COMPREHENSIVE FRAMEWORK FOR ENERGY PREDICTION IN ELECTRIC VEHICLES

A Project Report Submitted

by

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THESIS CERTIFICATE

This is to certify that the thesis titled **Comprehensive framework for energy prediction in electric vehicles**, submitted by **Muskan Gojra** , to the Indian Institute of Technology, Patna, for the award of the degree of **Bachelor of Technology**, is a bona fide record of the research work done by her under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

The rapid adoption of electric vehicles (EVs) presents both opportunities and challenges in the realm of sustainable transportation. One of the most critical aspects of EV infrastructure is efficiently managing energy consumption during the charging process. This thesis presents a comprehensive framework for predicting energy consumption in electric vehicles, combining simulation-based modeling with advanced machine learning and deep learning techniques.

The study is structured in two major phases. Initially, a DC fast charging system powered by a three-phase AC grid is modeled using MATLAB Simulink. The simulated environment generates high-resolution datasets comprising parameters like battery voltage, current, and state of charge (SOC). These features are used to train ensemble learning algorithms which demonstrated high prediction accuracy and strong generalization capabilities.

In the second phase, the model is modified to use solar photovoltaic (PV) energy as the primary source. The updated system simulates real-world variability in solar charging and generates a second dataset for deeper analysis. Given the time-dependent nature of this data, deep learning models are implemented. These models significantly enhance the prediction of energy consumption by capturing temporal patterns and non-linear interactions.

The results confirm that the proposed framework can accurately forecast energy usage under both grid and solar-based charging conditions. This work not only highlights the effectiveness of AI in EV energy prediction but also contributes to the development of smarter, more sustainable electric mobility solutions.

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CHAPTER 1

INTRODUCTION

The increasing global emphasis on sustainability and reducing carbon emissions has led to a significant increase in the adoption of electric vehicles (EVs). EVs are seen as the cornerstone in achieving a cleaner and greener future by replacing internal combustion engine vehicles. However, the transition to electric vehicles presents challenges, especially in terms of energy management, battery performance, and the efficiency of the charging infrastructure. To address these challenges, there is a growing need for advanced predictive models that can accurately predict energy consumption in electric vehicles.

This project focuses on using advanced simulation tools, machine learning (ML), and Deep Learning techniques to create a robust framework to predict energy usage in electric vehicles. The study aims to improve the understanding of energy consumption patterns and optimize key parameters such as state of charge (SOC), battery current, and voltage, which are critical to the performance and reliability of EVs.

1.1 Background

The global push towards sustainability and the urgent need to mitigate climate change have accelerated the adoption of electric vehicles (EVs) as an alternative to internal combustion engine vehicles. As countries aim to reduce greenhouse gas emissions and transition to cleaner energy systems, EVs are becoming central to modern transportation strategies. However, this shift presents new challenges, particularly in the domain of charging infrastructure, energy management, and battery optimization.

A fundamental aspect of electric vehicle operation lies in its energy consumption during the charging and discharging cycles. Accurate forecasting of energy usage is essential not only to improve battery efficiency and lifetime but also to ensure stable and effective integration of electric vehicles with the power grid. With the growing emphasis on renewable energy, there is a rising interest in designing EV charging systems that draw power from sustainable sources such as solar photovoltaics (PV). Integrating solar energy into EV charging infrastructure not only reduces dependence on fossil fuels but also offers an environmentally responsible and potentially off-grid solution.

This project addresses these pressing concerns by developing a comprehensive framework for predicting energy consumption in electric vehicles, focusing on both hardware simulation and the application of data-driven techniques. The solution involves designing a complete solar-powered EV charging station model in MATLAB Simulink and applying advanced machine learning and deep learning methods to analyze and predict energy usage patterns.

1.2 Motivation

Understanding and predicting how an electric vehicle consumes energy is essential for optimizing charging strategies, improving the reliability of the grid, and ensuring user convenience. Traditional approaches to modeling energy consumption often fall short in capturing the non-linear and dynamic behavior inherent in real-time EV operations, especially under variable environmental conditions.

The motivation for this work arises from several interrelated challenges:

- Efficient Charging Infrastructure: With increasing EV penetration, fast and smart charging stations are needed. Predicting energy demands can help avoid bottlenecks and balance the grid.
- Battery Longevity and Performance: Anticipating battery behavior under different loads and charging patterns can inform better battery management and prolong battery life.
- Integration of Renewable Energy: The use of solar energy for electric vehicle charging supports decarbonization, but introduces complexity due to fluctuations in solar irradiance and temperature. Predictive models are needed to effectively manage this variability.
- Real-Time Forecasting: Using machine learning and deep learning techniques, it is possible to develop systems that not only model energy consumption but also predict it in real time with high accuracy.
- These considerations form the backbone of this project, which aims to bridge simulation-based data generation with intelligent predictive analytics.

1.3 Problem Statement

Despite advancements in EV technology, there is a gap in effectively predicting energy consumption during charging cycles, particularly in renewable-integrated systems. Most existing models lack adaptability and do not accommodate the fluctuating conditions presented by solar-based power inputs. In addition, the absence of real-world datasets further restricts the development of accurate forecasting models. This project addresses these issues by simulating a realistic solar-powered EV charging system and applying robust predictive techniques, including deep learning architectures such as Multi-Layer Perceptrons (MLPs) and Long Short-Term Memory (LSTM) networks, to anticipate energy consumption behavior under dynamic conditions.

1.4 Objectives

The primary objective of this project is to develop and evaluate a predictive framework for energy consumption in EVs using simulation-based data. The goals are as follows:

- To design and simulate a solar-powered DC fast charging station for EVs using MATLAB Simulink.
- To generate a comprehensive dataset that captures battery voltage, current, state of charge (SOC), session time, solar irradiance, and temperature.
- To preprocess and engineer features from the simulated data to create a clean and meaningful dataset.
- To implement and compare predictive models, including traditional machine learning algorithms and advanced deep learning techniques such as MLP and LSTM.
- To evaluate the accuracy, robustness, and generalization performance of these models using standard metrics.

1.5 Scope of work

This project covers the design, simulation, and evaluation of a solar-based EV charging system along with a comprehensive data-driven prediction pipeline. The scope includes:

- Creating a MATLAB Simulink model that mimics real-world solar energy harvesting and EV charging dynamics.

- Designing control systems like MPPT (Maximum Power Point Tracking) and DC-DC converters to optimize energy transfer from PV panels to the battery.
- Generating high-resolution datasets that reflect instantaneous energy behavior during charging.
- Applying data preprocessing techniques such as normalization, outlier removal, and feature extraction to prepare the data for modeling.
- Developing and comparing deep learning models (MLP and LSTM) for predicting energy consumption.
- Analyzing the performance of each model and drawing insights for potential real-world deployment.

CHAPTER 2

Literature Review

The transition to electric mobility has driven researchers to explore innovative methods for improving the efficiency, reliability, and sustainability of electric vehicle (EV) charging systems. A growing area of interest involves integrating intelligent data-driven approaches such as machine learning (ML) and deep learning (DL) with simulation-based EV models. This chapter reviews the relevant literature in the areas of EV fast charging technologies, integration of renewable energy into the charging infrastructure, and the application of artificial intelligence (AI) techniques, particularly ML and DL, to predict energy consumption. It also highlights the key findings from previous work and identifies gaps that this project aims to address.

2.1 EV Charging Infrastructure and Control Strategies

The foundation of any EV energy prediction framework lies in the accurate modeling of the charging infrastructure. Traditional fast-charging stations typically rely on grid-supplied three-phase AC power, which is rectified and regulated using closed-loop control mechanisms. Joos and Freige (2010) presented a simulation of fast-charging stations for plug-in hybrid electric vehicles (PHEVs), emphasizing the role of efficient power electronic converters in achieving stable charging profiles.

Moreover, DC fast chargers have emerged as the preferred choice for high-power EV applications due to their ability to bypass onboard AC-to-DC conversion. Lan and Sobiro (2022) further explored a 12-pulse rectifier combined with a DC-side buck converter, demonstrating how such topologies can reduce ripple and enhance system stability.

In this project, similar principles were applied in Phase I, where a grid-based DC fast charger was developed in MATLAB Simulink, featuring a PLL-based control system and PI-regulated voltage output. The system successfully emulated real-world charging conditions and laid the groundwork for predictive data modeling.

2.2 Integration of Renewable Energy in EV Charging

The increasing emphasis on clean energy has motivated research into renewable-powered EV charging stations. Among these, solar photovoltaic (PV) systems are widely considered due to their scalability and cost-effectiveness. Khansole et al. (2024) modeled a solar generator using MATLAB Simulink to demonstrate the feasibility of standalone PV-based systems for various applications.

Reddy and Chengaiah (2024) further proposed a hybrid solar-wind EV charging station, highlighting the role of Maximum Power Point Tracking (MPPT) in maximizing energy harvest under variable atmospheric conditions. In alignment with these studies, our project's second phase involved modifying the EV charging system to operate using solar power, with MPPT control and DC-DC converters ensuring stable charging despite irradiance fluctuations.

This sustainability-focused transition not only contributed to environmental goals but also introduced dynamic and time-sensitive behavior into the system—making it an ideal testbed for more sophisticated prediction algorithms.

2.3 Application of Machine Learning in EV Energy Forecasting

Machine learning has proven effective in modeling non-linear and complex behaviors in EV energy consumption, especially when real-time prediction is necessary. A study presented at the 2023 ICACCS conference demonstrated how ML models could forecast EV charging behavior by analyzing historical session data and external variables such as traffic and weather conditions.

In this project, ML techniques were first applied to the dataset generated from the grid-powered charger. Gradient Boosting Regressor (GBR) and CatBoost were chosen for their ensemble learning capabilities and their robustness in handling non-linear feature interactions. These models achieved high accuracy in predicting SOC and energy metrics, validating the effectiveness of tree-based learners in structured prediction problems.

Notably, CatBoost's target-based encoding and efficient handling of categorical features made it suitable for real-world data, while GBR offered superior performance on continuous, engineered features such as power, current, and normalized SOC values.

2.4 Deep Learning for Time-Dependent Energy Prediction

While ML models are effective in general pattern recognition, they often fall short in capturing temporal dependencies, especially in datasets where behavior evolves, such as solar-powered EV charging sessions. To address this limitation, recent studies have explored the use of deep learning for sequence-level prediction tasks.

LSTM (Long Short-Term Memory) networks, a special class of recurrent neural networks, have been particularly successful in modeling time series with long-range dependencies. This project leveraged LSTM models to analyze the dataset collected from the solar-integrated charging station, which featured short-duration, high-frequency data influenced by solar irradiance, session time, and load conditions. LSTM's ability to retain historical context across time steps resulted in highly accurate forecasts of energy consumption.

In addition to LSTM, a feedforward deep neural network, also known as a Multilayer Perceptron (MLP), was used to provide a non-sequential baseline. Although MLPs lack memory mechanisms, they proved effective for snapshot-level predictions, especially when the input features were well-engineered and temporally smoothed.

These deep learning models demonstrated notable improvements in capturing intricate charging dynamics that traditional models could not fully exploit. Their performance supports the growing trend of integrating AI into EV management systems for smarter, real-time decision-making.

2.5 Research Gap and Contribution

Although several studies have investigated the individual components of EV charging, renewable energy integration, or energy forecasting through ML/DL, few have presented an end-to-end framework that begins with simulation-based data generation and continues through to deep learning-based energy prediction under sustainable charging scenarios.

My work fills this gap by:

- Combining simulation modeling with real-time data analytics.
- Evaluating both traditional and renewable-powered charging systems.
- Applying a comparative analysis of ML and DL techniques using identical datasets and performance metrics.
- Demonstrating the practical application of AI for enhancing EV energy forecasting.

This integrated approach provides a more holistic understanding of EV charging behavior under different energy sources and data modeling paradigms.

CHAPTER 3

System Overview

This chapter presents a comprehensive overview of the system architecture, simulation design, and modeling techniques used in this project to predict energy consumption in electric vehicles (EVs). The project follows a phased approach that begins with the development of a conventional DC fast charging model powered by the electric grid and later evolves into a more sustainable solar-powered charging system. Both models were simulated using MATLAB Simulink to replicate real-world EV charging scenarios and to generate high-fidelity datasets for predictive analysis.

3.1 Overview of the project workflow

The primary focus of this project is to design and evaluate a comprehensive framework that enables accurate prediction of energy consumption in electric vehicles (EVs). The workflow is structured in two major phases, each building progressively upon the previous:

1. **Phase I: DC Fast Charging System Based on Grid Power:**

- Design and simulation of a DC fast charger model using a conventional three-phase AC power supply.
- Data generation through the simulation of EV charging behavior under controlled input and load conditions.
- Application of traditional machine learning algorithms (Gradient Boosting Regressor and CatBoost) to predict energy consumption metrics like power and SOC.

2. **Phase II: Solar-Powered EV Charging System:**

- Transformation of the original model into a more sustainable design by incorporating solar photovoltaic (PV) energy as the primary source.
- Integration of components such as PV panels, MPPT controller, DC-DC converters, and battery management subsystems.

- High-resolution dataset generation reflecting dynamic, real-world solar charging conditions.
- Implementation of advanced deep learning models, including Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM), to predict energy consumption trends with greater temporal accuracy.

