batteries. A growing electrification of society thus leads to an increased demand for batteries, and it is therefore important to find out how this will affect the environment we live in.

The work will be carried out in the form of a survey of the recycling and reuse of lithium-ion batteries in the automotive industry with the aim of making use of hard-to-extract metals. Recycling is something that is generally important for making use of the finite resources that exist and when recycling batteries it is interesting to know which method gives the best results with the least environmental impact. The survey will also consider political directives as incentives for companies to invest more in battery recycling.

1.2 Purpose

The purpose of this work is to map out what the life cycle of lithium in electric vehicle batteries looks like, how these affect the environment and how politics contributes to reducing this environmental impact. The focus will be on the end of the life cycle, more specifically the recycling processes. Also, a thematic code will be and implemented as MATLAB model in order to increase the efficiency and storage of Li-ion batteries.

1.3 Boundaries

The boundaries chosen in this work are to focus primarily on lithium in electric vehicle batteries, as this is the basic building block in lithium-ion batteries, which are the most common battery type in electric vehicles today [1]. Other metals that are commonly found in these batteries are mentioned, but without much in-depth discussion to avoid the work being too extensive. It has also been chosen to focus on recycled lithium, i.e. lithium that ends up in landfills is not included in this work. Furthermore, it does not address lithium-ion batteries that end up in a so-called Second Life: batteries that can no longer be used in the automotive industry, but which still have a sufficiently high capacity to be used in other energy storage contexts [2]. These limitations have been chosen in order to be able to carry out the work within the given time frame.

1.4 Organisation of Thesis:

The thesis includes 5 chapters:

Chapter 1 The introduction section encompasses the background, aims of the research conducted, and its limitations.

Chapter 2 covers the literature review, which includes an introduction, methods for recycling batteries, and techniques for optimizing battery charging.

Chapter 3 addresses theoretical aspects, including the lithium extraction process, battery configurations employed in electric vehicles, the production of lithium-ion batteries, and recycling methods.

Chapter 4 presents the algorithms and techniques employed in charging optimization, along with their outcomes.

Chapter 5 presents results and discussion.

Chapter 6 concludes the work and discusses potential future developments.

CHAPTER 2

LITERATURE STUDIES

The work relies largely on literature studies. This was chosen because the subject of the work has been carefully studied and is under constant research, which means that there is access to many different sources that are of high relevance. The majority of the sources have been selected using the Scopus tool, which has made it possible to find the scientific articles used during the work. On Scopus it is also possible to see which other sources have used the articles and which other sources have been used. This makes it possible to find other sources that are relevant, but that focus on other points. Which in turn makes it possible to expand the search area. There are also sources that have been picked from websites other than Scopus, and these have been carefully checked.

2.1 INTRODUCTION

The purpose of this work is to map out what the life cycle of lithium in electric vehicle batteries looks like, how these affect the environment and how politics contributes to reducing this environmental impact. The focus will be on the end of the life cycle, more specifically the recycling processes [2].

This project also proposes a Particle Swarm Optimization (PSO) based technique for charging a plug-in Electric Vehicle considering real time pricing of the electricity grid. The technique was able to achieve a 30% reduction in the consumer's electricity via implementation of this strategy.

2.2 Extraction and Recycling of batteries

Brine extraction is the most used way to extract lithium. In South America, particularly in the so-called Lithium Triangle (Argentina, Chile, and Bolivia), lithium is produced from brines from subterranean reservoirs [3].

Rock sources can also be used to extract lithium. To do this, the lithium-containing rock source is ground into granules, which are then treated with different chemicals to extract and isolate the lithium. These approaches require more time and money in terms of resources. The extraction from brine will be the main topic of this paper.

Batteries come in a wide variety of shapes, both in terms of their chemical makeup and surface. This implies that depending on the batteries, recycling procedures may appear differently and yield different outcomes. Lithium-ion batteries are now produced using three methods: direct recycling, hydrometallurgy, and pyrometallurgy.

2.3 Charging optimization of EVs

PSO is used in EV charging to identify the optimal charging strategy that satisfies goals such as: shorter charging time,reducing the price of electricity,reducing the degradation of batteries and keeping the grid from overflowing

Particles in Swarm Optimization alter their charging method by using:
Personal best (pbest): The particle that has the best solution.
Global best (gbest): The best is found by the swarm as a whole.

2.4 Conclusion

Recycling is something that is generally important for making use of the finite resources that exist and when recycling batteries it is interesting to know which method gives the best results with the least environmental impact.

Also, PSO-based charging is an intelligent algorithm that determines the optimal charging schedule for an EV in order to lower costs, preserve battery life, and prevent grid overload.

CHAPTER 3

STUDY OF LIFE CYCLE OF BATTERIES

In this chapter, the theory that is considered necessary to be able to answer the question will be discussed and compiled.

3.1 Introduction

The most common extraction method for lithium is extraction from brine. Lithium is extracted from brines from underground reservoirs in, among other places, South America, mainly in the so-called Lithium Triangle (Argentina, Chile and Bolivia) [3].

Lithium can also be extracted from rock sources. The process for this involves granulating the rock source containing lithium and then treating the granulate with various chemicals to separate and extract the lithium. These types of methods are more resource-intensive both financially and in terms of time. In this report, the focus will be primarily on extraction from brine. The process for extraction from brine is explained below and illustrated in Figure 1 [4].

1. Extraction: The brine is pumped from the source to the surface and transported to outdoor evaporation ponds. Over time, exposure to the sun causes the water in the solution to evaporate, leaving behind a solution with high concentrations of lithium.

2. Purification: The function of the purification step is to remove impurities containing minerals such as magnesium, calcium and sodium chloride. This is done by treating the solution with sodium carbonate and lime, which form precipitates together with unwanted substances in the solution, which can then be more easily separated and removed.

3. Precipitation: The lithium is separated from the remaining solution by converting the dissolved lithium ions into a solid form to facilitate separation. A reagent (sodium carbonate or sodium hydroxide) is added and reacts with the lithium to form the lithium carbonate precipitate.

4. Filtration: The lithium precipitate needs to be removed from the remaining solution. By passing the solution through filtration devices such as filter presses, vacuum filters or

centrifuges. The solid lithium carbonate precipitate sticks to the filter and the remaining solution falls through. The precipitate is then washed to remove any impurities.

5. Drying: Finally, the lithium carbonate is dried, and the final product becomes a powder.

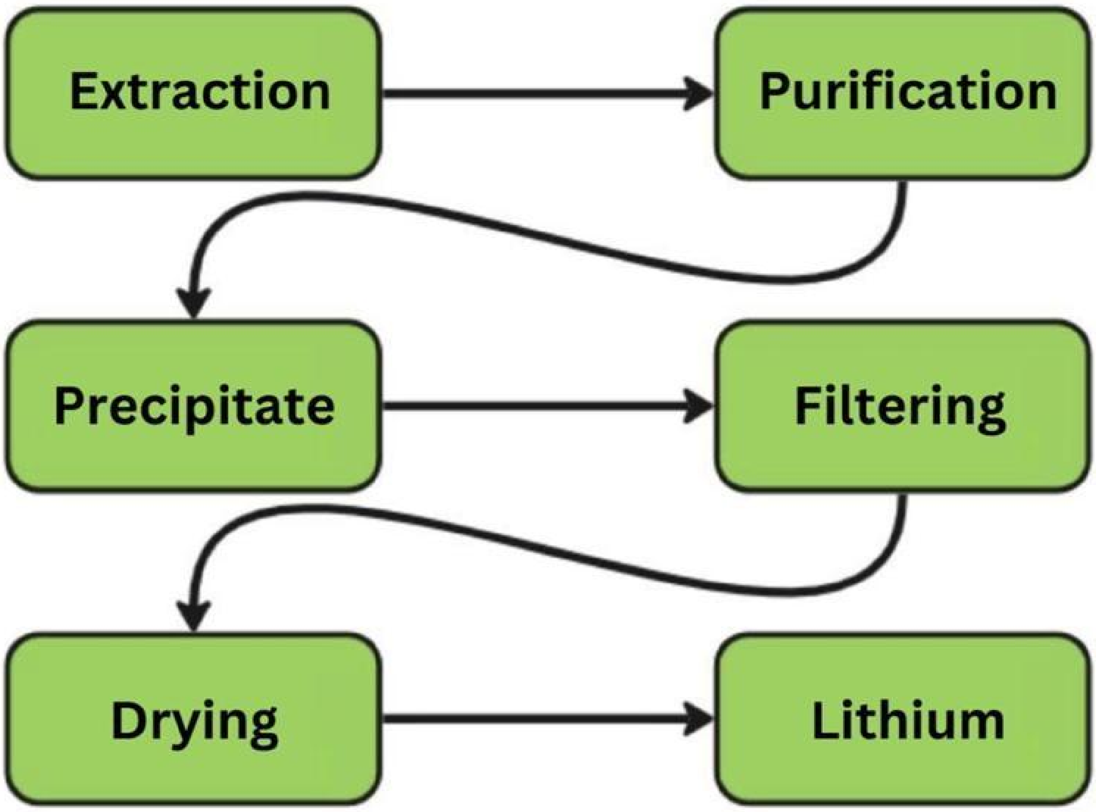


Figure 3.1: The process for extracting lithium from a saltwater source.

3.2 Battery structure in electric vehicles

Electric cars use so-called battery packs. A battery pack is made up of a number of modules, or batteries, which in turn are made up of cells. There are different types of battery cells to work with when it comes to lithium-ion batteries. In the automotive industry, it is most common to encounter one of these three types:

● Cylindrical

● Prismatic

● Pouches

These can be seen below in Figure 2. The three different cells work in the same way but come in different designs. Cylindrical and prismatic use the same type of principle: long strips of anodes, cathodes and separators that are rolled or folded together and then put into a container. Pouches also use strips of material but instead of being folded or rolled, a number of layers are stacked on top of each other [6].

