Energy Cost Minimisation To Support Electric Vehicle Charging Using Machine Learning

by

Mohammed Amir Fahad
21101182
Mst.Sanjida Ahmed
21301050
Ethika Adrita Niha
21301032
Sabbir Hossain Shaon
20301147
Samia Abdullah
20101595

A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

Department of Computer Science and Engineering
BRAC University
December 2025

Declaration

It is hereby declared that

1. This thesis submitted is a product of my/our original work in the completion of degree at Brac University.
2. No part of the work has been previously published or written by another party, except where appropriate reference is made in the text.
3. It is further understood that the thesis does notcontain material which has been accepted, or submitted in part, for another degree ordiploma at a university or other institution.
4. All the major sources of assistance have been acknowledged.

Student's Full Name & Signature:

Amir Fahad
21101182

Mst.Sanjida Ahmed
21301050

Sabbir Shaon
20301147

Ethika Adrita Niha
21301032

Samia Abdullah
20101595

Approval

The thesis/project titled "Energy cost minimisation to support electric vehicle charging using machine learning" submitted by

1. Mohammed Amir Fahad (21101182)
2. Mst.Sanjida Ahmed (21301050)
3. Ethika Adrita Niha (21301032)
4. Sabbir Hossain Shaon(20301147)
5. Samia Abdullah (20101595)

Examining Committee:

Supervisor:
(Member)

Amitabha Chakrabarty, PhD

Professor
Department of Computer Science and Engineering
BRAC University

Thesis Coordinator:
(Coordinator)

Md. Golam Rabiul Alam, PhD

Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Dr. Sadia Hamid Kazi, PhD

Associate Professor Chairperson
Department of Computer Science and Engineering
Brac University

Dedication

We dedicate this effort to the Almighty since we have the highest regard for Him.

We are also thankful to our esteemed supervisor, Dr. Amitabha Chakraborty for his advices, guidance and unimaginable supoort while completing this research.

And We will always be appreciative to our parents for their unwavering faith in our skills and support, and their cooperation that encouraged us to succeed academically.

Abstract

The rapid growth of EVs and the integration of renewable energy has made the administration of charging demand and reduction of electric expenses more complex. This paper introduces an dual machine learning forecasting of EV charging demand, solar photovoltaic (PV) energy generation, and PV-first smart charging scheduling and cost calculation.The realistic daily energy profiles were developed using real data on fifty EVs provided in the workplace. In the case of EV demand forecasting five deep learning models were tested, LSTM, GRU, TCN, Transformer Encoder and a Hybrid LightGBM-LSTM model where our proposed hybrid model had the lowest RMSE value 0.4049 and R2 value 0.8608. In the case of PV generation forecasting, eight ML models were experimented in the form of Random Forest, Decision Tree, Gradient Boosting, Linear Regression, LSTM, GRU, TCN as well as the hybrid model. Again, the highest PV prediction accuracy was obtained in Hybrid LightGBM + LSTM with RMSE value 273.55 and the R2 value 0.9321.The predicted EV and PV forecasts were combined in a PV- first scheduler that gave preference to solar power over grid power. In 7 days, the system made 41.87% cost savings and 52.3% contribution of solar; in 30 days, it made 17% savings under flat pricing and 24.9% savings under TOU that is aided by 37.7% renewable contribution. These findings indicate that dual hybrid forecasting and PV-first smart charging scheduling are effective in the reduction of charging expenses, minimization of grid reliance,minimize CO2 and in line with SDG 7 and SDG 13 on clean and sustainable energy.

Keywords: EV Charging, Machine Learning, , Solar PV Forecasting, TOU Pricing, Cost Optimization, Renewable Energy, Hybrid model.