3.2 DC Fast Charger Model Using Grid Supply

The initial model simulates a standard fast-charging setup powered by a three-phase AC grid. The Simulink-based system consists of the following key blocks:

- **Three-Phase AC Source:** Supplies a balanced three-phase voltage to replicate grid conditions.
- **AC-DC Rectifier:** Converts AC input to DC using controlled power electronics with feedback regulation.
- **Closed-Loop Control System:** Implements a Proportional-Integral (PI) controller and Phase-Locked Loop (PLL) for voltage and current regulation.
- **Battery Load:** A lithium-ion battery model with state of charge (SOC) tracking.

This model outputs real-time waveforms for voltage, current, and SOC. The control loop ensures stability by adjusting switching signals based on error feedback. The simulation environment was configured to record high-frequency data, which was then used to build a dataset for machine learning.

3.3 Applications of Machine Learning

From the simulation of the grid-based charger, the following key features were extracted:

- Battery Voltage (V)
- Battery Current (A)
- State of Charge (SOC)
- Derived Features: Instantaneous Power (Voltage × Current), SOC change rate, and temporal rolling averages

The data underwent preprocessing steps including normalization, outlier removal using the IQR method, and smoothing through rolling statistics.

Two ensemble learning algorithms were employed for prediction:

- **Gradient Boosting Regressor (GBR):** Known for capturing non-linear relationships using sequential decision trees optimized via gradient descent.
- **CatBoost:** Designed for categorical data handling and enhanced generalization, using gradient-based tree growth with minimal preprocessing.

The models were trained on 80% of the dataset and validated on the remaining 20%, with evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2) indicating high accuracy. Among the two, GBR showed marginally superior performance in both prediction accuracy and generalization.

3.4 Transition to Solar-Powered Charging

To make the system environmentally sustainable, the next phase replaced the grid supply with a solar photovoltaic (PV) source. This solar-powered fast-charging system was developed in Simulink with the following components:

- **PV Panel Array:** Simulated using irradiance and temperature-dependent models.
- **Maximum Power Point Tracking (MPPT) Controller:** Ensures the PV system always operates at its most efficient point by adjusting the duty cycle.
- **Boost and Buck Converters:** Regulate voltage levels between PV panels and the battery load.
- **Battery Management System (BMS):** Monitors SOC, voltage, and current to prevent overcharging and optimize battery health.
- **EV Controller:** Implements logic for constant current (CC) and constant voltage (CV) charging modes based on SOC thresholds.

The model was tested under varying environmental conditions (e.g., 500 W/m^2 at 25°C and 750 W/m^2 at 30°C), generating a second dataset that was richer in temporal variability due to fluctuations in solar input.

3.5 Deep Learning Implementation

The dataset obtained from the solar-based simulation included the following features:

- Battery Voltage (V)
- Battery Current (A)
- SOC (
- Solar Irradiance (W/m²)
- Charging Session Time (s)
- Derived Power and Energy Metrics

Given the sequential and time-dependent nature of this data, deep learning methods were selected for improved modeling:

- **Multilayer Perceptron (MLP):**
  A feedforward neural network with multiple hidden layers was implemented to capture complex, non-linear relationships. The model used ReLU activation, dropout regularization, and Adam optimization. MLP provided good baseline performance and was effective for snapshot-based predictions.
- **Long Short-Term Memory (LSTM):**
  To incorporate temporal patterns, an LSTM model was designed, leveraging its gated architecture to retain information across time steps. The model was trained on sequence windows of SOC, voltage, and current data, with predictions focused on energy consumption in the next interval. LSTM outperformed MLP in forecasting accuracy due to its temporal memory capability.

Both deep learning models were evaluated using the same metrics as in the machine learning phase. The MLP model achieved the highest R^2 score, demonstrating its suitability for time-series energy prediction.

CHAPTER 4

Charging Station Design using three-phase supply

The EV charging station is designed on Simulink first as a DC fast charger using three-phase energy, and then later modified to use solar energy. Knowing energy consumption patterns can help design efficient and fast charging stations, reducing downtime for EV users.

4.1 DC Fast charger

As a first step, we begin by developing a DC fast charger for Electric vehicles, whose output will be used for further data analysis.

4.1.1 Battery Charging method

The boost charger CC/CV charging algorithm develops the constant current/constant voltage algorithms. Instead of using the constant voltage and current in the entire charging period, it boosts the charging efficiency by maximizing voltage in the first period, with the battery reaching approximately 30% of its nominal charging capacity. After this period, the charging algorithm is then switched to the standard CC/CV. Due to the initial higher charging voltage, the CC/CV can charge the battery faster than the CC/CV, but it is required to fully discharge the battery before charging. As the charger needs to provide variable voltage, all components need to accept the highest voltage generated by the boost charger. Discharging the battery before recharging is important as this will influence the efficiency charging algorithm and the life cycle of batteries. DC Fast Charging bypasses all of the limitations of the onboard charger and required conversion, instead of providing DC power directly to the battery, charging speed has the potential to be greatly increased. Charging times depend on the battery size, the output of the dispenser, and other factors, but many vehicles can get an 80% charge in about or under an hour using most currently available DC fast chargers. DC fast charging is essential for high-mileage/long-distance driving and large fleets. The quick turnaround enables drivers to recharge during their day or on a small break as opposed to being plugged in overnight or for many hours, for a full charge.

4.1.2 Principle and Working

EV batteries store charge in DC power, while the electric grid supplies alternating current (AC) power. When we use Level 1 or Level 2 charging, the EV receives AC power that must be converted to DC before storing it in the car's battery. To do this, EV has an onboard charger. DC fast charging, though as its name implies, provides DC power straight to the EV's battery; the AC-to-DC conversion happens in the charging station before the electrons enter the vehicle. That's why DC fast charging can provide a much faster charge than Level 1 or Level 2 charging. The concept of this project is to design a MATLAB Simulink model for a DC fast charger that is capable of charging EV batteries. Control algorithms of DC fast chargers are implemented in such a way that, depending upon the State-of-Charge (SOC) of the battery, the charging method is adopted. If battery SOC is less than 80%, then the DC fast charger will implement Constant Current (CC) charging, and for SOC more than 80% it will go for Constant Voltage (CV) charging. DC fast chargers are capable of charging the battery up to its full capacity within 1-2 hours. This will reduce the charging time of the battery, which is about 6-8 hours in the case of AC charging of the battery.

4.1.3 Why DC charger?

An AC charger is always coupled with a built-in setup with an AC charging infrastructure, known as the onboard charger. The role of an onboard charger is energy conversion from AC to DC and supplies the current to the heart of the EV, i.e., the battery pack.
AC charging, also referred to as 'Slow Charging', is the most common form of charging due to the high charging point and ease of installation. AC chargers can be installed at home (type 1) or are readily present at EV charging stations (type 2). A range anywhere between 22kW and 43kW per km/h is achieved with fast AC chargers.
Depending upon the intake capacity of the onboard charger, it may take a couple of hours or overnight to fully charge an electric car. But AC charging of the battery has

the following limitations

1. Charging is slower over time due to much higher losses during conversion from AC to DC.
2. Cannot be as fast as a DC charger.
3. Every vehicle has to carry on board charging circuitry.
4. Interconnection with renewable energy sources might require complex conversion circuits.
5. Battery charging up to full capacity may require 8 to 12 hours.
6. Due to the high charging period, it is not suitable for large fleets.

However, DC fast chargers can overcome all the drawbacks of AC chargers. Hence, we are developing a DC fast Charger for battery charging.

4.2 Simulation Design

The charger model begins with the input of three-phase AC voltage, which is converted to DC using a rectifier. A Phase-Locked Loop (PLL) synchronizes the phase angles for accurate signal processing. The DC voltage is regulated through a closed-loop control system, employing proportional-integral (PI) controllers to maintain the desired voltage and current levels. The control subsystem calculates the error between reference and measured values, adjusting the output accordingly. The output DC voltage is then used to charge the EV battery. The overall system ensures efficient power conversion with minimized ripple in voltage and current.

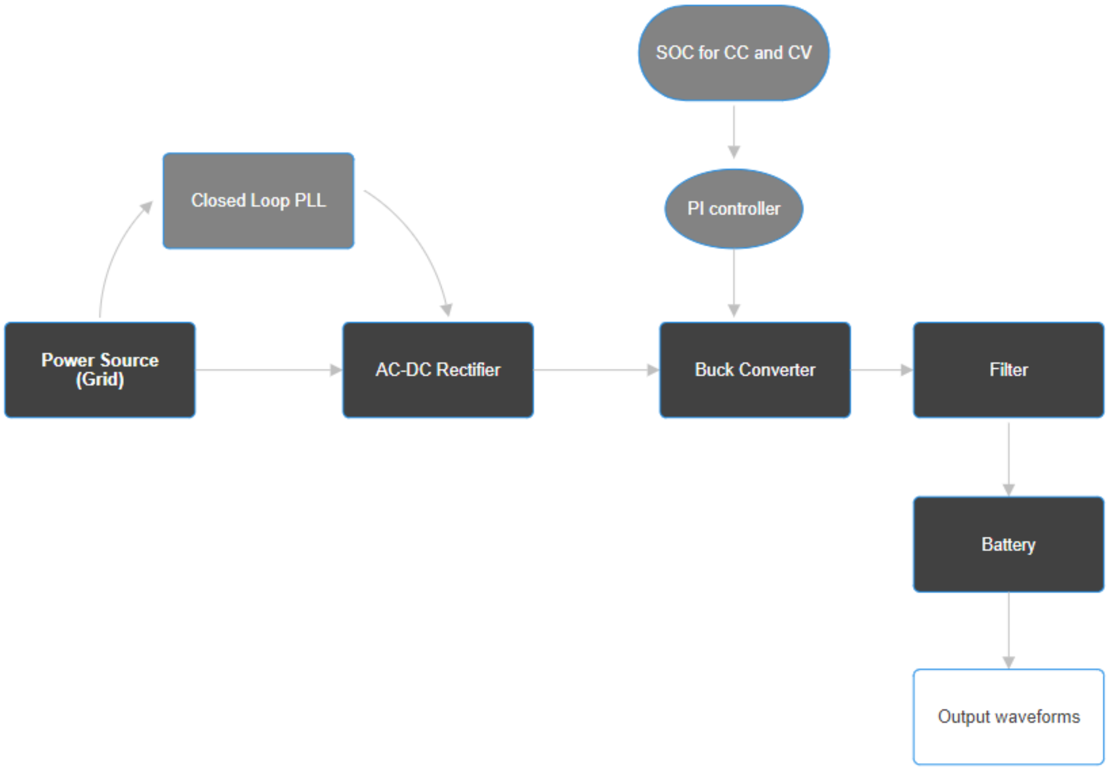

Figure 4.1: Flow chart for the DC fast charger Model

4.2.1 Power Grid

The three-phase power supply sub-system generates a balanced three-phase AC voltage, represented by the three lines A, B, and C. This voltage is applied to the load, represented by resistances and inductances connected in each phase. The outputs V_{abc} and I_{abc} represent the measured three-phase voltage and current, respectively. This setup is commonly used for delivering stable power to systems.

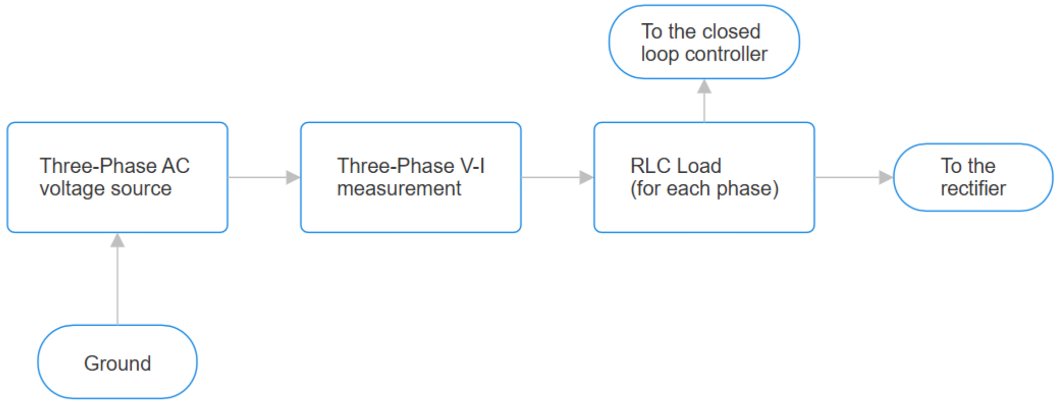

Figure 4.2: Flow chart for the Power Grid

Table 4.1: Values Used in Power Grid Block

S. No.	Block Name	Value/Parameter
1	Three-Phase AC Voltage Source	400V, 50Hz
2	RLC Load (Phase A,B,C) - Resistor	0.1 Ohms
3	RLC Load (Phase A,B,C) - Inductor	1e-3 H

4.2.2 Three-Phase AC-DC Rectifier

The three-phase AC-DC rectifier converts the three-phase AC power into DC voltage and current. It receives a Pulse Width Modulation (PWM) signal from the closed-loop controller circuit to control the switching of the MOSFETs in the rectifier circuit. The PWM signal modulates the switching of the six switches (S1 to S6) to control the rectification process and maintain stability in the output DC voltage (V_{dc}) and current (I_{dc}). The current (I_{dc}) and voltage feedback (V_{dc}) are monitored and fed back into the control system to ensure proper regulation of the output. The feedback control helps in adjusting the PWM signals for efficient rectification and smoother DC output.