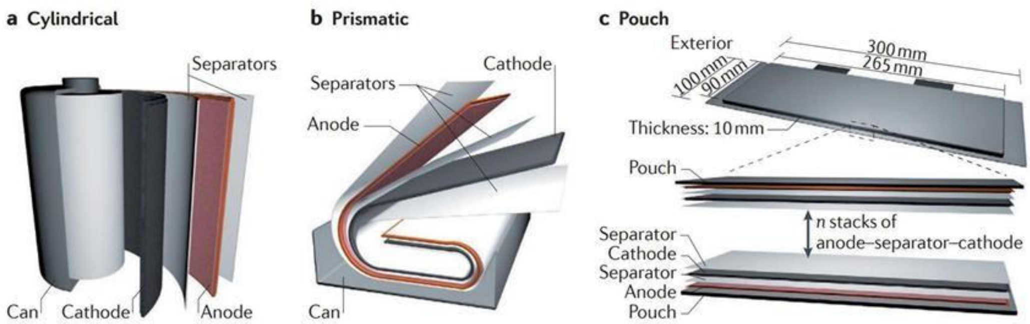


Figure 3.2: The three most common battery cells used in electric vehicle battery packs: a Cylindrical, b Prismatic and c "Pouch". Taken from the article: "Promise and reality of postlithium-ion batteries with high energy densities" [6]

In addition to the fact that the cells can look different, the cathode in the cells can also have different chemical compositions to obtain varying properties, such as energy density, cyclic life, calendar life and more. The different chemical compositions found in lithium-ion batteries today can be seen in Table 1 below, where LCO is the first commercial cathode in lithium-ion batteries and NMC is the latest [7]. The abbreviations are a way of identifying the chemical composition used and stand for the metals that distinguish them from each other, for example LCO which stands for Lithium [Li] Cobalt [Co] Oxides [O] and NMC which stands for Nickel [Ni] Manganese [Mn] Cobalt [Co].

The table also shows that the NCA and NMC cathodes vary in the amount of these metals used. In NMC, the amount of cobalt varies based on how much nickel and manganese is used. NMC 111 is a cathode with as much nickel as manganese as cobalt, and this is being developed more and more to use as little cobalt as possible. The latest NMC variant, 811, is then eight parts nickel to one part manganese and one part cobalt.

Chemical composition	Shortening	Meaning
LiCoO2	LCO	Lithium cobalt oxide
LiFePO4	LFP	Lithium iron phosphorous
LiMn2O4	LMO	Lithium manganese oxide
LiNixCoyAl1-x-yO2	NCA	Nickel cobalt aluminium
LiNixMnyCo1-x-yO2	NMC	Nickel manganese cobalt

Table 3.1: Table of the different chemical compositions of cathode materials used in lithium-ion batteries today and their abbreviations used to distinguish them.

3.3 The manufacture of lithium-ion batteries

The manufacture of a battery cell begins with the electrode manufacture. This begins with the metals that will be included in the cathode being mixed into a solution, usually NMP (this is also used in direct recycling as described in section 2.4.3.). The same process occurs for the anode, which consists of graphite dissolved in deionized water, and the final product at this stage is thus a slurry of cathode material and a slurry of anode material [8].

The solutions then continue through pipes and storage tanks to the part of the factory where the next step takes place. In the next step in the manufacturing process, the slurry of cathode material is applied to both sides of an aluminium foil, the slurry of anode material is applied to a copper foil.

The foils with coatings of cathode and anode slurry then continue into a room that is heated to dry the coating onto the metal foil. In the drying room, the solution the slurry is mixed in evaporates and the active materials stick to the foil, the solution the cathode material is mixed in is either captured and reused or the gas is used through thermal recovery.

After the foil has dried, it is rolled up into a large roll, the roll is then moved to undergo a process called calendaring. This means that the foil is rolled out along a number of rollers that will hold the foil under a certain pressure. The foil is electrostatically discharged by either an air flow or brushes on each side, then it is pulled through two larger rollers that give the foil a desired thickness and then the foil is rolled up again.

The rollers are then rolled out once more and now it is to cut it down into so-called “daughter rolls”. The daughter rolls are then dried under vacuum for 12–30 hours to remove the remaining moisture, after which they are ready for cell production. The rolls look different if these are for pouches versus prismatic and cylindrical.

This has to do with the fact that they are stacked together instead of rolled together, and to make this possible, sheets of cathode and anode material are pressed out of corresponding rolls before they are stacked.

The manufacture of the cells looks slightly different but ultimately involves the same steps in different designs. First, the cathodes and anodes are packed together, which is done by either rolling together or stacking together, the design of the interior itself can be seen in Figure 2.

Separators are used between the electrodes to avoid short circuits; these are made of a mixture of plastics such as polyethylene and polypropylene. This packing is then sealed in a container: either a bag, a prismatic box or a cylindrical package. These three are usually in some form of metal, or metal foil when it comes to the pouch design. Before these are completely sealed, they are filled with an electrolyte, a solution of lithium salts, often $LiPF_6$. It is very important that this happens in a sterile environment as the lithium salts are very reactive.

After these cells have been manufactured, a number of cells are connected together either in series or parallel, or in some cases a mixture of both, to achieve a desired effect. This creates a battery. A number of batteries are then connected together to create a battery pack that can then be installed in an electric vehicle. Figure 3 below compares three battery packs from three different car manufacturers that use different cell designs.

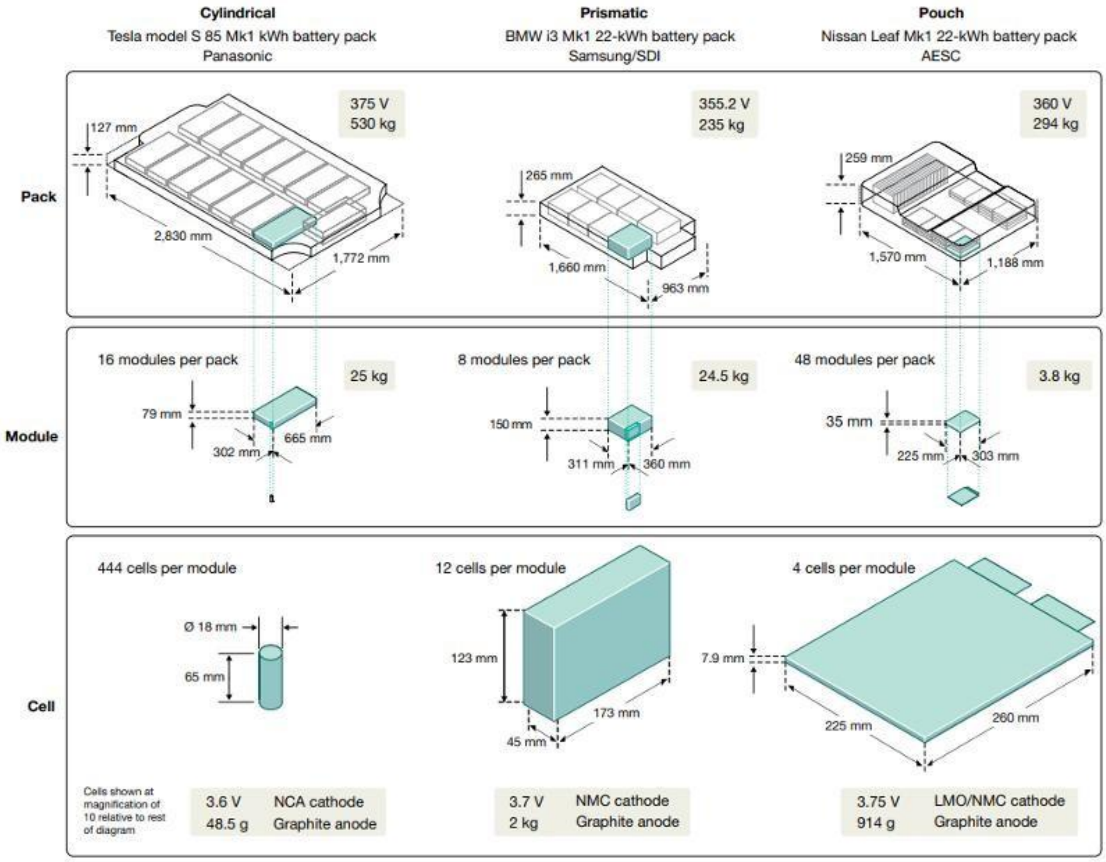


Figure 3.3: Comparison of battery packs from three different car manufacturers that use different cells. Taken from the article: Recycling lithium-ion batteries from electric vehicles [7]

When producing lithium-ion batteries, where the electricity for the production plant comes from determines the environmental impact of production. Production requires large amounts of energy, especially during the drying phases of manufacturing the electrodes. The impact of geographical location is discussed in section 2.6.

3.4 Recycling processes

As described in chapter 2.2, batteries can take many different forms, both in terms of surface and chemical composition. This means that recycling processes can look different and produce different results depending on the batteries. The three processes used for lithium-ion batteries today are pyrometallurgy, hydrometallurgy and direct recycling.

3.4.1 Pyrometallurgy

Pyrometallurgy is basically about heat treating the insides of batteries to separate the different components and extract the desirable metals, lithium and cobalt. This recycling process uses fewer chemicals than hydrometallurgy and is easier to adapt to a larger scale. However, it is more rudimentary and does not produce as fine end products. The end products for this process are cobalt in the form of cobalt oxide and slag products [9].