Table of Contents

List of Figures

Chapter 1

Introduction

1.1 Background

The United Nations Sustainable Development Goals (UNSDGs)), are likewise, in 2015 to alleviate poverty, protect the environment and achieve sustainable developments worldwide. Peace, Justice and Prosperity for all by 2030[18]. To achieve those goals, the world will have to transform its energy system, notably in transportation, one of the largest sources of greenhouse gasses (GHG) emissions. Mobility has thus developed as a crucial route to decarbonization by electrification. As road transport moves away from fossil fuel and toward electricity, the electric vehicle (EV) fleet is growing rapidly. However, such surge in adoption results in significant energy management problems particularly in urban and office environments where many electric vehicles are being simultaneously charged. EV sales in Australia are growing rapidly, with 6,900 EVs sold in all of 2020 and 8,688 in the first half of 2021 (however still only accounting for 0.78% of the national market), which is much less compared to Norway (75%), United Kingdom (10.7%), China (6.2%) and United States (2.3%). It demonstrates the potential market growth and imperative needs of high-level energy management platforms for large-scale EV integration. Unmanaged charging at the workplace could cause demands proliferating peaks, stress on infrastructures and peak hour price of electricity inflation; e.g. in TOU rates. A more sustainable option is to equip the workplace charging area with solar photovoltaic (PV) based charging; however integration of intermittent PV generation and non-uniform EV behavior does not permit a simple occurrence of supply matching demand. To address such issues, in this paper, we propose an ML-inspired PV-first scheduling model with the EV charging for workplace. LSTM,TCN,GRU,Transformer,Lightgbm+LSTM to forecast EV charging demand and LSTM, GRU TCN and Transformer Encoder, Hybrid models , Random Forest (RF), XGBoost, LightGBM, Decision Trees(DT) for predicting PV generation. Meanwhile, a conflict-aware scheduler is designed to schedule charging based on PV availability and TOU tariff. We have been able to save 41.87% of the EV charging cost in 7 days and 24.9% for the 30 days, by using renewable more efficiently adapted to preferences of consumers with TOU tariffs reduces the peak load by another 4-5%. Overall, the scheme is a scalable and durable warehouse-wide solution that has the potential to work towards SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action) by optimising workplace energy efficiency in order to reduce grid dependency.

1.2 Rational of the Study or Motivation

There are several present EV charging System available which concentrate towards integration of renewable energy or on predictive analytics. These solutions have been valuable contributions, but are often not complete enough to be deployed in the city where electricity demand forecasting and renewable energy utilization has to work together. The majority of related studies do not simultaneously optimize the renewable power consumption while ignoring the uncertainty of EV demand, or focus solely on prediction without involving renewable energy dynamics. This leads to a lack of complete frames which could integrate both aspects in a realistic charging network in urban areas. Another major difficulty for prediction is the problem of responses errors. Bad prediction of electric vehicle (EV) charging demand will result in inefficient energy management, in which the charging station can under- or over-utilize grid and renewable resources and generate unnecessary operational costs especially when the time-of-use tariff is considered and the minor forecast errors could become large financial penalties. Current demand prediction models lack the capacities to model the complexities and uncertainties associated to urban mobility, with EV charging behavior being very erratic and exhibiting sharp peaks when users all charge at the same time. These features make optimization tasks, as scheduling, resource allocation and cost minimization extremely difficult to solve. While several earlier works attempted to tackle these challenges, they generally do not jointly take into account the impact of time-varying EV demand and renewable generation uncertainties or consider tariff-based cost structures. This gap motivates our work to present a more coherent, intelligent framework that integrates machine learning methods of demand prediction with optimized economic dispatch for better operational efficiency and lower cost to enable smooth integration of renewable energy in urban EV charging network.

1.3 Problem Statement

The proliferation of electric vehicle (EV) adoption and workplace charging infrastructure has led to many problems in controlling daily charging demand, scheduling energy consuming time and reducing electricity cost. Despite contributing to the reduction of emissions, a simultaneous charging profile of EVs, may exert unbearable strain on the grid during peak hours and under TOU tariffs. Meanwhile, the solar PV systems are also a clean and economic energy source, but faced with an intermittent-pad electrical generation characteristic due to weather-dependent fluctuation in solar radiance and changing need for EV charging. This timing mis-match frequently results in under-utilised PV energy and a continued reliance on costly grid supply. In traditional EV charging systems, estimation of the stable prediction for both EV demand and solar availability are not found, static or heuristic scheduling is given and no real tariff variations are considered. Thus, energy isn't used efficiently and the potential savings are not realised and there is a low use of renewable.