Table 4.2: Values Used in Rectifier

S. No.	Block Name	Value/Parameter
1	Repeating Sequence	[0,0.0001,0.0002]
2	FET Resistance	0.1 Ohms

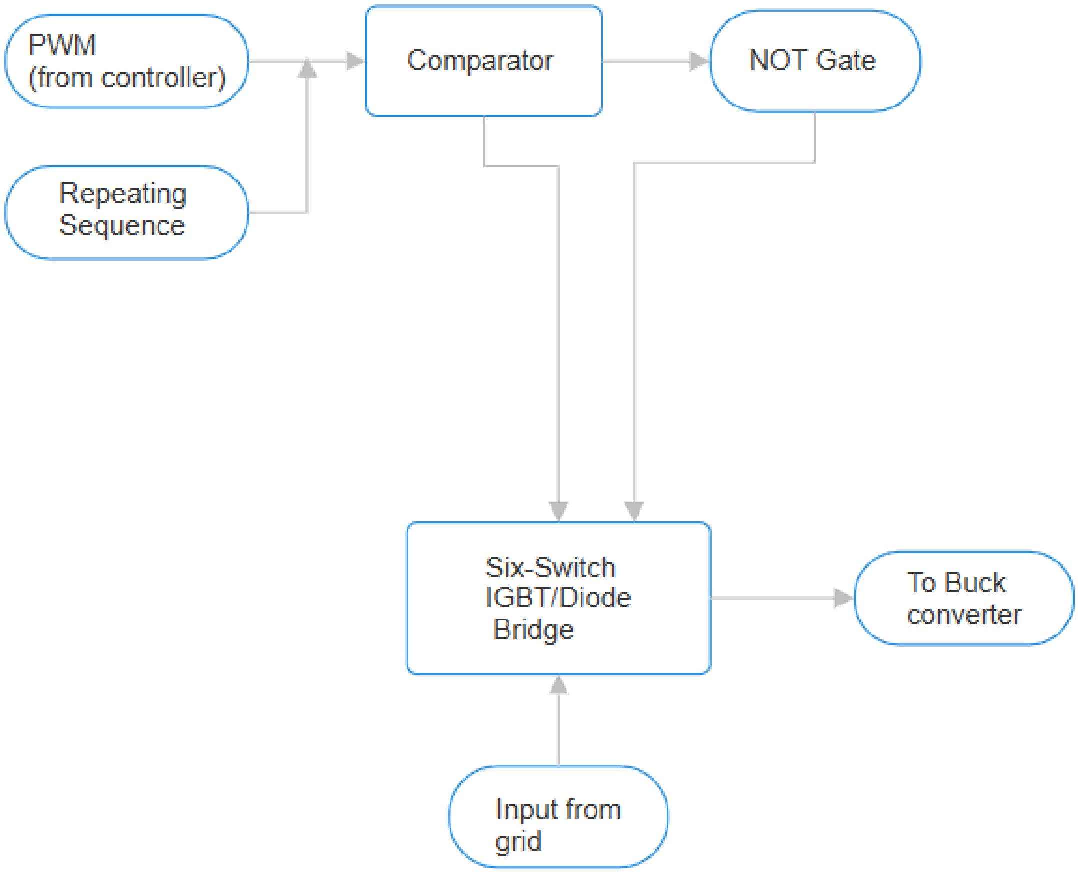

Figure 4.3: Three-Phase AC-DC Rectifier

4.2.3 Closed Loop Control

The three-phase power supply feeds the AC input to the rectifier, which converts AC to DC. The PWM signal generated by the PLL-based closed-loop control is used to regulate the switching of the transistors in the rectifier. This ensures proper control of the DC output voltage and current. The output is then fed to the DC bus, which supplies power to the rest of the system, maintaining a stable and controlled DC voltage for the load.

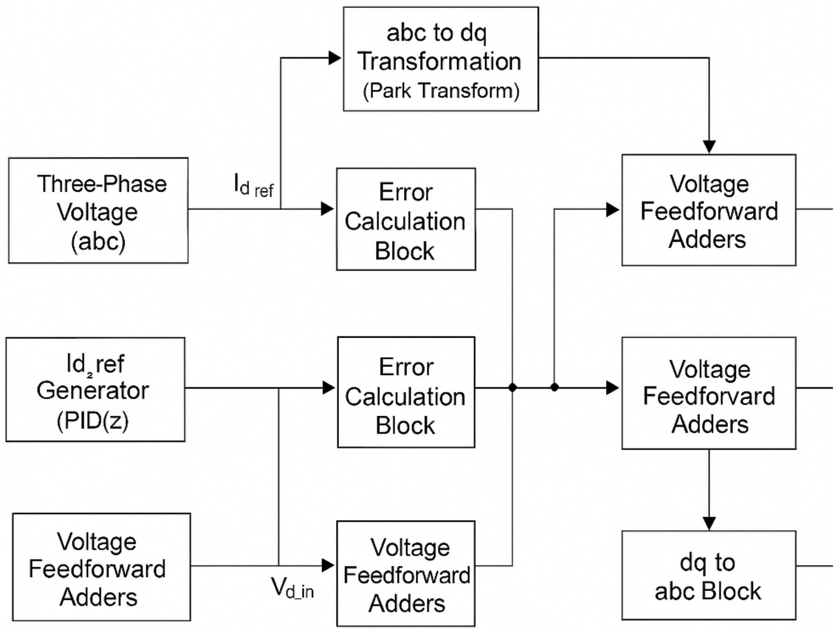

Figure 4.4: Closed Loop Controller, output goes into rectifier

4.2.4 Overall Model

We use a MATLAB function that switches between constant current (CC) and constant voltage (CV) modes based on the battery's state of charge (SOC). It is designed for controlling an EV charging system where the charging mode needs to switch from constant current to constant voltage when the SOC exceeds a threshold.

Table 4.3: Values Used in Model

S. No.	Block Name	Value/Parameter
1	PI Controller	P=0.75, I=50
2	Saturation Limit	0.975
3	PWM Generator	20e3 Hz
4	Inductance	10e-6 H, 1e-2 H
5	Capacitance	100e-6 F
6	Battery(Lithium-Ion)	360V, 56.3Ah

4.3 Result and Conclusion

We get the following output waveforms on running our model:

1. For Battery State-of-Charge (SOC) below 80% : Under this condition, the charger will provide constant current charging. The magnitude of the charging current is about 125 A, and the battery charging voltage is 400 V.

2. For battery State-of-Charge (SOC) above 80% : Under this condition, the charger will provide constant voltage charging. The magnitude of the charging current is 25 A, and that of the charging voltage is 395 V.

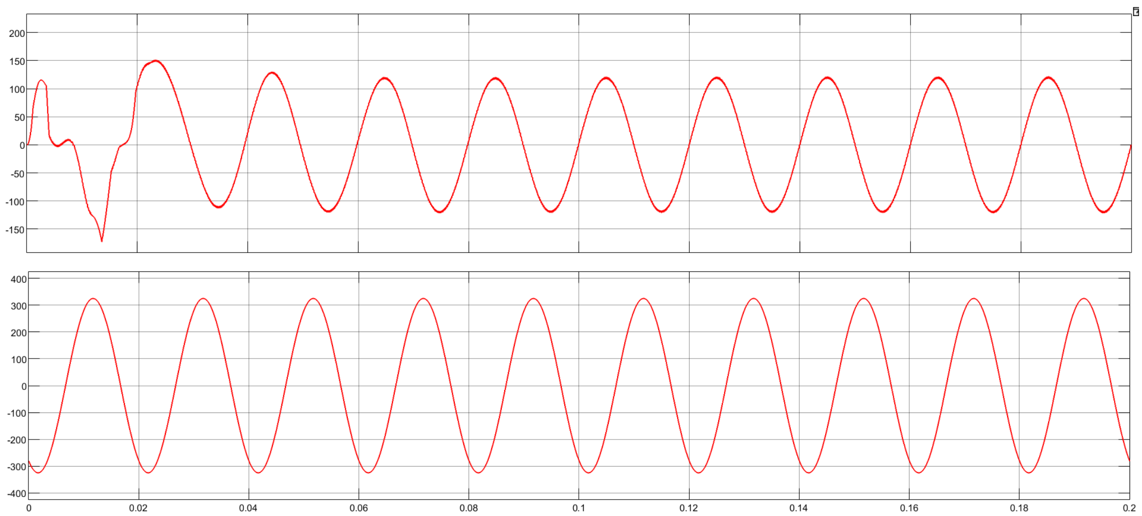

Figure 4.5: waveform 1: AC Voltage, waveform 2: AC current from power grid

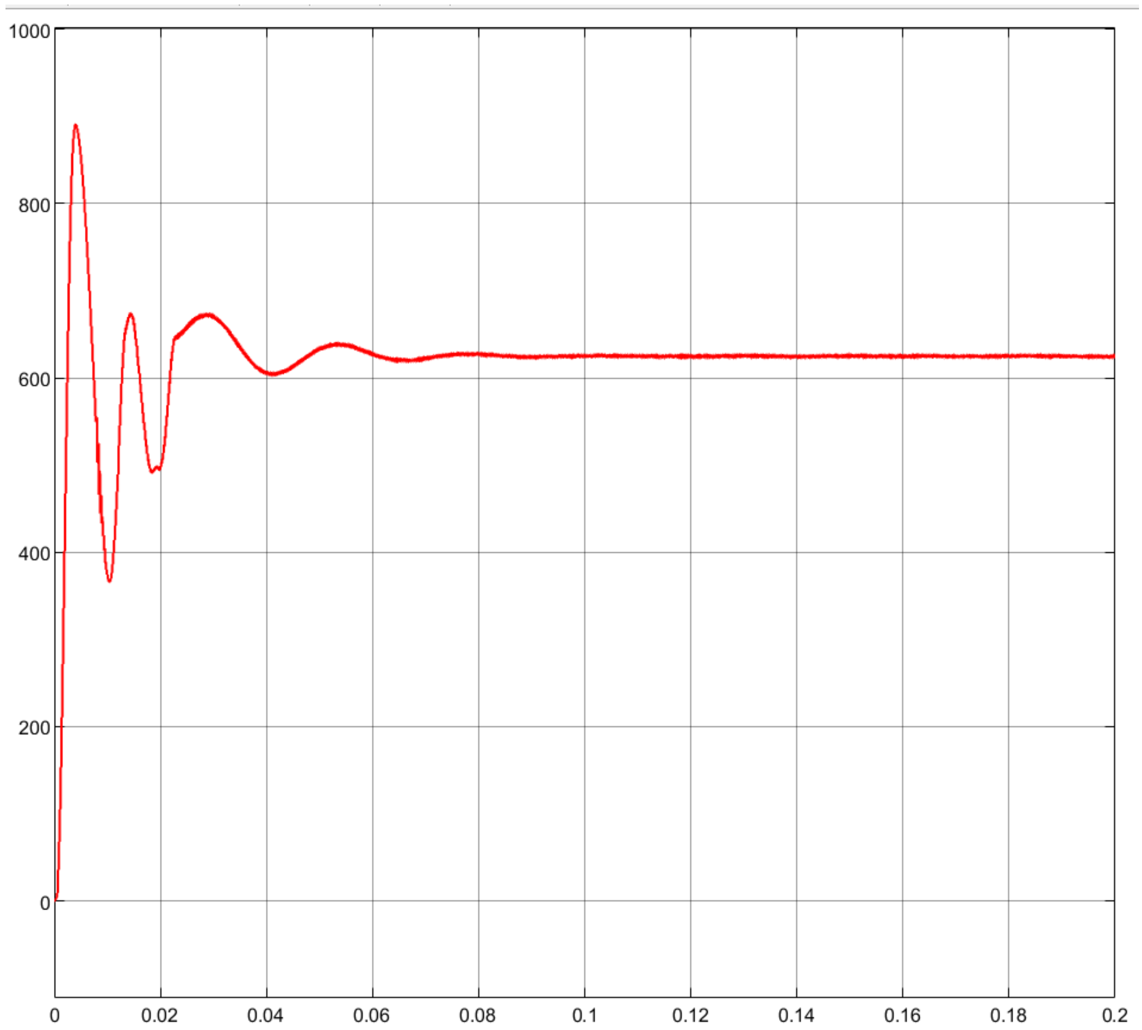

Figure 4.6: DC Current after rectifier

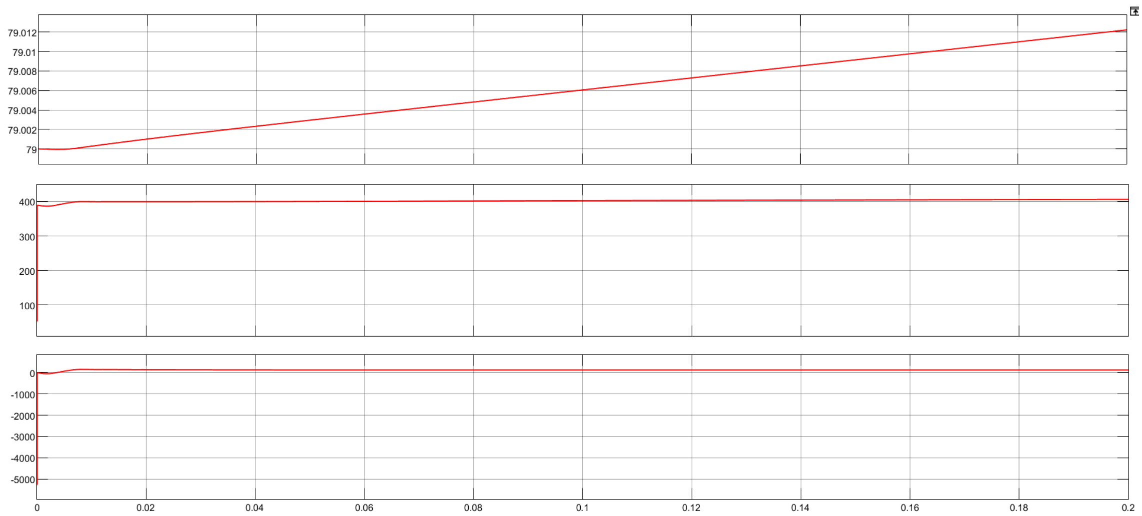

Figure 4.7: waveform 1: Battery SOC, waveform 2: Battery Output Voltage, waveform 3: Battery Output Current

CHAPTER 5

ML implementation in Model

Machine learning (ML) has emerged as a transformative technology in recent years, revolutionizing a wide range of industries, including the power sector. ML enables systems to learn from data, identify patterns, and make predictions or decisions without being explicitly programmed. This capability is particularly valuable in complex domains like electric vehicles (EVs) and power systems, where dynamic, non-linear, and interdependent factors govern performance and efficiency.