Sorting is the first thing that happens before the recycling process, and it means that the type of batteries is sorted depending on size, design and its chemical composition. This step is generally for batteries, but not as important in pyrometallurgy as the melting point of the metals does not change significantly in different compositions.

Mechanical pretreatment is the first step in the process. The batteries are pretreated by first and foremost discharging them using a salt bath, a solution of NaCl (salt water). This is necessary because otherwise there are risks such as short circuits that can lead to spontaneous combustion of the batteries when they are later crushed. After the batteries are crushed, the plastic casing and metal container are sieved away from the materials within the battery: the electrolyte, the cathode and the anode.

The materials are separated and sieved using mechanisms that utilize gravity, magnets and compressed air. Heat treatment is central to pyrometallurgy, and this is done in stages with different high temperature levels to be able to separate the materials. The first stage is in a range of around 150–500 degrees Celsius that separates the cathode from the anode and electrolyte. When these are separated and removed, the next heating takes place, which is in a range of approximately 1400–1700 degrees Celsius.

During this heating, various reducing agents and slag modifiers are added. The end products at this stage are the slag products and an alloy of cobalt oxides. These products need some form of post-treatment before they can be reused. In order to extract lithium from the slag products, they must undergo hydrometallurgy.

In battery recycling, almost all metals are extracted through this process, regardless of their chemical composition. Cobalt, nickel and copper are bound together in the alloy obtained in the last step and can then be separated, for example using hydrometallurgy.

Lithium, manganese and aluminium, on the other hand, end up among the slag products. Aluminium cannot be extracted from this slag, only a very small amount of lithium and a small amount of manganese can be extracted.

3.4.2 Hydrometallurgy

Hydrometallurgy is broadly defined as the use of acids to dissolve battery materials and extract valuable metals such as lithium, but cobalt and nickel can also be extracted.

Reagents are then added that bind with the metals, creating a solid mass that can be filtered out. This allows valuable metals to be recovered from lithium-ion batteries. The amount of metal recovered from the batteries varies greatly depending on the chemicals and procedures used, but newer methods have resulted in 98% recovery of lithium in the leaching process [10]. The hydrometallurgy process is described below and illustrated in Figure 4.

<u>Disassembly</u>: The battery is disassembled to separate the anode, cathode, and separator. These components are heat-treated and then separated from each other for metal recovery. Most often, the cathode material is bonded to aluminium. To dissolve the bonds between them, a solution (different depending on the material to be dissolved) and further heat treatment are used.

This step is among the more time-consuming and the step that could be improved by designing the batteries with end-of-life recycling in mind. Heat treatment also involves safety risks as the toxic gas hydrogen fluoride is produced during heating.

<u>Pulverization</u>: The cathode material is crushed and ground into smaller pieces to make it easier to extract metals. In some cases, separation using magnets may also be added.

<u>Leaching</u>: The crushed cathode material contains metal substances in solid form. The goal is to break down the material and the metals in it to a liquid state. This is done by dipping it in hydrogen-based acids and in this way ‘sucking out’ the metals.

<u>Precipitation</u>: Once the material has released the metals, it is time to separate them from the solution. This is done using a chemical process that creates precipitates with the metals so

that they change from liquid to solid form. By adding reagents such as a carbonate, the lithium can be obtained as lithium carbonate.

Separation: Finally, the lithium compound must be separated from the solution by filtration and drying.

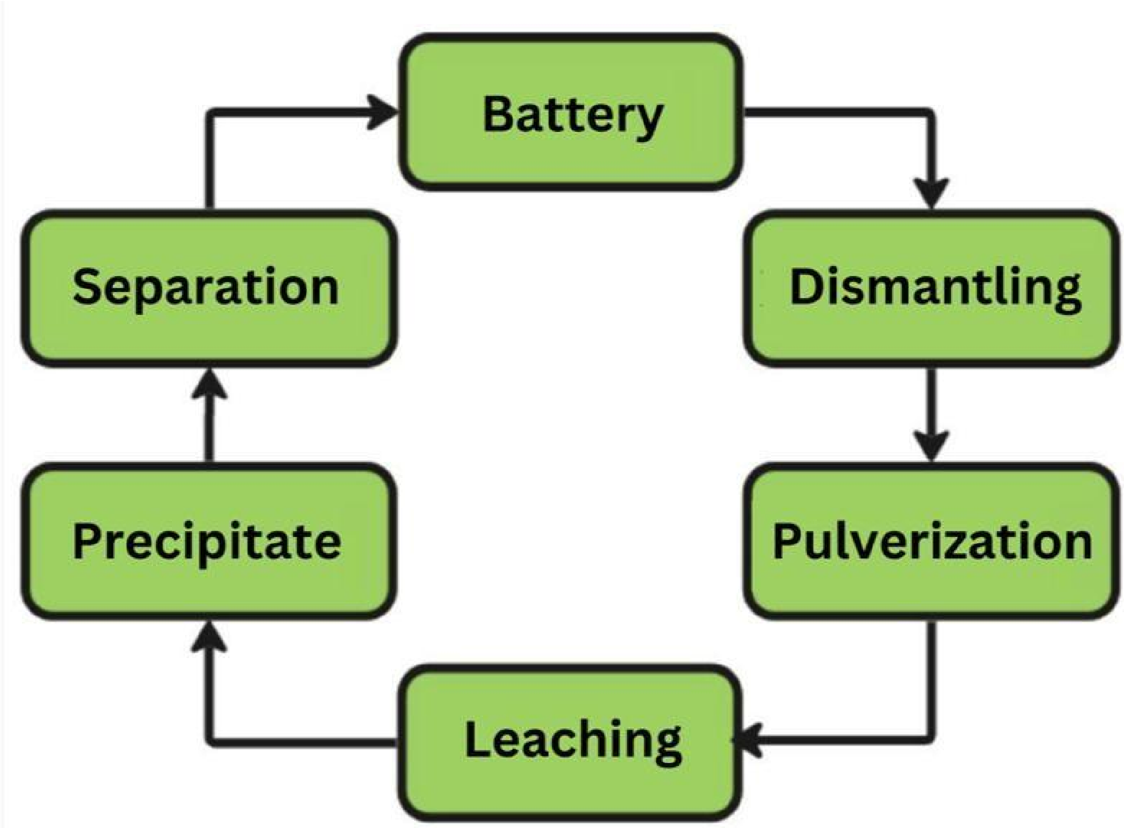


Figure 3.4: The cycle of lithium being recovered from a battery and reused in a battery.

Risks - environment and people: The hydrometallurgical recycling process can have a negative impact on the environment both before and during the process itself. Before the process begins, the battery contents need to be neutralized. There are risks when handling lithium-ion batteries such as spontaneous combustion or short circuiting. To avoid this, the used lithium-ion batteries need to be discharged first.

For larger batteries, such as those used in electric vehicles, the battery is immersed in a salt solution to discharge it. During disassembly, manual or mechanical separation, the outer shell of the battery is first removed, and then liquid nitrogen is used to further neutralize harmful substances. This step creates toxic gases that are harmful to both the environment and people if not handled correctly [11].

3.4.3 Direct recycling

Direct recycling is the newest of these three processes. The process does not use complex chemical methods and thus avoids toxic gas emissions [12].

The battery is discharged and disassembled into thousands of small cells. These cells are then treated with supercritical carbon dioxide: carbon dioxide that is above its critical pressure and temperature. This is done to extract the electrolyte from the battery cell. The electrolyte and carbon dioxide are then separated by regulating the pressure and temperature, and the electrolyte can then be reused in battery manufacturing.

Once the electrolyte has been separated from the cells, they can either be crushed or picked apart to extract the cathode strips. After the strips have undergone some form of post processing, they can be used in new batteries. One form of post-processing is to dip the strips in a solvent, usually NMP, and subject them to sonication: the use of sound to separate particles. The final product is a form of metallic powder that contains the various metals that were included in the cathode material.

Then, either Li_2CO_3 is added in the form of a powder that is mixed in while heating, or a liquid containing $LiOH/Li_2SO_4$ which is then heated while mixing the remaining powder. Regardless of which of these methods is used, the final product is then annealed to obtain a solid piece of metal that can be used in the manufacture of new batteries [7].

Things that should be considered during this process are that the solvent NMP is a toxic liquid that can cause discomfort to the operators, which means that safety equipment is important. A by-product of the process can also be hydrofluoric acid when breaking down polyvinylidene fluoride that can occur in lithium-ion batteries as a binder.

3.4.4 Comparison of recycling processes

The pyrometallurgical process is the oldest, cheapest and easiest method for recycling batteries. The problem is that this process requires a lot of energy to operate and a large amount of lithium is lost in the process.

The little lithium that remains must also undergo more processes, usually hydrometallurgy, in order to be extracted. Pyrometallurgy, on the other hand, extracts a lot of cobalt in the process, which is a critical raw material. As stated in section 2.4.1, the remaining metals in the battery are also extracted when they alloy with the cobalt, while aluminium ends up in the same slag as lithium and cannot be extracted. The hydrometallurgical recycling process is slightly newer and more complex than the pyrometallurgical one, but not so new that the technology is too difficult to apply. It is slightly more expensive to build but does not require as much energy to operate and this process generates less waste.

Since this process uses acids and other chemicals that emit toxic gases, the recycling needs to be done in a sterile environment with good safety equipment for the people working during the process. In addition to a larger amount of lithium and manganese than pyrometallurgy, all other metals contained in the battery are also recovered, although copper is present in slightly lower amounts than in pyrometallurgy [7].