In the context of this project, machine learning plays a critical role in accurately predicting energy consumption in electric vehicles. EV energy consumption is influenced by multiple factors, including battery characteristics, charging patterns, and environmental conditions. Traditional methods often struggle to model these complex relationships effectively. ML bridges this gap by:

Learning from Simulation Data: By utilizing data generated from a detailed Simulink model, ML models can uncover insights and patterns that are difficult to capture with conventional algorithms. Handling Non-Linear Relationships: Advanced ML algorithms such as Gradient Boosting Regressor (GBR) and CatBoost excel at identifying non-linear interactions among features like state of charge (SOC), battery voltage, and current.

We begin by extracting key parameters like SOC, battery voltage, and current from the simulation for dataset creation. Applying advanced preprocessing techniques such as normalization, outlier removal, and feature smoothing to ensure high-quality data. Leveraging machine learning models like Gradient Boosting Regressor (GBR) and CatBoost to predict energy consumption with high accuracy. Evaluating the performance of the models using established metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared(R^2).

5.1 Machine Learning Techniques Used

Two Machine Learning Algorithms are used to predict the energy consumption and are compared to find the best one that suits our needs.

5.1.1 Gradient Boost Regressor

- Ensemble Learning: Combines multiple weak learners (decision trees) into a strong predictive model.
- Gradient Descent: Optimizes the model by minimizing prediction errors.
- Feature Importance: Automatically identifies the most impactful features, such as SOC and voltage fluctuations.

Table 5.1: Summary of Gradient Boosting Regressor (GBR) for Energy Consumption Prediction

Component	**Description**
Model	`GradientBoostingRegressor` from `sklearn.ensemble`
Algorithm Type	Gradient Boosting (tree-based, sequential learners)
Input Features	SOC, B_Vol, B_Curr, SOC change rate, voltage/current std. dev., rolling stats
Target	`Power` (energy consumption during EV charging)
Goal	Learn complex, nonlinear relationships to accurately predict energy usage
Strengths	Good for structured/tabular data; handles nonlinearity well
Limitations	Slower training than simpler models; needs more hyperparameter tuning

5.1.2 CatBoost

- Efficient Categorical Data Handling: CatBoost encodes categorical variables using target-based encoding, which improves accuracy and reduces preprocessing time.
- Gradient-Based Boosting: Builds models incrementally to correct errors of previous iterations.
- Leaf-Wise Splitting: Focuses on high-error areas of the dataset, leading to precise predictions.

Table 5.2: Summary of CatBoost Regressor for Energy Consumption Prediction

Component	**Description**
Model	`CatBoostRegressor` from the `catboost` library
Algorithm Type	Gradient Boosting (optimized for categorical and tabular data)
Input Features	SOC, B_Vol, B_Curr, SOC change rate, voltage/current std. dev., rolling stats
Target	`Power` (energy consumption during EV charging)
Goal	Learn patterns and dependencies to predict power output accurately
Strengths	High performance with minimal tuning; handles missing values natively; robust to overfitting
Limitations	Slightly larger memory usage; longer training times on very large datasets

5.2 Steps for prediction

The process of machine learning involves several key steps to build effective models. It begins with data collection, where relevant data is gathered from simulations, sensors, or real-world systems. Next is data preprocessing, which includes cleaning the data by handling missing values, removing outliers, and normalizing features to ensure consistency. This is followed by feature engineering, where meaningful attributes are selected or derived to enhance model performance. The processed dataset is then split into training and testing subsets to develop and validate the model. The model training phase involves selecting and optimizing algorithms like Gradient Boosting or CatBoost to learn patterns from the training data. The model's accuracy is assessed during evaluation, using metrics such as Mean Squared Error (MSE) or R-squared (R^2). Finally, the trained model is deployed for real-world predictions, with periodic updates to maintain accuracy as new data becomes available.

5.2.1 Dataset

We start off by collecting our dataset from the Simulink model. We gather Input parameters such as Input Voltage, Control parameters, and output parameters such as Battery SOC, Battery Current, and Battery Voltage. Our dataset consisted of approximately 1,00,000 values, which further helps us in exploratory data analysis and training our model better.

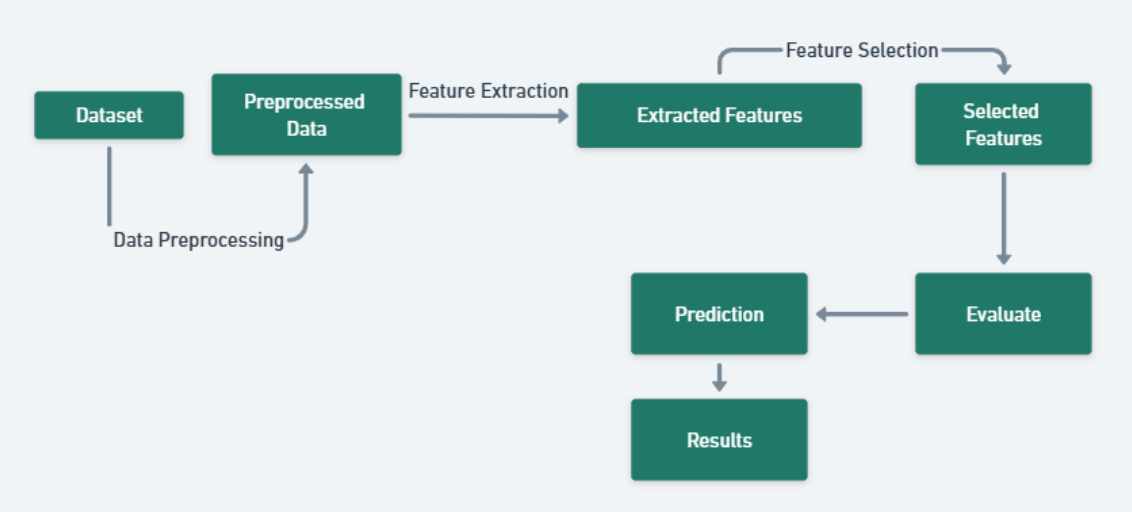

Figure 5.1: Steps to follow

5.2.2 Data Preprocessing

- **Normalization:** Min-Max Scaling:
  - Features like SOC, battery voltage, and current were scaled to a range of [0, 1] to ensure uniformity.
  - This method is particularly effective for SOC values as their ranges are naturally confined.
- **Handling Missing Data:** Missing or NaN values were identified and either filled or dropped to avoid distortions during training.
- **Outlier Removal** IQR Method:
  - The Interquartile Range (IQR) was calculated to detect outliers: Q1 (25th percentile) and Q3 (75th percentile) determined the middle 50% of the data.
  - Outliers fell outside the range of [Q1 - 1.5 × IQR, Q3 + 1.5 × IQR].
  - Outliers were removed to reduce noise and improve model performance.
- **Redundant Data Removal:** Duplicate entries were identified and eliminated to enhance training efficiency.
- **Derived Metrics:** Power: Power=BatteryVoltage×BatteryCurrent
  SOC Change Rate: Calculated using SOC/t, capturing temporal fluctuations.
- **Feature Smoothing** A rolling standard deviation with a window size of five was applied to stabilize data fluctuations in voltage and current.

5.2.3 Feature Extraction

From the raw dataset generated by the Simulink model, several key features were extracted:

- **Power Consumption:**
  Formula: Power=BatteryVoltage×BatteryCurrent
  Significance: Power consumption is directly related to the energy usage of the EV. This feature helps the model predict how efficiently the battery delivers energy under different conditions.

- **State of Charge (SOC) Change Rate:**

  Formula:
  $$\Delta SOC = \frac{SOC[i] - SOC[i-1]}{\Delta t}$$

  Significance: This captures the rate at which the battery's state of charge changes over time, offering insights into discharge or charging behavior.

- **Rolling Standard Deviation of Voltage and Current:**
  Method: A rolling window of size 5 data points was applied to compute the standard deviation.
  Significance: This feature smooths fluctuations in battery voltage and current, enabling the model to capture stable trends while filtering out noise.

- **Temporal Features:**
  Derived by analyzing data over time intervals to understand patterns such as peak energy usage, battery behavior during fast charging, and other time-dependent characteristics.

- **Normalized SOC, Voltage, and Current:**

  Using Min-Max scaling, these features were normalized to a range of [0, 1].
  Significance: Normalized features ensure that the model treats all parameters equally, avoiding bias toward larger numerical ranges.

5.2.4 Evaluation

The model is evaluated using two Machine Learning techniques: Gradient Boost Regressor and CatBoost Regressor, and is further compared for their performance.

- **1. Gradient Boosting Regressor (GBR)**
  Key Features: Combines decision trees in an ensemble learning framework.
  Sequential training with gradient descent minimizes prediction errors.
  Uses weighted predictions for robust performance.

- **2. CatBoost**
  Advantages: Handles categorical data efficiently.
  Requires minimal preprocessing.
  Leaf-wise splitting and gradient-based optimizations enhance accuracy.
  Employs target-based encoding for categorical features.

Training and Testing: The dataset was split into an 80/20 ratio for training and testing, respectively.

5.2.5 Evaluation Metrics

- Mean Absolute Error (MAE): Measures average prediction error.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

- Mean Squared Error (MSE): Penalizes larger errors by squaring them.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- R-Squared: Indicates the proportion of variance explained by the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

- Comparison graphs for actual vs. predicted SOC values revealed close alignment.
- Validation and training loss graphs further validated the robustness of both models.

where,

y_i : Actual Values

$\hat{y}_i$: Predicted Values

$\bar{y}$: Mean of Actual Values

n : Number of data points

5.3 Result and Conclusion

For Gradient Boost Regressor:

Table 5.3: Error Table

Parameter	**Value**
Mean Absolute Error (MAE)	3.571499539524622e-05
Mean Squared Error (MSE)	2.5336488544665887e-09
R^2 Score	0.9999251842728011

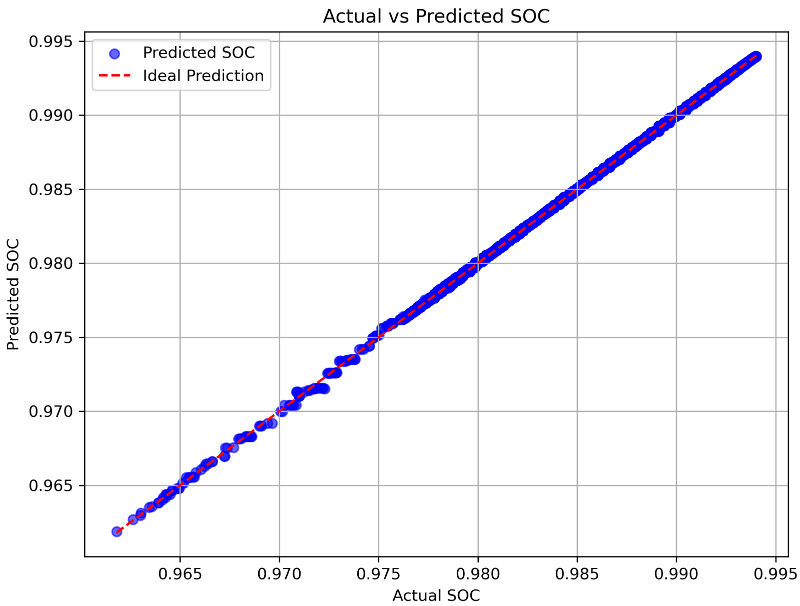

Figure 5.2: Actual SOC vs Predicted SOC

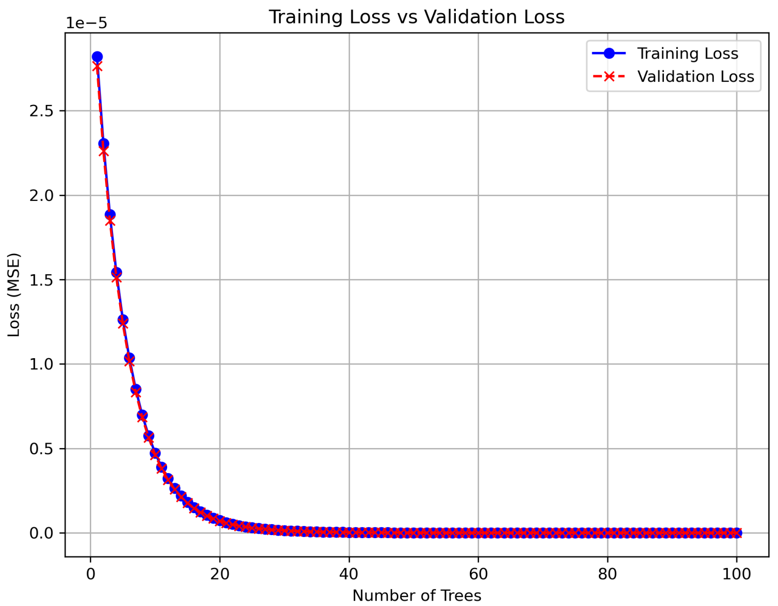

Figure 5.3: Validation Loss Vs Training Loss

Table 5.4: Cross Validation Error Table

Parameter	Value
Cross Validation R^2 Scores	[0.99992333 0.9999285 0.99974079 0.99992961 0.99992871]
Mean R^2 Score	0.9998901877852034

For CatBoost Regressor:

Table 5.5: Error Table

Parameter	Value
Mean Absolute Error (MAE)	2.2103526877398923e-05
Mean Squared Error (MSE)	3.456425756143719e-09
R^2 Score	0.9998986582387154

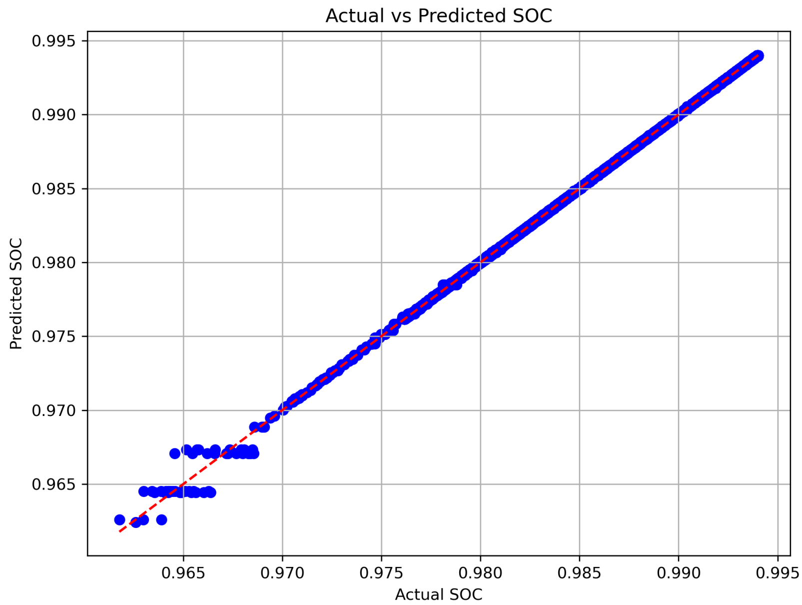

Figure 5.4: Actual SOC vs Predicted SOC

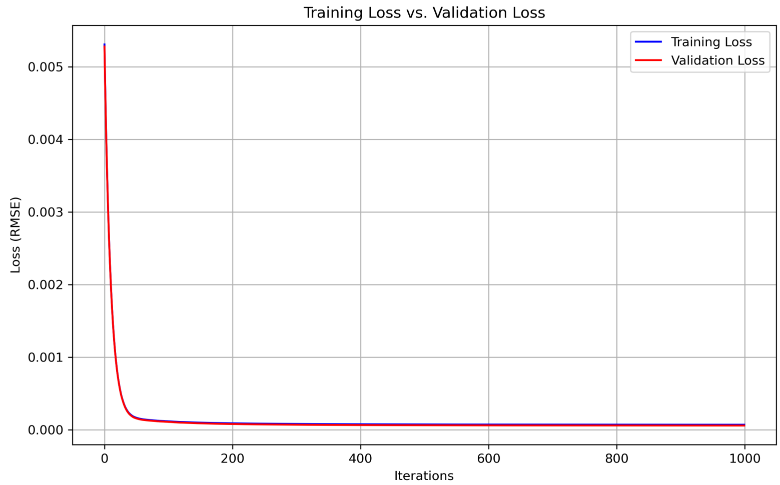

Figure 5.5: Validation Loss Vs Training Loss

5.4 Graph Analysis

- Actual SOC vs. Predicted SOC: Gradient Boosting Regressor (GBR):

  The graph shows an almost perfect overlap between actual and predicted SOC values, confirming GBR's ability to accurately capture patterns in the data. The minimal deviation indicates highly precise predictions.
  CatBoost:

  The graph shows a similar trend but with slightly more deviation compared to GBR. This indicates that while CatBoost performed well, it was less precise than GBR for this dataset.

- Validation Loss vs. Training Loss: Gradient Boosting Regressor (GBR):

  The training loss decreases consistently, while the validation loss remains very low. The small gap between training and validation losses indicates that the model avoided overfitting and generalizes effectively.
  CatBoost:

  The validation loss is slightly higher than that of GBR, suggesting a marginally reduced generalization capability. The training loss curve is smooth, but the gap with validation loss is slightly larger than in GBR, reflecting its lower accuracy.

- Residual Analysis (Error Analysis): For both models, the residuals (differences between actual and predicted values) are centered around zero, indicating unbiased predictions.
  GBR's residuals are smaller and more tightly distributed, confirming its superior predictive power.
  CatBoost's residuals, while still small, show slightly more variability, explaining its lower R^2 score.

Insights from Results:

- Model Accuracy:
  Gradient Boosting Regressor (GBR) demonstrated higher predictive accuracy with an R^2 of 0.999, making it the better model for this task.
  CatBoost, with an R^2 of 0.998, still performed exceptionally well and is a competitive alternative.

- Generalization: Both models showed strong generalization to unseen data, but GBR achieved a lower validation loss, indicating better robustness.

- Error Distribution: The error analysis confirmed that GBR consistently made more accurate predictions compared to CatBoost.

The results validate that both GBR and CatBoost are powerful tools for predicting energy consumption in EVs. However, Gradient Boosting Regressor (GBR) outperformed CatBoost in terms of accuracy and generalization, making it the preferred model for this project. The close alignment between actual and predicted SOC values in the GBR graphs highlights its reliability. These results provide a strong foundation for future enhancements, such as testing deep learning models or integrating additional features for further optimization.

5.5 Conclusion

The study demonstrated that both Gradient Boost Regressor and CatBoost models are highly effective for predicting EV energy consumption, with accuracy levels above 99%. These models provide a reliable foundation for future investigations and practical applications in EV energy management.

- 1. Gradient Boosting Regressor (GBR):
  R-Squared Value: 0.999
  GBR explained 99.9% of the variance in the SOC values, indicating excellent predictive performance.
  Key Strengths: GBR is robust for capturing non-linear relationships between features such as SOC, battery voltage, and current. It uses ensemble learning with sequential tree training, correcting errors in previous iterations.
  Validation Loss: Very low validation loss shows that GBR effectively generalized to unseen data.

- 2. CatBoost:
  R-Squared Value: 0.998
  CatBoost explained 99.8% of the variance, still an excellent performance, but slightly lower than GBR.
  Key Strengths: CatBoost efficiently handles categorical data and uses advanced

gradient-based tree building. Leaf-wise splitting helps focus on high-error areas, making it suitable for complex datasets.
Validation Loss: Slightly higher than GBR, indicating a marginally reduced ability to generalize compared to GBR.

CHAPTER 6

Charging station design using Solar energy

Conventional EV charging stations rely primarily on grid electricity, often sourced from non-renewable energy, leading to concerns about carbon emissions and energy sustainability. To address these challenges, integrating renewable energy sources such as solar power into EV charging stations has emerged as a promising solution. This project focuses on developing a Simulink-based DC fast charger model that utilizes solar energy as its primary power source, replacing the conventional three-phase AC supply.

6.1 Introduction

The model incorporates a photovoltaic (PV) energy system to generate the required power for EV charging. Solar panels are modeled in Simulink to simulate real-world energy harvesting conditions, considering factors such as irradiance variations and temperature effects. Since the output power of PV panels fluctuates due to environmental conditions, a Maximum Power Point Tracking (MPPT) controller is implemented to optimize power extraction. The MPPT algorithm dynamically adjusts the duty cycle of the converter to ensure that the solar panels operate at their peak efficiency, maximizing energy utilization.

A key component of the charging system is the power conversion stage, which consists of a DC-DC converter designed to regulate the voltage and current supplied to the EV battery. The regulated output ensures stable and efficient charging while protecting the battery from overvoltage or overcurrent conditions. To evaluate the system's performance, parameters such as battery state of charge (SOC), voltage, current, session time, and charging patterns are analyzed under varying input conditions. The model captures real-time charging behavior over a short duration of 0.2 seconds, generating high-frequency data for further analysis.

This study aims to explore the feasibility of integrating solar energy into EV charging infrastructure and assess its impact on charging efficiency and system stability. By reducing dependence on grid electricity and utilizing clean energy sources, this project contributes to the development of a more sustainable and eco-friendly EV charging solution.

6.2 Why Solar Energy?

The transition from a conventional three-phase supply to a solar-powered EV charging system is driven by the need for a more sustainable, cost-effective, and environmentally friendly energy source. Traditional three-phase AC supply for EV chargers relies on grid electricity, which is often generated from fossil fuels, leading to high carbon emissions and contributing to environmental degradation. Additionally, the increasing demand for electric vehicles puts a strain on the electrical grid, potentially leading to energy shortages and higher electricity costs during peak demand hours. By integrating solar energy into EV charging infrastructure, we can significantly reduce reliance on grid electricity and lower operational costs. Solar power is a renewable and abundant energy source that offers long-term sustainability with minimal environmental impact. Unlike grid electricity, which is subject to fluctuations in cost and availability, solar energy provides a decentralized and self-sufficient power solution. Furthermore, the use of solar energy enhances energy resilience, particularly in remote or off-grid areas where grid connectivity is limited or unreliable. Solar-powered EV charging stations can operate independently, reducing the burden on the central grid while promoting energy accessibility in underserved regions.

Additionally, the incorporation of a Maximum Power Point Tracking (MPPT) controller ensures that the solar panels operate at their highest efficiency, dynamically adjusting to variations in sunlight conditions. This enhances the overall energy yield and ensures that the EV charging system remains stable and efficient. As the world moves towards cleaner energy alternatives, integrating solar energy into EV charging infrastructure aligns with global efforts to reduce carbon footprints and promote the adoption of green technologies. By leveraging solar energy, this project aims to demonstrate the feasibility of sustainable EV charging solutions that are both efficient and environmentally responsible.

6.3 Simulation Design

The Simulink model developed for this project represents a solar-powered DC fast charging system for electric vehicles, integrating key components to ensure efficient and stable power delivery. The system includes a solar panel array as the primary energy source, coupled with a Maximum Power Point Tracking (MPPT) controller to optimize the power extraction from the solar panels under varying sunlight conditions. The generated DC power is then regulated and converted using a power electronic converter, ensuring that the output voltage and current meet the required levels for EV charging. A closed-loop control system is implemented to maintain a stable charging voltage and current, enhancing the efficiency and reliability of the charging process.

Additionally, battery management and protection mechanisms are incorporated to prevent overcharging and ensure the safety of the EV battery. The model also includes real-time monitoring and control functionalities, allowing for adjustments based on environmental conditions and load demand. By simulating various operational scenarios, the model helps analyze system performance, efficiency, and the impact of fluctuating solar irradiance on the charging process. This comprehensive approach ensures that the solar-powered charging system is both technically viable and sustainable, offering an alternative to grid-based EV charging solutions.

6.3.1 Working Principle

The Simulink model operates on the principle of harnessing solar energy, converting it into a stable DC output, and efficiently delivering it to charge an electric vehicle. The system begins with a solar panel array that captures sunlight and converts it into electrical energy. Since solar power varies with irradiance and temperature, an MPPT (Maximum Power Point Tracking) controller is implemented to extract the maximum possible power from the panels. The generated DC voltage is then regulated through a power converter, ensuring a stable and controlled output suitable for EV charging. A closed-loop control system monitors and adjusts the voltage and current to maintain optimal charging conditions. Additionally, protection mechanisms prevent overvoltage and overcurrent scenarios, safeguarding both the charger and the EV battery. The model enables real-time analysis of system behavior under different environmental and load conditions, ensuring efficient and reliable charging.

6.3.2 Model

The Simulink model consists of several key blocks, each performing a specific function to ensure efficient solar-based EV charging:

1. Solar Panel Block – This block models the photovoltaic (PV) array, converting sunlight into DC electricity. It considers parameters like irradiance and temperature to simulate real-world conditions.