Direct battery recycling is the newest of these processes, which means that it is the most expensive to produce and the technology is very new. The process, like hydrometallurgy, uses less energy than pyrometallurgy, and very little waste is generated in direct recycling. This process also uses chemicals that can emit toxic gases and therefore requires good safety equipment. In direct recycling, all metals are recovered from the batteries and can all be used directly in the manufacture of new batteries, which is not possible for any of the other recycling processes.

A disadvantage of this is that the batteries need to be sorted very carefully, as the chemical structure means that different separation methods are used, which is not as accurate in pyrometallurgy where the metals are separated by heating intervals and that is the only thing that needs to be adjusted.

Table 3.2 provides a brief summary of some of the advantages and disadvantages of the process

Process	Advantages	Disadvantages
Pyrometallurgy	Relatively simple and short process Highly efficient	High energy consumption Needs to supplement with hydrometallurgy to extract lithium
Hydrometallurgy	High percentage of recycled material Low energy consumption High selectivity	Long process High water consumption Gas emissions
Direct Recycling	Low energy consumption Environmentally friendly process High recycling rate	Strong dependence on the right equipment Use of harmful chemicals

Table 3.2: Summary of the advantages and disadvantages of the three recycling processes.

3.5 Society - politics, policies and regulations

On December 11, 2019, the European Commission introduced the initiative ''The European Green Deal''. The Green Deal is an initiative aimed at making the EU economy sustainable and climate neutral by 2050. The plan includes targets such as reducing greenhouse gas emissions, increasing the use of renewable energy, energy efficiency and the circular economy [13].

Part of this, linked to the Green Deal's areas of industrial strategy and circular economy action plan, is for the EU to review and develop rules for batteries. A proposal adopted in March 2022 includes rules on:

<u>Limited carbon footprint:</u>

To reduce the carbon footprint of batteries, batteries will be labelled with a special label to increase transparency of their environmental impact. This will be mandatory for lithium-ion batteries used in electric vehicles, light transport and industrial batteries that are rechargeable and have a capacity of more than 2 kWh. The labelling will cover the entire life of the battery and guarantee that new batteries contain minimum levels of certain raw materials [14].

<u>Raw materials:</u>

Battery production is highly dependent on critical raw materials such as cobalt, lithium, nickel and manganese, which have significant environmental and social impacts.

To combat human rights abuses and promote ethical batteries, MEPs have proposed that battery manufacturers should be required to carry out a due diligence process. This process will include requirements aimed at addressing social and environmental risks related to the procurement, processing and trade of raw materials and secondary raw materials.

All economic operators selling batteries on the EU market, except small and medium-sized enterprises, will be required to develop and implement this due diligence policy [14].

<u>Battery recycling & minimum levels</u>:

Waste batteries from, among others, light transport vehicles, car batteries and electric vehicles should be collected free of charge for users, regardless of the manufacturer or condition of the battery.

New minimum levels for the reuse of certain recycled materials in batteries will be introduced. This means that new lithium-ion batteries will need to contain at least cobalt (16%), lead (85%), lithium (6%), and nickel (6%) [14].

CHAPTER 4

PSO STRATEGY FOR CHARGING OPTIMIZATION

4.1 PARTICLE SWARM OPTIMIZATION (PSO)

Particle Swarm Optimization (PSO) algorithm was developed by Kennedy and Eberhart in 1995, which is a kind of heuristic global optimization technology and belongs to the category of swarm intelligence methods.

PSO is used in EV charging to determine the best charging approach that meets objectives like:

- Reduction of charging time
- Lowering the cost of power
- Minimizing battery deterioration
- Preventing grid overflow

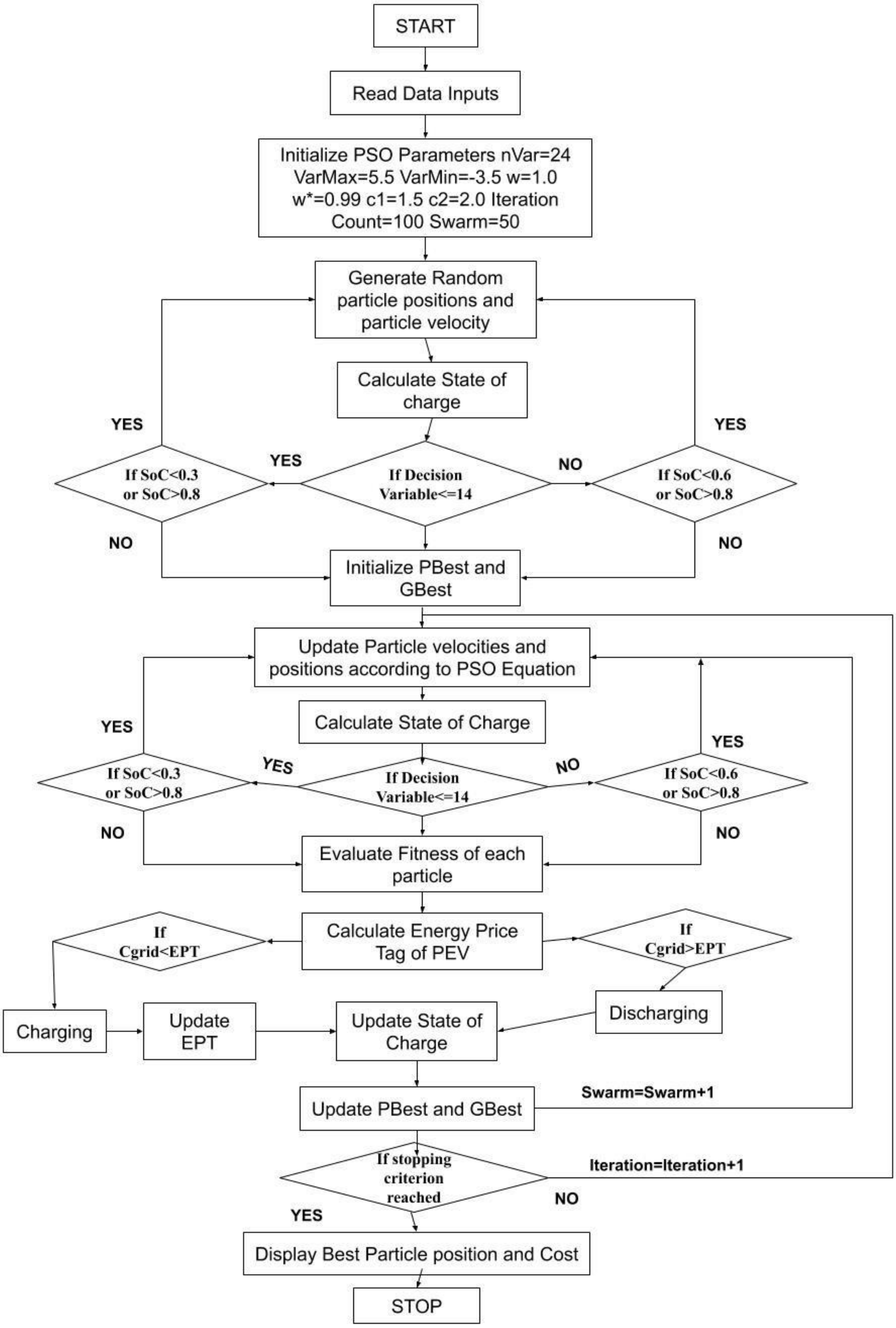
In Swarm Optimization particles modify their charging strategy by utilizing:

- Personal best (pbest): The particle with the best answer found.
- Global best (gbest): The swarm as a whole finds the best.

For EV Charging, PSO is popular because of its fast convergence; compatibility with sophisticated, highly nonlinear battery models; ease of implementation; suitability for multi objective charging; and resilience in the face of unpredictable grid conditions.

Thus, PSO-based charging is an intelligent algorithm that determines the optimal charging schedule for an EV in order to lower costs, preserve battery life, and prevent grid overload.

4.2 Proposed PSO Based Charging strategy flowchart



The EV charging optimization problem is resolved using Particle Swarm Optimization (PSO) where each particle represents a 24 hour charging schedule. And the below given algorithm iteratively updates the candidate solutions to minimize the total energy cost while satisfying SOC and the charging limits.

- Step 1: Define objective function and penalty for SOC violation.
- Step 2: Initialise swarm particles randomly within the charging limits.
- Step 3: Initialise velocities and evaluate particle costs.
- Step 4: Update personal best and global best.
- Step 5: Update the particle velocities using inertia, cognitive and social terms.
- Step 6: Update the positions and apply boundary constraints everywhere.
- Step 7: Repeat evaluation and update until maximum iterations are reached.
- Step 8: Output optimal charging schedule and minimum costs.

CHAPTER 5
RESULTS AND DISCUSSION

5.1 Introduction

The optimization is performed over a 24 hour scheduling horizon where each decision variable represents the charging and discharging power of the EV battery at a specific hour. The objective of this is to minimise the total energy cost while ensuring operational feasibility through state-of-charge constraints. The system model is incorporated by grid price and load demand data which varies with time and the battery is characterized with a fixed capacity of 54 kWh with an initial SOC of 0.4. Also, the charging and discharging power are bounded to reflect the practical operating limits and a penalty based constraint handling approach is integrated into the objective function to ensure that SOC limits are strictly maintained at each step of the optimization process.

The key experimental parameters used in the PSO implementation are as follows: Optimization horizon: 24 hours ;Battery capacity: 54 kWh ; Initial SOC: 0.4 ; SOC limits: 0.3–0.8 (hours 1–13), ≥ 0.6 (hours 14 24) , Charging power limits: −3.5 kW to 5.5 kW , Swarm size: 50 particles; Maximum iterations: 100 ; Inertia weight (w): 1;Learning coefficients: c_1 = 1.5, c_2 = 2.0 The simulation is done in MATLAB using a modular structure where the main PSO routine, an objective function, and visualization modules are operated independently. More number of runs are conducted to verify convergence consistency and the robustness. Finally, the results are evaluated using convergence curves, final cost values, SOC feasibility, and load demand comparison before and after optimization.

5.2 PROGRAM RESULTS:

5.2.1 PEV Energy Price Tag Curve

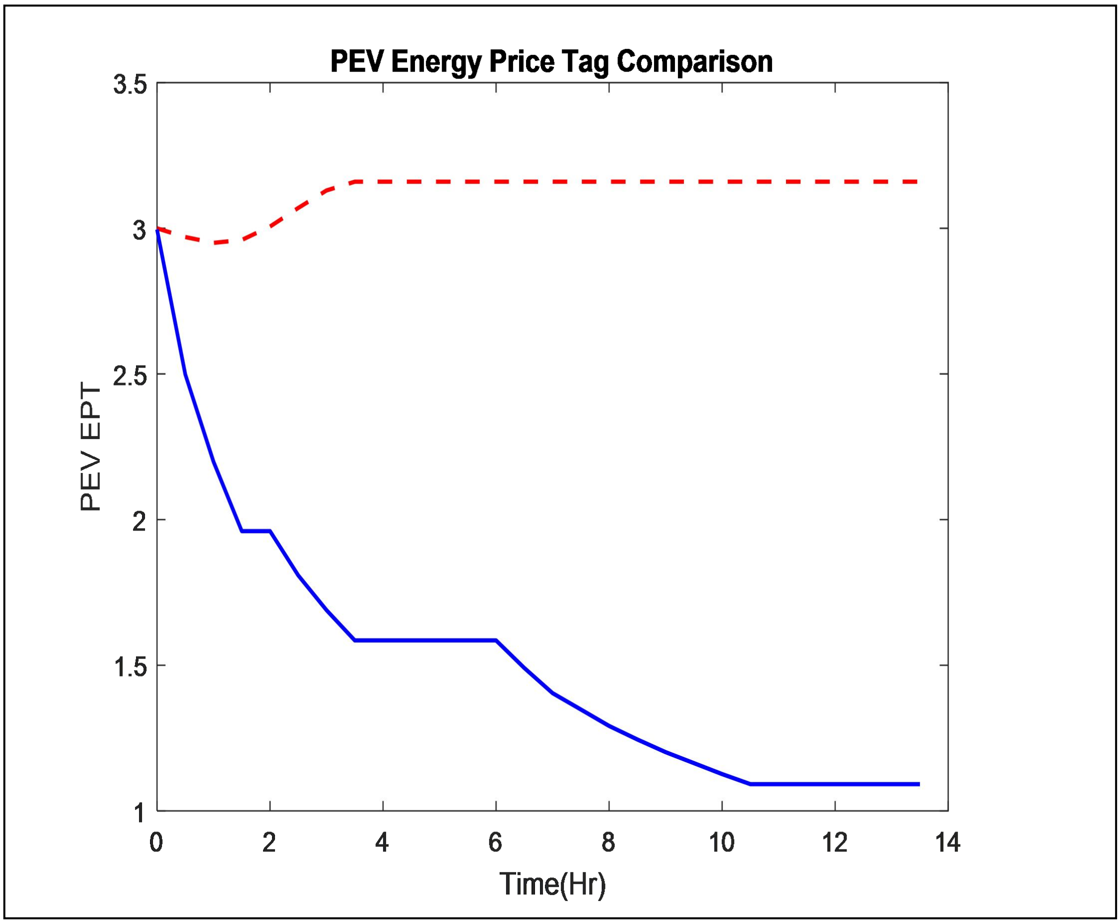


Fig 5.1: PEV EPT comparison curve

5.2.2 Energy Grid Demand Comparison Curve

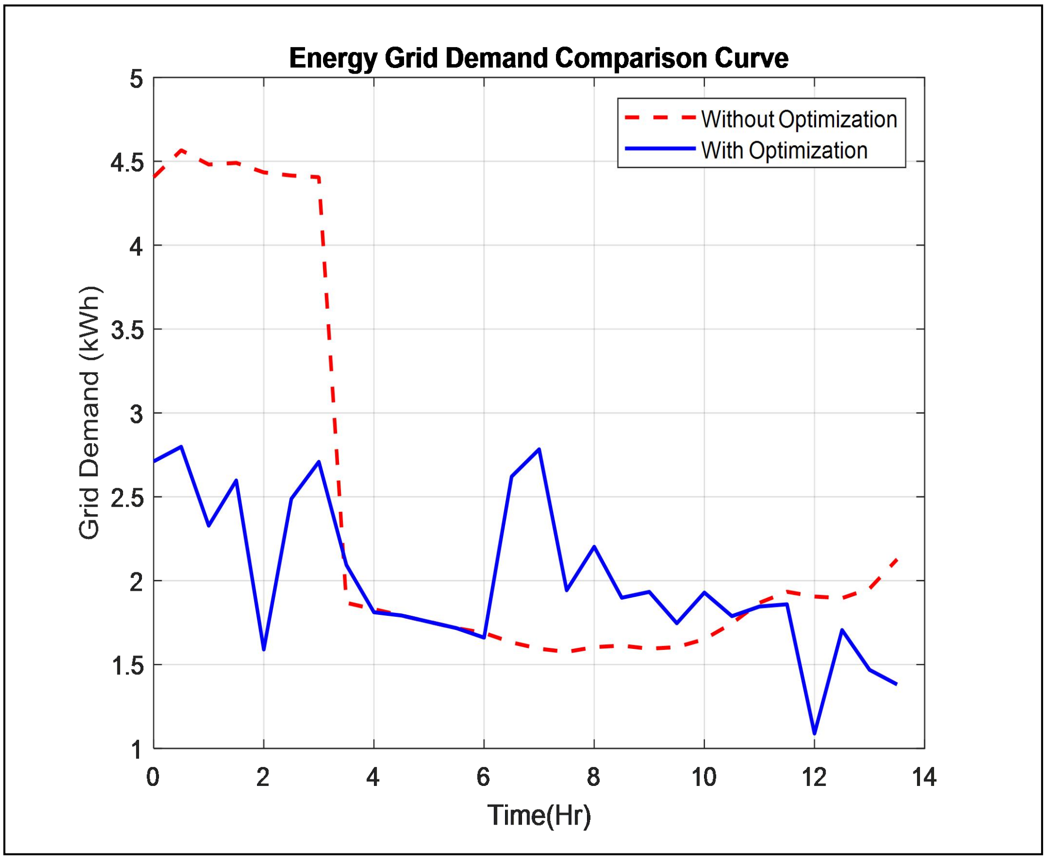


Fig 5.2: Energy Grid Demand Comparison Curve

5.2.3 PSO Convergence Curve

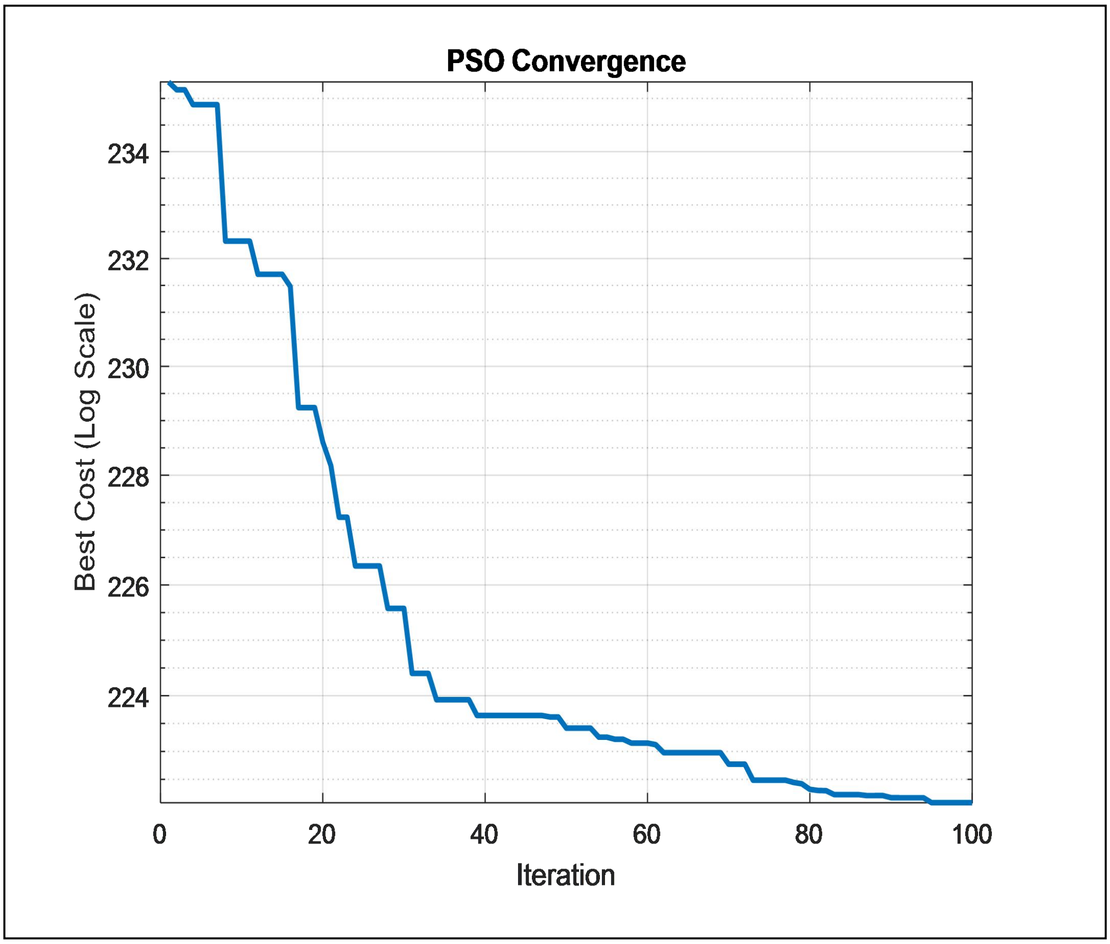


Fig 5.3: PSO Convergence curve of best cost vs iteration

As shown in Fig.5.3, the best cost decreases during the initial phase of optimisation which specifies a strong global search capability and rapid information sharing among all particles. In the early iterations ~1–15 the cost drops from around 244 to nearly 228–230 that shows the efficient exploration of the solution space which highlights the impact of the inertia and cognitive components in guiding particles toward promising regions. And after the rapid reduction the improvement becomes more gradual which demonstrates the swarm transitions from exploration to exploitation. During the mid to later iterations ~20–100 the convergence curve in Fig.5.3 flattens steadily that stabilizes the near a final value of about 223. The absence of oscillations or abrupt spikes confirms algorithmic stability and effective parameter tuning as well as the damping of the inertia weight contributes to controlled convergence and prevents divergence or the premature stagnation.