2. MPPT Controller Block – The Maximum Power Point Tracking (MPPT) controller dynamically adjusts the operating point of the solar panels to extract the maximum available power, compensating for variations in sunlight and temperature.

3. DC-DC Converter Block – A power converter (such as a boost or LLC converter) regulates the fluctuating DC output from the solar panels, ensuring a stable voltage level required for charging the EV battery.

4. Battery Management System (BMS) Block – This block monitors the state of charge (SOC), voltage, and current of the EV battery, ensuring safe and efficient charging while preventing overcharging or deep discharge.

5. Control System Block – A closed-loop controller continuously adjusts the converter operation to maintain the desired voltage and current levels. It includes feedback mechanisms to optimize power transfer.

6. Load & Monitoring Block – This represents the EV battery as the load and includes measurement components to analyze voltage, current, and power flow, providing insights into system performance.

Each of these blocks works together to simulate an effective solar-powered EV charging system, optimizing energy utilization and ensuring stable operation under varying conditions.

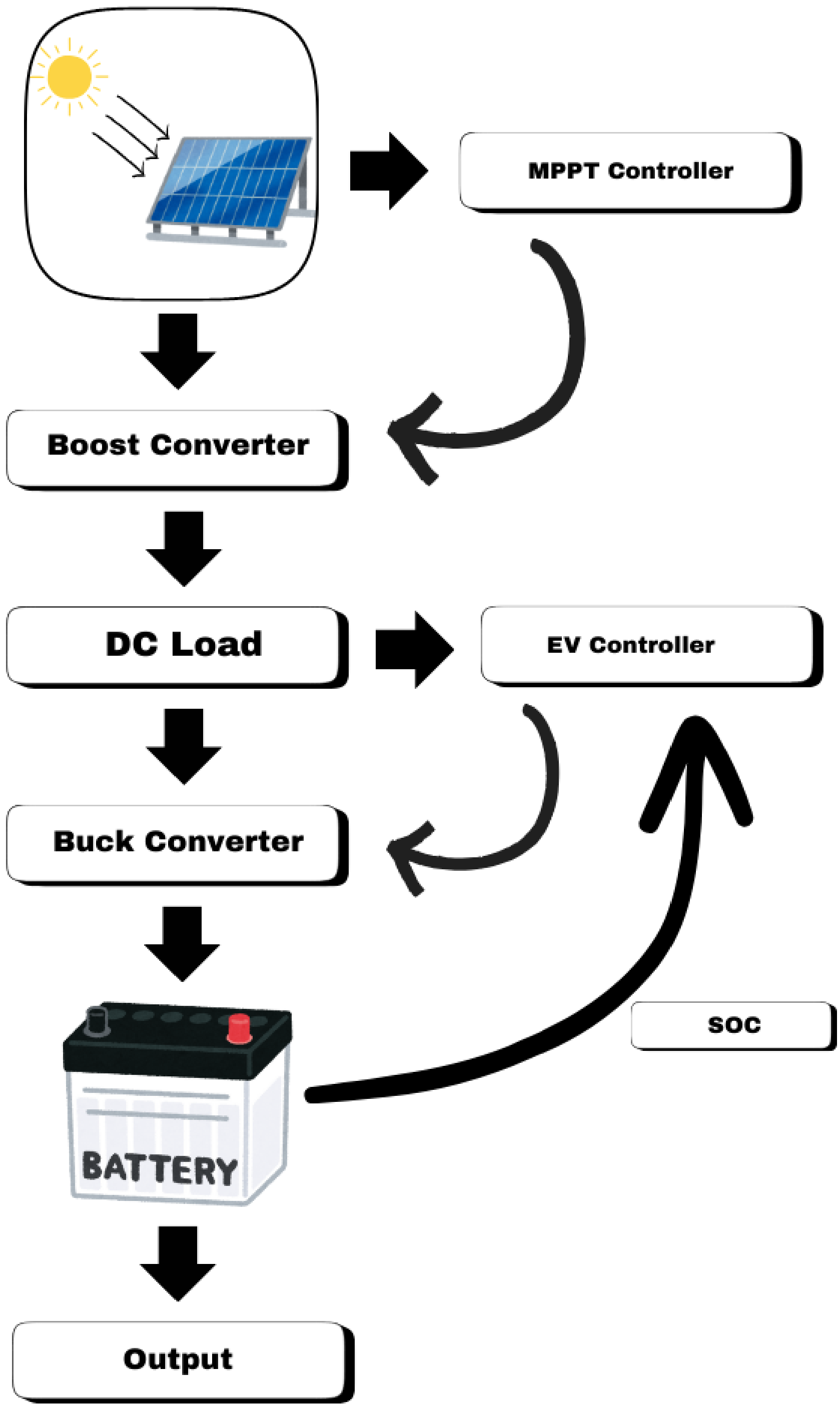

Figure 6.1: Model Overview

PV System

The photovoltaic (PV) system designed in this project serves as the primary power source for an electric vehicle (EV) charging station. The system consists of solar panels that convert sunlight into electrical energy, which is then processed through a Maximum Power Point Tracking (MPPT) controller and a DC-DC converter to optimize and regulate the power output. The photovoltaic system is tested under two different environmental conditions to analyze its performance:

Case 1: Irradiation of 500 W/m² at a temperature of 25°C

Case 2: Irradiation of 750 W/m² at a temperature of 30°C Under these conditions, the PV array generates a total power output of 4000 W, which is then fed into the converter for further processing. The MPPT controller ensures that the system operates at the optimal voltage and current levels to extract the maximum possible power from the solar panels. The generated power is used to charge an electric vehicle battery, making the system an eco-friendly and sustainable alternative to conventional grid-based charging.

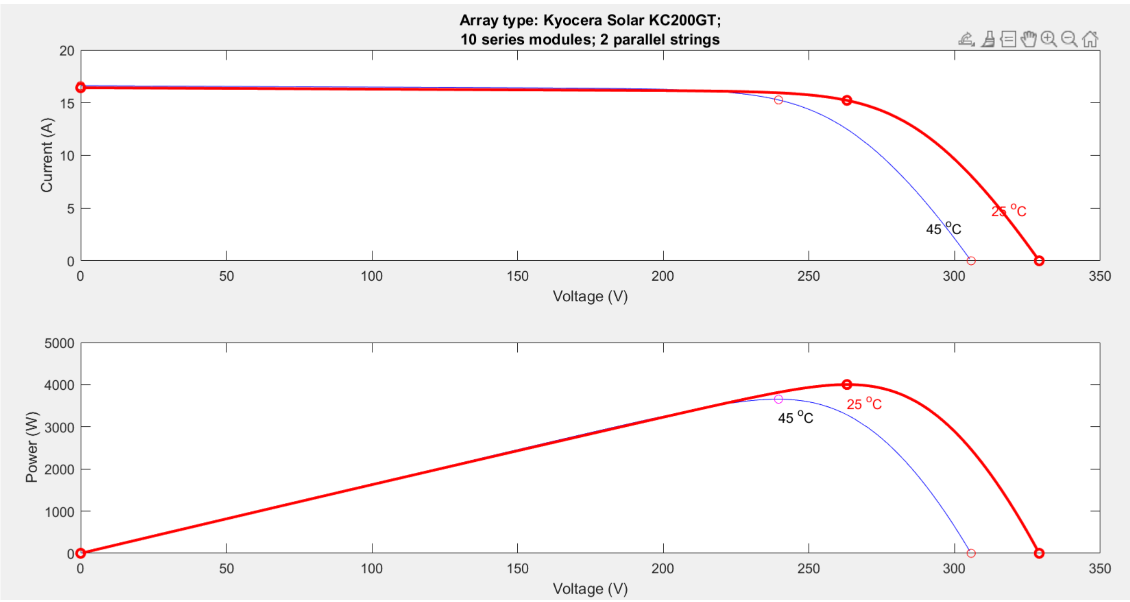

Figure 6.2: PV array I-V and P-V characterstics

MPPT Controller

The Maximum Power Point Tracking (MPPT) controller is a crucial component in the photovoltaic (PV) system, ensuring that the solar panels operate at their peak efficiency by extracting the maximum possible power under varying environmental conditions.

In this model, the MPPT controller continuously adjusts the duty cycle of the DC-DC converter to maintain the operating point of the PV array at its maximum power point.

Working Principle in the Model:

1. Input Variables: The MPPT controller takes the real-time voltage (Vpv) and current (Ipv) from the PV array as input parameters. These values are continuously monitored to determine the power output of the solar panel.

2. Power Calculation & Perturbation: The controller calculates the instantaneous power ($P = Vpv \times Ipv$) and applies an algorithm to track the maximum power point. In this model, an Incremental Conductance (IncCond) algorithm or Perturb and Observe (P&O) algorithm is implemented to adjust the duty cycle dynamically.

3. Duty Cycle Adjustment: The MPPT controller generates a duty cycle (d) signal, which is fed into the DC-DC converter (Boost Converter). By adjusting this duty cycle, the controller regulates the converter's switching operation to modify the output voltage and current, ensuring that the PV array remains at its optimal operating point.

4. Environmental Adaptability: Since the model considers two different operating conditions (500 W/m² at 25°C and 750 W/m² at 30°C), the MPPT controller plays a vital role in dynamically adjusting to these changes. As sunlight intensity and temperature fluctuate, the voltage and current characteristics of the PV panel also change, requiring continuous duty cycle updates to maintain the 4000 W power output.

5. Interfacing with the Converter: The adjusted duty cycle is applied to the gate terminal of a switching device (typically a MOSFET or IGBT) in the DC-DC boost converter. This regulates the power supplied to the charging system and ensures efficient energy transfer from the solar panels to the battery.

Significance in the Model:

- Maximizes power extraction from the PV array under different conditions. - Ensures stable and optimized power delivery to the electric vehicle charging system. - Enhances energy efficiency, reducing power losses and improving overall system performance. - Enables real-time adaptability, responding dynamically to fluctuations in irradiation and temperature.

In summary, the MPPT controller in this model acts as an intelligent optimizer, continuously adjusting the system parameters to ensure that the PV array delivers its maximum available power to the load, making solar energy utilization highly efficient and reliable for EV charging applications.

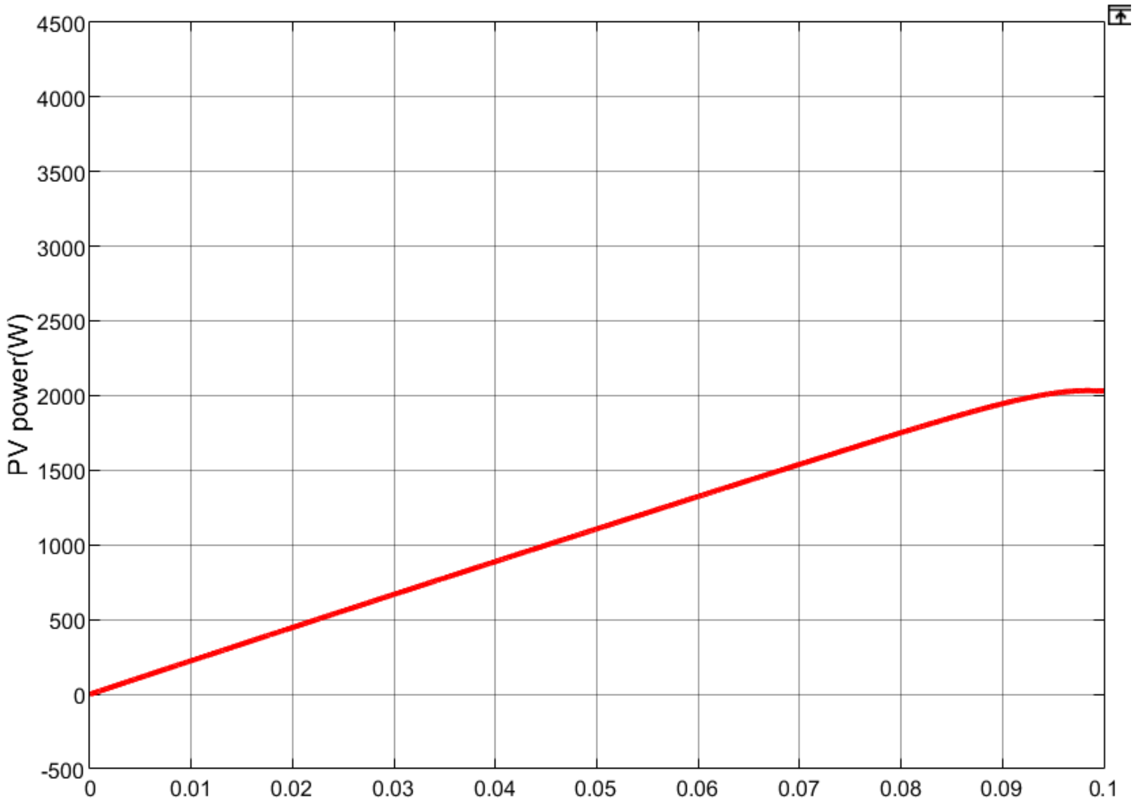

Figure 6.3: PV plot for 500 W/m² Irradiance and 25°C

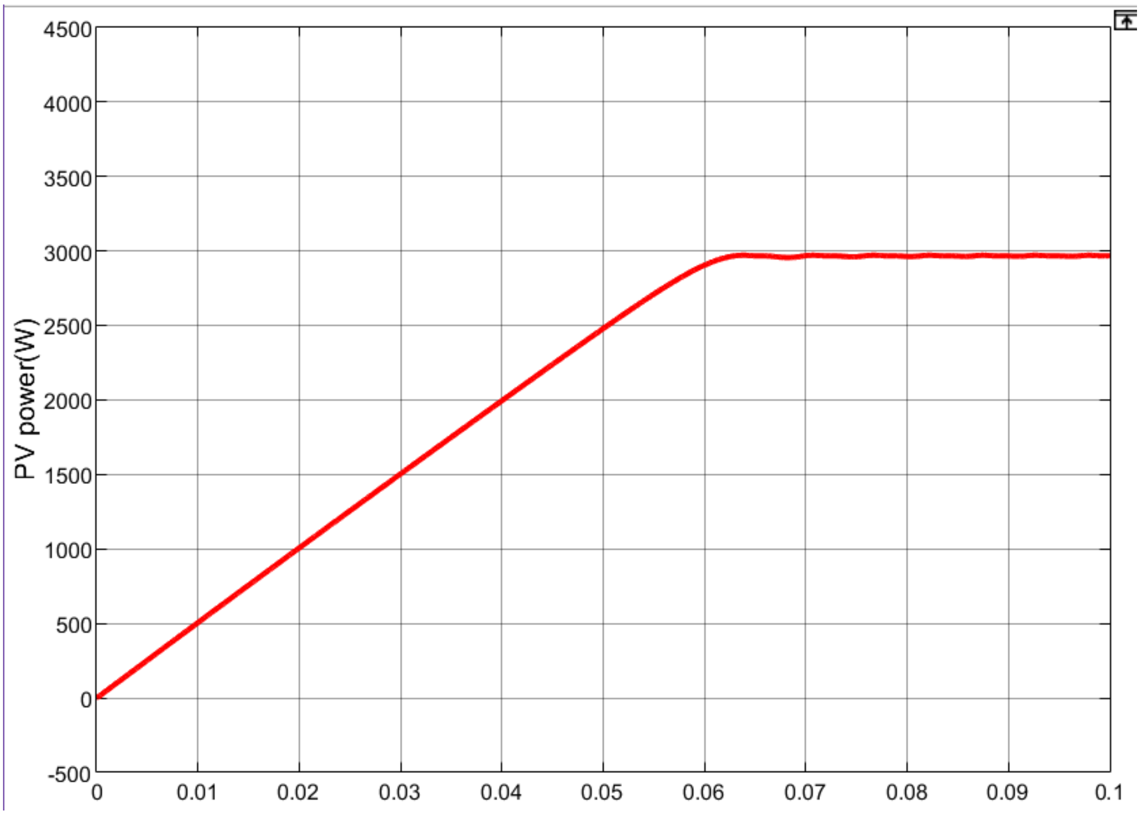

Figure 6.4: PV plot for 750 W/m² Irradiance and 30°C

Boost Converter

The boost converter in this circuit serves to step up the voltage from the PV system to a suitable level for charging the battery efficiently. Since the PV output voltage varies based on irradiation and temperature conditions, the boost converter, controlled by the MPPT algorithm, ensures that the voltage is regulated and optimized for maximum power transfer. By adjusting the duty cycle of the switching device, the converter increases the lower DC voltage from the solar panels to match the required charging voltage, ensuring efficient energy transfer and minimizing power losses. This enables stable and reliable charging of the battery, even under fluctuating environmental conditions.

Table 6.1: Values Used in Boost Converter

S. No.	Block Name	Value/Parameter
1	Input Capacitance	3000e-6 F
2	Output Capacitance	470e-6 F
3	Inductance	20e-3 H

EV Controller

The EV controller is responsible for managing the charging process of the electric vehicle's battery. It monitors parameters such as battery State of Charge (SOC), voltage, and current to ensure optimal charging conditions. The controller adjusts the power supply to the battery based on predefined charging limits, preventing overcharging and ensuring battery longevity. It also controls the switching operation of the power electronics components to regulate the energy flow from the PV system to the EV battery, ensuring safe and efficient charging.

Buck Converter

The buck converter is used in the circuit to step down the voltage to a suitable level for the battery or the DC load. Since the boost converter increases the PV voltage, a buck converter may be required in certain conditions to regulate and control the output voltage as per the battery's charging requirements. By efficiently reducing the voltage while maintaining stable current flow, the buck converter ensures that the battery receives power at the correct voltage level, preventing overvoltage damage and improving overall system efficiency.

Table 6.2: Values Used in Buck Converter

S. No.	Block Name	Value/Parameter
1	RL Branch	2 Ohms, 1e-3 H
2	Output Capacitance	10e-6 F

Battery

The battery in this system is a Lithium-Ion type with a nominal voltage of 325V and a rated capacity of 60Ah. It serves as the primary energy storage unit, storing excess power generated by the PV system and supplying energy when solar power is insufficient. The initial state of charge (SOC) is set at 50%, ensuring a balanced charge-discharge cycle. The battery response time of 30 seconds allows for stable energy delivery and prevents abrupt voltage fluctuations. This setup ensures efficient energy management for EV charging, enhancing system reliability and performance.

6.4 Result and Conclusion

The obtained results provide insight into the performance of the PV-based EV charging system under varying irradiation and temperature conditions. The system successfully generated 4000 W of power, with two different readings taken at 500 W/m² and 25°C and 750 W/m² and 30°C. The voltage, current, and SOC trends confirm the effectiveness of the MPPT and power conversion stages in regulating energy flow.

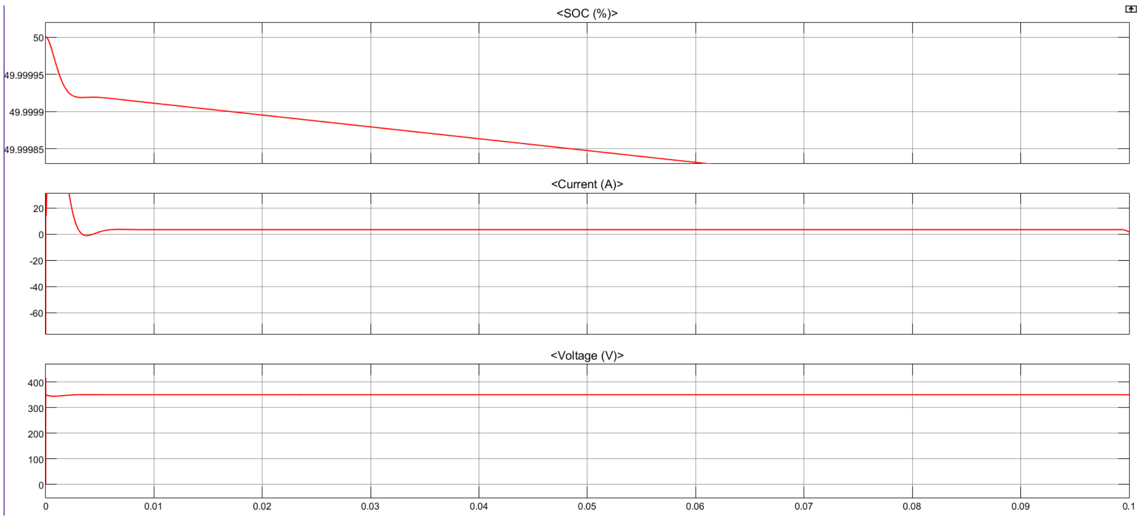

Figure 6.5: Battery Output for 500 W/m² Irradiance and 25°C

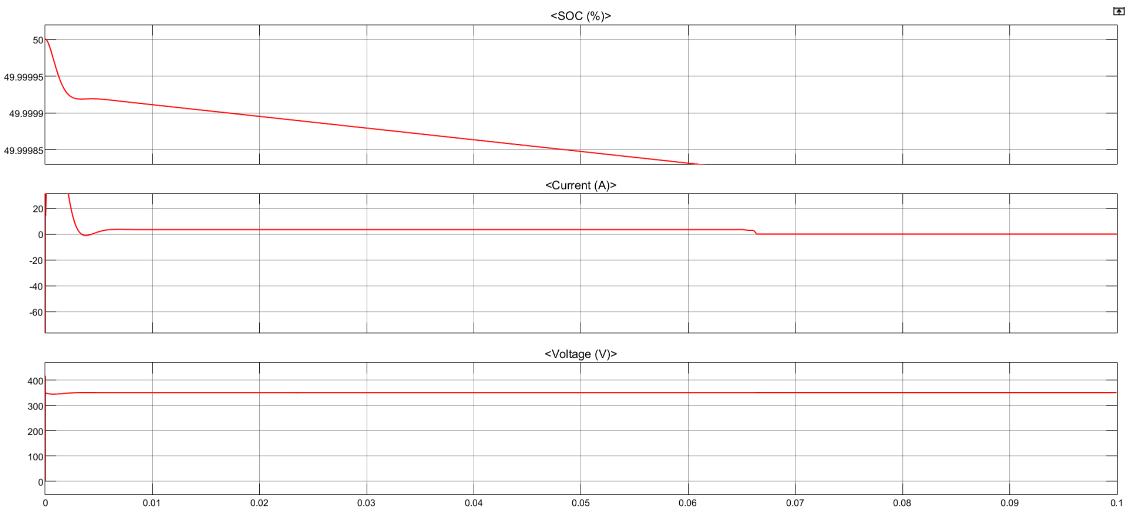

Figure 6.6: Battery Output for 750 W/m² Irradiance and 30°C

Comparison between Battery output using solar energy and three phase supply:

State of Charge (SOC) (%): In the solar energy-based system, the SOC exhibits a gradual decline over time, indicating a stable energy transfer process. The three-phase AC supply results in a more linear increase in SOC, suggesting a consistent power supply without major fluctuations.

Battery Current (A): The solar-powered system shows an initial fluctuation in current before stabilizing, reflecting the variability of solar energy input. The three-phase AC supply maintains a nearly steady current, providing a continuous and predictable charging pattern.

Battery Voltage (V): The voltage in the solar-powered system experiences an initial drop before stabilizing, likely due to variations in solar irradiance. In contrast, the three-phase AC supply maintains a stable voltage with minimal fluctuations, ensuring a uniform charging process.

CHAPTER 7

Deep Learning Implementation in Model

As a final step, we focus on developing predictive models to estimate the amount of solar power consumed by the battery during EV charging, based on multiple input features. We implement two advanced deep learning methods: a Multilayer Perceptron (MLP) and a Long Short-Term Memory (LSTM) network, and compare their performance using regression metrics.

7.1 Data Description

The dataset contains features captured from an EV charging station powered by solar energy. Key features used for prediction include:

Solar Power (kW)

Solar Irradiance (W/m²)

Temperature(°C)

Charging Power (kW)

Charging Duration (minutes)

Initial and Final State of Charge (SOC) of the battery (%)

Battery SOC (%) at the time of logging

Battery Current and Voltage (A, V)

These variables reflect both environmental and battery-related factors influencing solar energy usage. Now, we engineer features from our given dataset such as,

$$\text{Energy}_{\text{solar}}\ (\text{kWh}) = \text{Solar Power (kW)} \times \left(\frac{\text{Charging Duration (minutes)}}{60} \right)$$

Now, we'll use this to futher preproces our data by removing any mishandles value, normalization and splitting data into training and testing for unbiased evaluation

7.2 Techniques Used:

7.2.1 MultiLayer Perceptron (MLP)

A Multilayer Perceptron is a type of feedforward artificial neural network that maps input features to output through layers of interconnected neurons. It is particularly effective for tabular data. MLP treats our input features as a fixed-length input vector, and processes them through layers of neurons to approximate the target value: Energy consumed by the battery (in kWh) from solar power.

Model Architecture: Input Layer: 7 features

Hidden Layers: [128, 64, 32] neurons with ReLU activation and dropout

Output Layer: 1 neuron (for regression)

Training Configuration Loss Function: MSE

Optimizer: Adam

Metrics: R^2 Score and MSE

7.2.2 Long Short Term Memory(LSTM)

LSTM is a type of Recurrent Neural Network (RNN) designed to handle sequential or time-series data. It introduces memory cells and gates (input, forget, output) to retain long-term dependencies.

In theory, we could interpret EV charging logs as sequences (for example, how features evolve over the course of charging), but our dataset represents single events, not temporal sequences. So we had to reshape the data artificially into a sequence of one timestep (e.g., (1, numberoffeatures)).

LSTM then tries to learn patterns between input features across this "sequence" — though the "sequence" is only of length 1, which greatly limits the LSTM's learning capacity here.