5.2.4 SOC Profile Of Best Solution Curve

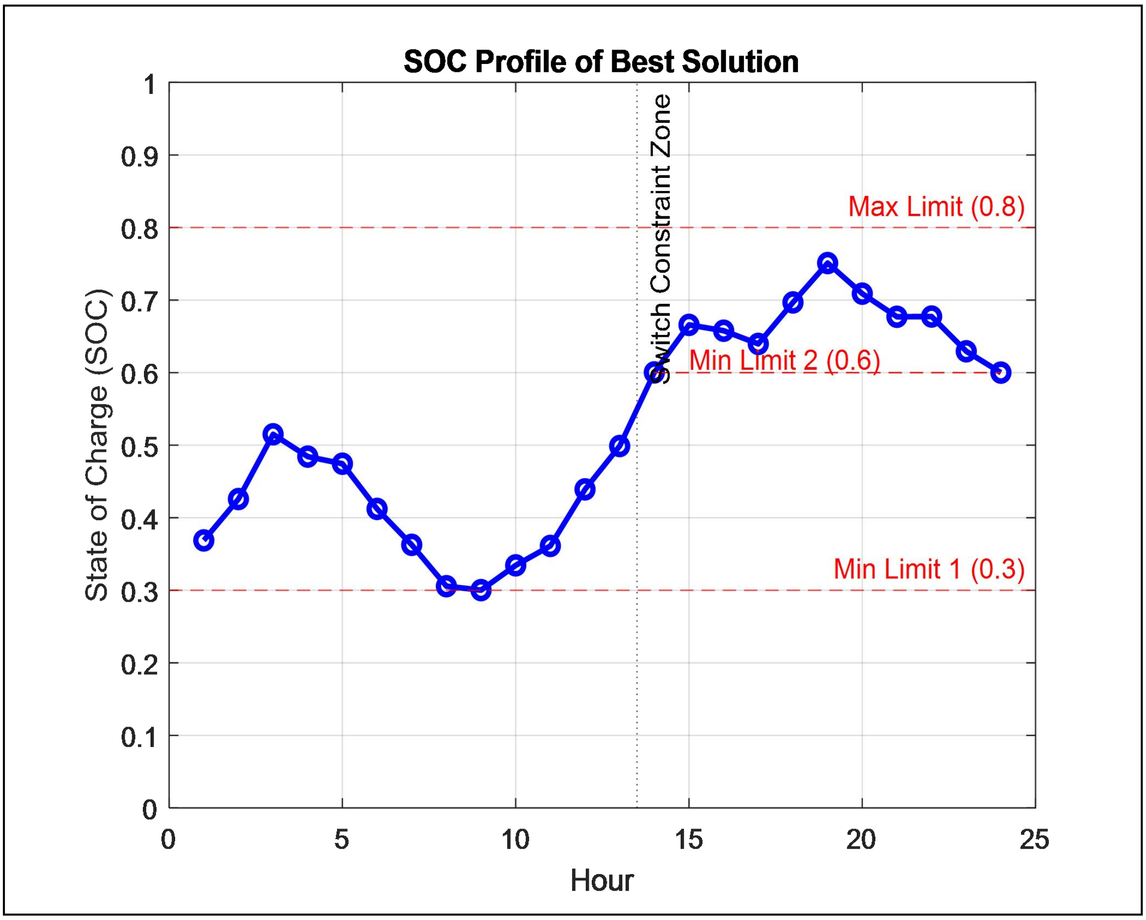


Fig 5.4: SOC Profile of Best Solution Curve

The SOC training behaviour of the optimal solution is shown in Fig. 5.4 where the SOC trajectory evolves in accordance with charging decisions determined by PSO. The SOC initially increases then decreases toward its minimum around hour 10 and subsequently rises again after the switching constraint zone. Most important is that all SOC values remain within prescribed operational limits that shows the successful constraint learning through the penalty mechanism.

Overall, the training confirms that the PSO algorithm converges smoothly and maintain a feasibility throughout the optimisation and effectively balances cost minimisation with constraint satisfaction.

5.3 DISCUSSION

The results highlights the effectiveness and robustness of Particle Swarm Optimization (PSO) in solving the EV charging optimization problem under practical system constraints. The convergence behaviour shows that PSO is able to explore the solution space rapidly in the early iterations to achieve a substantial reduction in cost and then gradually movement towards the exploitation leading to stable convergence without noticeable oscillations or any divergence. This behaviour simply demonstrates a good balance between exploration with exploitation which is a critical factor for nonlinear as well as constrained optimisation problems.

The ultimate converged cost shows that meaningful economic benefits can be achieved through optimized charging strategies compared to traditional uncoordinated charging. From a system operation perspective the optimized state-of-charge (SOC) profile remains within the specified limits overall during the scheduling horizon which confirms that battery safety and operational constraints are not violated at all. The SOC fall during early hours followed by a controlled recovery after the switching constraint reflects the smart load shifting where charging is deferred from less favourable periods and scheduled during more optimal time intervals.

With the perspective of qualitative analysis the smooth SOC trajectory indicates less battery load and realistic charging behaviour while quantitatively the SOC values remain well bounded between the minimum and maximum thresholds validating the feasibility. Additionally, the modular MATLAB based implementation supports the originality and the repeatability that allows an easy adjustment of parameters such as cost functions, constraints, and swarm size. This confirms that PSO is a reliable and scalable optimisation technique for EV charging applications and is capable of delivering cost efficient constraint-compliant and practically implementable solutions in power system environments.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

The shift to widespread electric mobility has been made possible in great part by charging optimization, which provides an organized method of controlling energy consumption, battery performance, and grid stability. Optimized solutions greatly improve system efficiency and customer convenience by employing real-time data on user preferences and renewable energy availability, intelligently coordinating charging schedules, and adjusting to dynamic power pricing. These methods help prolong battery life and boost the overall dependability of EV charging infrastructure in addition to lowering operating expenses and peak load strain.

Furthermore, charging optimization is positioned as a key component of future sustainable energy systems due to the integration of smart grid technologies, sophisticated control algorithms, and energy-sharing mechanisms like V2G and V2H. In the end, charging optimization supports a more seamless and robust transition to clean transportation by ensuring that EV deployment is scalable, economically feasible, and ecologically responsible.

6.2 FUTURE SCOPE

With the increasing use of electric vehicles and the growing complexity of power infrastructure, the field of charging optimization is expected to increase significantly in the future. Chargers will be able to make intelligent, real-time decisions based on user behavior, electricity costs, traffic patterns, and the availability of renewable energy thanks to developments in artificial intelligence, machine learning, and predictive analytics. Future systems will be deeply integrated with V2X technology, enabling EVs to assist homes, buildings, microgrids, and the main grid through intelligent, two-way energy flow in addition to efficiently charging.

As wireless and ultra-fast charging technologies advance, optimization strategies will concentrate on protecting battery health while guaranteeing little energy loss and maximum convenience. The creation of secure communication protocols and networked IoT-enabled charging infrastructures will make it possible to coordinate multi-EV charging on a wide scale without taxing the grid. Charging optimization will eventually result in an energy and transportation ecosystem that is more intelligent, resilient, and ecologically conscious as sustainability, interoperability, and standards become more important.