Model Architecture: Input Shape: (timesteps=1, features=7)

LSTM Layers: [64 → 32 units]

Dropout applied after each LSTM layer

Output: 1 neuron

Training Configuration: Loss Function: MSE

Optimizer: Adam

Early stopping used to avoid overfitting

7.3 Result and Conclusion

For MLP:

Table 7.1: Error Table

Parameter	Value
Mean Squared Error (MSE)	1.28
R^2 Score	0.9970

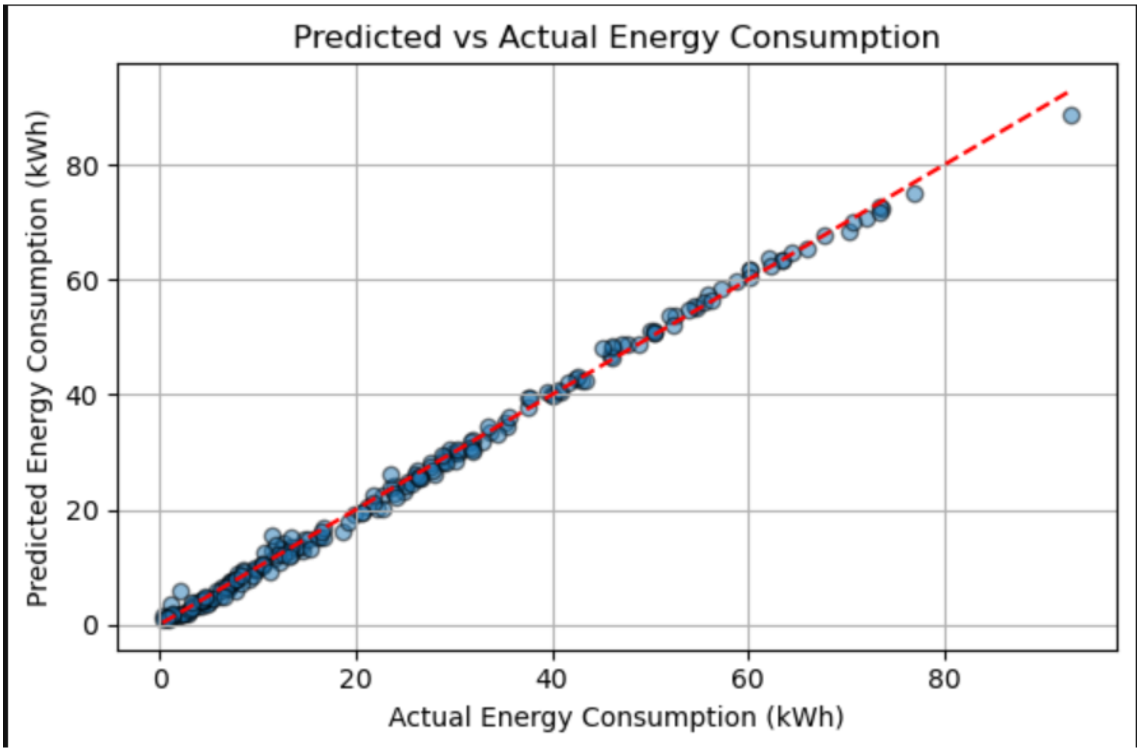

Figure 7.1: Predicted VS Actual Energy Consumption using MLP

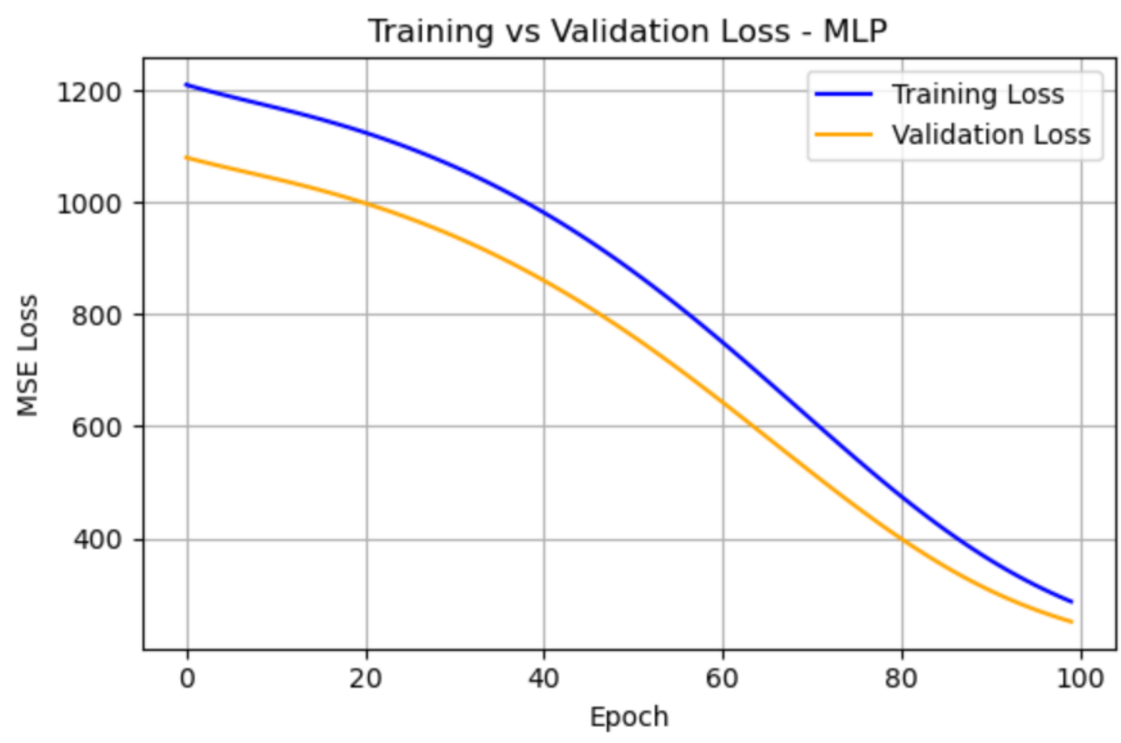

Figure 7.2: Training vs Validation Loss using MLP

For LSTM:

Table 7.2: Error Table

Parameter	Value
Mean Squared Error (MSE)	11.11
R^2 Score	0.9741

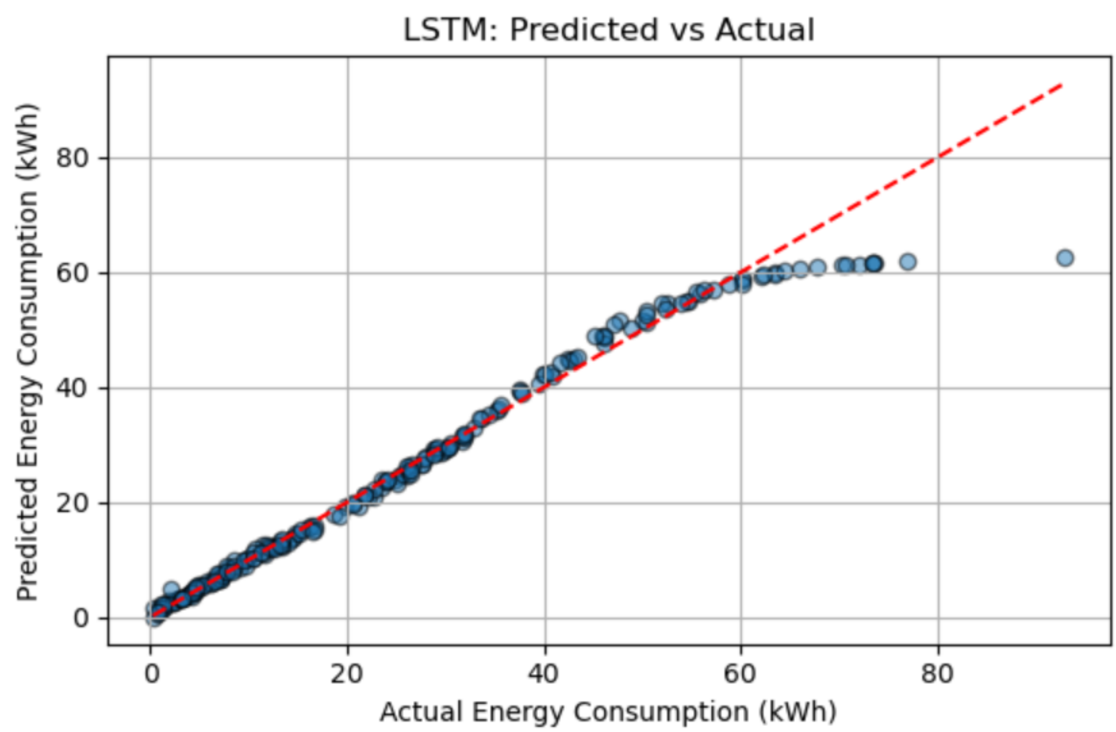

Figure 7.3: Predicted VS Actual Energy Consumption using LSTM

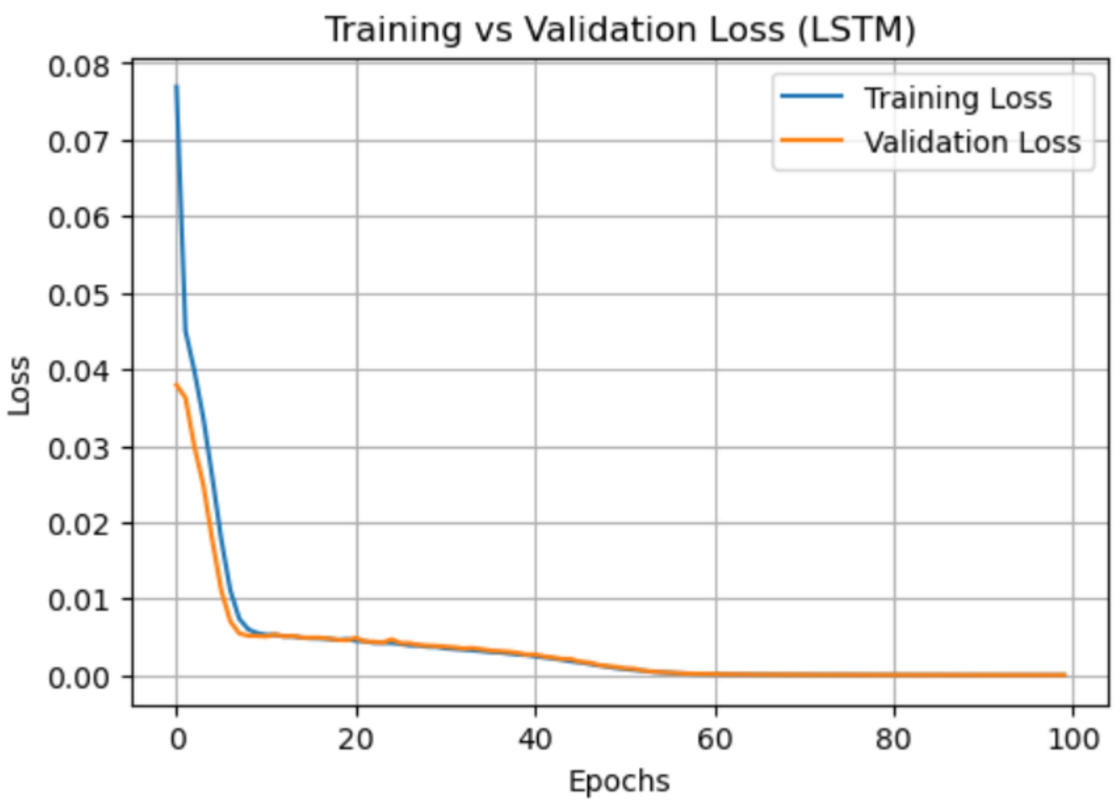

Figure 7.4: Training Vs Validation Loss using LSTM

These results clearly demonstrate that MLP outperforms LSTM for this task. This can be attributed to the nature of the data: it is tabular and non-sequential, making MLP a more appropriate architecture. LSTM, while powerful for time-series or sequence-dependent problems, did not offer additional benefit here due to the absence of temporal dynamics in the input features. Given the high R^2 score of the MLP model and its lower computational complexity compared to LSTM, MLP is the preferred model for this prediction task and will be recommended for deployment or further optimization.

CHAPTER 8

Conclusion

This thesis presented a comprehensive, data-driven approach to forecasting energy consumption in electric vehicles (EVs) through simulation modeling and predictive analytics. The work evolved across two significant phases, each addressing a critical aspect of EV charging infrastructure—efficiency and sustainability.

In the first phase, a detailed DC fast charger model was developed using MATLAB Simulink, powered by a conventional three-phase AC supply. This system incorporated core subsystems such as rectification, closed-loop PI control, and battery state monitoring. The simulated data generated from this model provided insights into energy flow and battery behavior under controlled conditions. Leveraging this dataset, ensemble machine learning models—Gradient Boosting Regressor (GBR) and CatBoost—were implemented to predict energy consumption patterns. The models delivered high accuracy, validating their effectiveness in capturing complex feature interactions.

Recognizing the environmental imperative for greener energy systems, the second phase introduced a solar-powered version of the charging station. The modified model included photovoltaic panels, an MPPT controller, DC-DC converters, and a smart EV controller. This transition introduced variability and time-dependency into the dataset, which necessitated more advanced modeling strategies. Deep learning methods, including a feedforward Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) networks, were employed to address this challenge. Among these, the MLP model demonstrated superior performance in capturing temporal trends and delivering reliable forecasts.

Overall, this thesis establishes a scalable and adaptable framework for predicting EV energy consumption using both traditional machine learning and state-of-the-art deep learning approaches. It bridges the gap between simulation-based modeling and intelligent analytics, laying a strong foundation for smarter, cleaner, and more responsive EV charging systems. The results highlight the potential of integrating renewable energy with AI-powered prediction to advance the goals of energy efficiency and environmental sustainability in electric mobility.

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