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APPENDIX

1. PROGRAM CODE FOR EPT CALCULATION:

```
clc; clear; close all;

%% 1. Input Data
% Battery Power Final (Multiplied by 2 as per original code)
bpFinal = 2 * [0.8058 0.7322 0.3469 0.6069 -0.3441 0.5729 0.8030 0.2257 ...
           -0.0181 0 0 0 0 0.9888 1.1886 0.3673 0.5982 0.2853 ...
           0.3388 0.1422 0.2781 0.0430 -0.0221 -0.0748 -0.8167 ...
           -0.1902 -0.4846 -0.7461];

% Load Demand
loadDemand = [3.811 4.132 3.962 3.981 3.868 3.83 3.811 3.736 3.66 3.585 ...
          3.509 3.434 3.321 3.264 3.189 3.151 3.208 3.226 3.189 ...
          3.208 3.302 3.491 3.736 3.868 3.811 3.792 3.906 4.255];

% Grid Price
grid_price = [2.946 2.865 2.842 3.039 3.34 3.595 3.629 3.398 3.015 2.714 ...
          2.517 2.448 2.008 1.718 1.683 1.718 1.683 1.637 1.614 ...
          1.625 1.625 1.614 1.637 1.822 2.286 2.842 3.27 3.525];

%% 2. Calculations
OP_demand = bpFinal + loadDemand;

ept = zeros(1,28);
soc = zeros(1,28);
battery_cap = 54;
initial_soc = 0.4;

% Loop 1: Calculate State of Charge (SOC)
for a=1:28
  if(a==1)
    soc(a) = initial_soc + ((OP_demand(a))/battery_cap);
  else
    soc(a) = soc(a-1) + ((OP_demand(a))/battery_cap);
  end
end

% Loop 2: Calculate Energy Price Tag (EPT)
for i=1:28
  if(bpFinal(i) > 0)
    % Charging phase
    if(i==1)
      % Initial calculation (using 3 as base price estimate from original code)
      ept(i) = (3*initial_soc*battery_cap + bpFinal(i)*grid_price(i)) / ...
           (initial_soc*battery_cap + bpFinal(i));
```

```
        else
           % Update weighted average price
           ept(i) = (ept(i-1)*soc(i-1)*battery_cap + bpFinal(i)*grid_price(i)) / ...
                    (soc(i)*battery_cap + bpFinal(i));
        end
    else
        % Discharging or Idle phase (Price holds steady)
        if i > 1
           ept(i) = ept(i-1);
        else
           % Fallback for i=1 if bpFinal is negative (not triggered by this data)
           ept(i) = 3;
        end
    end
end

%% 3. Plotting
x = 0:0.5:13.5; % Time vector (28 points)
y1 = [3 2.97 2.95 2.96 3.006 3.07 3.13 3.16 3.16 3.16 3.16 3.16 3.16 ...
      3.16 3.16 3.16 3.16 3.16 3.16 3.16 3.16 3.16 3.16 3.16 3.16 ...
      3.16 3.16 3.16];

figure;
plot(x, y1, 'r--', 'LineWidth', 1.5);
hold on
plot(x, ept, 'b-', 'LineWidth', 1.5);

title('PEV Energy Price Tag Comparison');
xlabel('Time');
ylabel('PEV EPT');
```

2. PROGRAM CODE FOR PLOTTING LOAD DEMAND

```
clc; clear; close all;

%% 1. Raw Battery Profiles (24 points each)
bp1 = [-1.4515 3.7202 3.2495 -0.4211 0.5138 -0.4088 2.5714 -1.2155 -2.4577 0.2387 3.9377 -3.5891 2.9884 4.7521 1.5966 0.8434 2.7935 -1.2133 -0.8841 0.7054 -2.4292 -0.4390 0.0941 -2.6951];
bp2 = [1.2406 0.3841 -0.6282 1.0360 1.9452 -0.5125 2.1012 0.3542 0.3232 3.7982 -1.8558 3.4615 1.9710 -0.3405 0.6249 -1.7308 1.3714 -0.7060 0.9401 2.4691 -3.3259 -1.2803 -0.4955 -0.3452];
bp3 = [5.4999 -0.9956 -0.5663 4.6212 3.7876 1.5395 2.5201 -1.6724 -0.9824 5.1236 -1.5434 0.2796 2.2708 -1.3253 0.9628 1.1296 -1.2004 -0.8721 1.3671 -1.7229 -1.6127 2.4786 -0.7021 -3.0431];
bp4 = [1.0045 -2.1109 -0.2811 3.7085 -1.0655 4.0989 4.4326 3.5243 1.0298 1.0964 1.0919 1.7347 -1.6285 -0.8672 0.9261 -0.5108 -0.1116 2.6343 -0.8541 -0.1812 0.2413 -3.3556 -0.1479 -3.6089];
bp5 = [3.1533 3.4558 -0.3017 3.8477 -2.8085 0.9562 0.6927 2.0246 -1.5794 -2.0568 5.4987 -0.4386 4.3104 -0.8739 -0.8431 -2.5644 -0.0664 0.8122 4.2481 -2.7544 -2.0990 -1.1769 0.5382 -1.1749];
bp6 = [0.6328 -0.8028 -0.9890 2.9224 0.3078 -1.7896 -0.2408 -0.0298 4.7362 3.9217 3.3871 2.0878 1.0452 1.7399 0.9795 0.5742 -0.1007 -3.3345 -1.0192 2.0025 -2.1207 -0.1374 -2.0999 -0.8726];
bp7 = [2.8588 2.0469 2.2740 -2.2996 -2.3546 1.4680 -0.6776 -0.0716 0.4387 0.5001 4.7146 2.1299 1.6760 0.3134 -0.3575 1.4184 -0.9162 0.8483 -0.7857 2.0028 -1.7315 -0.2921 -1.7396 -0.6639];
bp8 = [1.1482 3.0562 -0.2674 -1.7453 -2.9963 4.3301 2.6266 -0.0175 -0.4760 3.8908 3.4201 -0.9552 0.1774 -0.4499 1.7849 1.1326 1.3681 0.3152 -0.8711 -0.9779 -1.5391 0.1463 -0.7164 -1.5843];
bp9 = [-0.9967 3.4438 3.0149 -1.4147 -2.7641 3.0515 2.0220 -1.9655 0.9536 3.4764 2.6462 0.5366 0.0604 -0.7413 0.7789 -0.3358 1.1364 3.1408 -2.3165 -2.0524 -0.3715 1.6065 -1.7821 -0.3275];
bp10 = [3.0267 2.4457 1.4335 1.8834 -1.4475 -1.2747 0.0118 3.5836 -2.3478 -0.2132 2.4754 2.0994 -0.9075 3.4994 0.3223 2.8877 1.2875 -0.7659 -0.2657 -0.9876 -1.3448 -1.3549 -2.6408 -0.6059];

% Average of raw profiles (24 points)
bp = (bp1+bp2+bp3+bp4+bp5+bp6+bp7+bp8+bp9+bp10)/20;

%% 2. Optimized Data and Load Demand (28 points)
bpFinal = 2 * [0.8058 0.7322 0.3469 0.6069 -0.3441 0.5729 0.8030 0.2257 ...
        -0.0181 0 0 0 0 0.9888 1.1886 0.3673 0.5982 0.2853 ...
        0.3388 0.1422 0.2781 0.0430 -0.0221 -0.0748 -0.8167 ...
        -0.1902 -0.4846 -0.7461];

loadDemand = [3.811 4.132 3.962 3.981 3.868 3.83 3.811 3.736 3.66 3.585 ...
        3.509 3.434 3.321 3.264 3.189 3.151 3.208 3.226 3.189 ...
        3.208 3.302 3.491 3.736 3.868 3.811 3.792 3.906 4.255];
```

```
OP_demand = bpFinal + loadDemand;

%% 3. Plotting
x = 0:0.5:13.5; % Time vector (28 points)
y1 = [8.811 9.132 8.962 8.981 8.868 8.83 8.811 3.736 3.66 3.585 ...
      3.509 3.434 3.377 3.264 3.189 3.151 3.208 3.226 3.189 3.208 ...
      3.302 3.491 3.736 3.868 3.811 3.792 3.906 4.255];

figure;
% Plot Without Optimization
plot(x, y1/2, 'r--', 'LineWidth', 1.5);
hold on

% Plot With Optimization
plot(x, OP_demand/2, 'b-', 'LineWidth', 1.5);

title('Energy Grid Demand Comparison Curve');
xlabel('Time');
ylabel('Grid Demand (kWh)');
legend('Without Optimization', 'With Optimization');
grid on;

hold off;
```

3. Program code for plotting PSO Curve

```
clc; clear;

close all;

%% Problem Definition

CostFunction=@(x) obj2(x);  % Cost Function nVar=24;

% Number of Decision Variables

VarSize=[1 nVar];    % Size of Decision Variables Matrix

VarMin= -3.5; % Lower Bound of Variables VarMax= 5.5;

% Upper Bound of Variables

%% PSO Parameters

MaxIt=100; % Maximum Number of Iterations

nPop=50; % Population Size (Swarm Size)

% PSO Parameters w=1; %

Inertia Weight

wdamp=0.97;  % Inertia Weight Damping Ratio

c1=1.5;           % Personal Learning Coefficient

c2=2.0;           % Global Learning Coefficient

% Velocity Limits

VelMax=0.2*(VarMax-VarMin);

VelMin=-VelMax; %%

Initialization

empty_particle.Position=[];

empty_particle.Cost=[];
```

```
empty_particle.Velocity=[];
empty_particle.Best.Positio
n=[];
empty_particle.Best.Cost=[]
;
particle=repmat(empty_par
ticle,nPop,1);
GlobalBest.Cost=inf; for
i=1:nPop x=1; while x==1
x=0; % Initialize Position
particle(i).Position=unifrnd
(VarMin,VarMax,VarSize);
soc=zeros(1, nVar); %
State of charge calculation
for a=1:nVar if(a==1)
soc(a)=0.4+((particle(i).Po
sition(a))/54); else
soc(a)=soc(a-
1)+((particle(i).Position(a))
/54); end end
% State of charge limitation
for a=1:nVar
```

```
if(soc(a)>0.8)

x=1; break;

end end for

a=1:13

if(soc(a)<0.3)

x=1; break;

end end for

a=14:nVar

if(soc(a)<0.6)

x=1; break;

end end end




% Initialize Velocity

particle(i).Velocity=zeros(VarSize); % Evaluation


particle(i).Cost=CostFunction(particle(i).Position);

% Update Personal Best

particle(i).Best.Position=particle(i).Position; particle(i).Best.Cost=particle(i).Cost;

% Update Global Best

if particle(i).Best.Cost<GlobalBest.Cost

GlobalBest=particle(i).Best; end end

BestCost=zeros(MaxIt,1);
```

```
%% PSO Main Loop

for it=1:MaxIt for

i=1:nPop x=1;

while x==1;

x=0; % Update

Velocity

particle(i).Velocity = w*particle(i).Velocity ...

+c1*rand(VarSize).*(particle(i).Best.Position-particle(i).Position) ...

+c2*rand(VarSize).*(GlobalBest.Position-particle(i).Position);

% Apply Velocity Limits

particle(i).Velocity = max(particle(i).Velocity,VelMin); particle(i).Velocity =
min(particle(i).Velocity,VelMax);

% Update Position

particle(i).Position = particle(i).Position + particle(i).Velocity;

% Velocity Mirror Effect

IsOutside=(particle(i).Position<VarMin | particle(i).Position>VarMax);

particle(i).Velocity(IsOutside)=-particle(i).Velocity(IsOutside);

% Apply Position Limits

particle(i).Position = max(particle(i).Position,VarMin);

particle(i).Position = min(particle(i).Position,VarMax);

for a=1:nVar if(a==1)

soc(a)=0.4+((particle(i).Position(a))/54); else

soc(a)=soc(a-1)+((particle(i).Position(a))/54); end end
```

```
for a=1:nVar if(soc(a)>0.8) x=1; break; end end for

a=1:13

if(soc(a)<0.3)

x=1; break;

end end for

a=14:nVar

if(soc(a)<0.6)

x=1; break;

end end

end %

Evaluation

particle(i).Cost = CostFunction(particle(i).Position);

% Update Personal Best

if particle(i).Cost<particle(i).Best.Cost

particle(i).Best.Position=particle(i).Position; particle(i).Best.Cost=particle(i).Cost;

% Update Global Best

if particle(i).Best.Cost<GlobalBest.Cost

GlobalBest=particle(i).Best; end end

end

BestCost(it)=GlobalBest.Cost; disp(['Iteration ' num2str(it) ': Best Cost

= ' num2str(BestCost(it)/48)]);

 w=w*wdamp;

end
```

```
BestSol = GlobalBest;

%% Results

figure;

%plot(BestCost,'LineWidth',2)

semilogy(BestCost/48,'LineWidth',2)

xlabel('Iteration'); ylabel('Best Cost'); grid on;

for b=1:nPop for a=1:nVar if(a==1)

soc(a)=0.4+((particle(i).Position(a))/54); else

soc(a)=soc(a-1)+((particle(i).Position(a))/54);

end end end
```

4. PROGRAM CODE FOR PSO TESTER:

```
obj2 clc;
clear;
close all;

%% Problem Definition

% NOTE: The objective function is defined at the bottom of this script.
% We wrap it here to include the Penalty for constraints.
CostFunction = @(x) CostWithPenalty(x);

nVar = 24;          % Number of Decision Variables (Hours)
VarSize = [1 nVar];   % Size of Decision Variables Matrix

VarMin = -3.5;       % Lower Bound (Max Discharge Rate)
VarMax =  5.5;       % Upper Bound (Max Charge Rate)

%% PSO Parameters

MaxIt = 100;     % Maximum Number of Iterations
nPop = 50;       % Population Size (Swarm Size)

% PSO Parameters
w = 1;           % Inertia Weight
wdamp = 0.98;    % Inertia Weight Damping Ratio
c1 = 1.5;        % Personal Learning Coefficient
c2 = 2.0;        % Global Learning Coefficient

% Velocity Limits
VelMax = 0.2 * (VarMax - VarMin);
VelMin = -VelMax;

%% Initialization

empty_particle.Position = [];
empty_particle.Cost = [];
empty_particle.Velocity = [];
empty_particle.Best.Position = [];
empty_particle.Best.Cost = [];

particle = repmat(empty_particle, nPop, 1);

GlobalBest.Cost = inf;
GlobalBest.Position = [];

disp('Initializing Swarm...');
```

```
for i = 1:nPop

    % Initialize Position
    particle(i).Position = VarMin + rand(VarSize).*(VarMax - VarMin);


    % Initialize Velocity
    particle(i).Velocity = zeros(VarSize);

    % Evaluation
    particle(i).Cost = CostFunction(particle(i).Position);

    % Update Personal Best
    particle(i).Best.Position = particle(i).Position;
    particle(i).Best.Cost = particle(i).Cost;

    % Update Global Best
    if particle(i).Best.Cost < GlobalBest.Cost
        GlobalBest = particle(i).Best;
    end
end

BestCost = zeros(MaxIt, 1);

%% PSO Main Loop

for it = 1:MaxIt

    for i = 1:nPop

        % Update Velocity
        particle(i).Velocity = w * particle(i).Velocity ...
            + c1 * rand(VarSize) .* (particle(i).Best.Position - particle(i).Position) ...
            + c2 * rand(VarSize) .* (GlobalBest.Position - particle(i).Position);

        % Apply Velocity Limits
        particle(i).Velocity = max(particle(i).Velocity, VelMin);
        particle(i).Velocity = min(particle(i).Velocity, VelMax);

        % Update Position
        particle(i).Position = particle(i).Position + particle(i).Velocity;

        % Velocity Mirror Effect (Reflect if hitting bounds)
        IsOutside = (particle(i).Position < VarMin | particle(i).Position > VarMax);
        particle(i).Velocity(IsOutside) = -particle(i).Velocity(IsOutside);

        % Apply Position Limits
        particle(i).Position = max(particle(i).Position, VarMin);
```

```
        particle(i).Position = min(particle(i).Position, VarMax);

        % Evaluation (Cost + Constraint Penalty)
        particle(i).Cost = CostFunction(particle(i).Position);

        % Update Personal Best
        if particle(i).Cost < particle(i).Best.Cost

            particle(i).Best.Position = particle(i).Position;
            particle(i).Best.Cost = particle(i).Cost;

            % Update Global Best
            if particle(i).Best.Cost < GlobalBest.Cost
                GlobalBest = particle(i).Best;
            end

        end

    end

    BestCost(it) = GlobalBest.Cost;

    % Damping Inertia Coefficient
    w = w * wdamp;

    % Display Iteration Information
    disp(['Iteration ' num2str(it) ': Best Cost = ' num2str(BestCost(it))]);

end

%% Results

% 1. Convergence Plot
figure;
semilogy(BestCost, 'LineWidth', 2);
xlabel('Iteration');
ylabel('Best Cost (Log Scale)');
title('PSO Convergence');
grid on;

% 2. Analyze the Best Solution (Recalculate SOC)
best_pos = GlobalBest.Position;
soc_curve = zeros(1, nVar);
soc_curve(1) = 0.4 + (best_pos(1) / 54);
for a = 2:nVar
    soc_curve(a) = soc_curve(a-1) + (best_pos(a) / 54);
end
```

```
% 3. SOC Plot
figure;
plot(1:nVar, soc_curve, 'b-o', 'LineWidth', 2);
hold on;
yline(0.8, 'r--', 'Max Limit (0.8)');
yline(0.3, 'r--', 'Min Limit 1 (0.3)');
xline(13.5, 'k:', 'Switch Constraint Zone');
% Draw the 0.6 limit for the second half
line([14 24], [0.6 0.6], 'Color', 'r', 'LineStyle', '--');
text(15, 0.62, 'Min Limit 2 (0.6)', 'Color', 'r');

xlabel('Hour');
ylabel('State of Charge (SOC)');
title('SOC Profile of Best Solution');
ylim([0 1]);
grid on;
hold off;

%% -------------------------------------------------------
%  HELPER FUNCTIONS
%  -------------------------------------------------------

function z = CostWithPenalty(x)
   % 1. Calculate the base Economic Cost
   real_cost = obj2(x);

   % 2. Calculate State of Charge (SOC) to check constraints
   nVar = length(x);
   soc = zeros(1, nVar);

   % Initial SOC is 0.4
   soc(1) = 0.4 + (x(1) / 54);
   for a = 2:nVar
      soc(a) = soc(a-1) + (x(a) / 54);
   end

   % 3. Calculate Penalties for violations
   Penalty = 0;
   beta = 10000; % High penalty weight

   % Constraint 1: SOC must not exceed 0.8
   violation_max = sum(max(0, soc - 0.8));

   % Constraint 2: SOC must be > 0.3 (Hours 1-13)
   violation_min1 = sum(max(0, 0.3 - soc(1:13)));

   % Constraint 3: SOC must be > 0.6 (Hours 14-24)
   violation_min2 = sum(max(0, 0.6 - soc(14:nVar)));
```

```
    total_violation = violation_max + violation_min1 + violation_min2;

    % Final Cost = Real Cost + Penalty
    z = real_cost + (beta * total_violation);
end

function z = obj2(x)
    % Ensure x is column vector for math
    x = x(:);

    % Grid Price (24 hours subset)
    gp = [2.946; 2.865; 2.842; 3.039; 3.34; 3.595; 3.629; 3.398; ...
          3.015; 2.714; 2.517; 2.448; 2.309; 2.008; 1.718; 1.683; ...
          1.718; 1.683; 1.637; 1.614; 1.625; 1.625; 1.614; 1.637];

    % Load Demand (24 hours subset)
    ld = [3.811; 4.132; 3.962; 3.981; 3.868; 3.83; 3.811; 3.736; ...
          3.66; 3.585; 3.509; 3.434; 3.377; 3.321; 3.264; 3.189; ...
          3.151; 3.208; 3.226; 3.189; 3.208; 3.302; 3.491; 3.736];

    % Check size
    n = length(x);
    if n > length(gp)
        % Pad or error handle if necessary,
        % here we just truncate x if it's too long or GP if x is short
        current_gp = gp(1:n);
        current_ld = ld(1:n);
    else
        current_gp = gp(1:n);

        current_ld = ld(1:n);
    end

    % Cost Calculation: Sum of (Load + Battery) * Price
    z = sum((current_ld + x) .* current_gp);
                                                        end
```