Thus, a "smart" data-driven and forecast enabled framework which can:

- To predict daily EV charging demand rightly
- Predict hourly solar PV electricity generation

- Match the charging schedule with renewable generation by adopting a PV-first approach
- Minimize the cost of charging under flat and TOU pricing

This gap is the focus of this study, which proposes an ML-based EV–PV integrated optimization framework that can minimize charging cost and maximize solar energy utilization, reduce reliance on grid power, and contribute to sustainability goals (SDG 7, SDG 13).

1.4 Objective

The primary goal of this study is to design a smart machine learning-based EV–PV charging strategy which can help minimize the charging cost, optimal usage of the renewable solar energy, reduction in CO emission and distribution infrastructure support. To this end, our work emphasizes precise prediction through advanced ML and DL models (LSTM, GRU, TCN, Transformer Encoder and Hybrid LightGBM + LSTM model) trained on historical driving distance and energy per kilometer data to predict next day EV charging demand. At the same time, solar PV generation is predicted using historical renewable series based on machine learning regressors and deep learning networks that take into account daily variations in solar power production. These ML powered predictions are then used in a unified decision framework to calculate the energy equilibrium among renewable availability and EV charging demand.

Central to the study is a PV-first smart charging scheduling mode, which places EV charging within six 4-hour pushing time windows. This way main energy source during daytime is provided by PV, synthesized with grid electricity in case the renewable generation is insufficient and attaining maximal solar penetration minimizing the dependency of grid. The economic analysis about the system is carried out for Flat Rate and Time-of-Use (TOU) tariffs considers the Levelised Cost of Energy (LCOE's) to highlight real cost for solar power. The tool further computes 7 and 30 day operational cost, savings, renewable penetration, grid use of low-emission resources and emission reduction.

Putting it all together, the ML-driven PV-centric approach is aligned with global sustainability targets (in particular SDG 7: Affordable and Clean Energy; SDG 13: Climate Action) providing cost-effective renewable penetration, intelligent energy use and zero emissions workplace EV charging.

1.5 Scopes and Challenges

1.5.1 Scopes

The objective of this work is to create Machine Learning based EV–PV integrated charging optimization model which can be used for workplaces. The investigation comprises three main parts, the first being daily EV charging demand prediction via ML/DL models including LSTM, GRU, TCN, Transformer and Hybrid LightGBM + LSTM; the second is solar PV generation forecasting using machine-learning regressors and deep-learning architectures like Random Forest, Decision Tree, Gradient Boosting, Linear Regression along with DL Hybrid LightGBM +LSTM, LSTM, GRU, TCN; the last part involves combining both forecasts into a PV-first charging strategy to allocate hourly-based charging loads across six 4-hour slots so that the RE utilization is maximized while grid consumption is minimized. Furthermore, cost performance is as well evaluated under Flat Rate and Time-of-Use (TOU) tariffs, Levelized Cost of Energy (LCOE) are adopted in the model by used to describe real PV energy costs. Performance of the system is evaluated for both 7-day and 30-day operation horizons in terms of the cost savings, reductions in grid draw, and share of solar PV electricity. In general, this coverage shows that ML-based predicting paired with PV-aware scheduling can have an important positive impact on workplace charging sustainability and contribute to world environmental goals (SDG 7: Affordable and Clean Energy, SDG 13: Climate Action).

1.5.2 Challenges

The following technical and computational challenges were met during the process of developing our ML-based EV–PV charging optimization system:

- **The temporal discrepancy of EV charging demand and solar PV generation:**

  Electric vehicle charging load is distributed over day, while photovoltaic generation is only available in daytime. This essentially mis-match in time makes it difficult to maximize solar during charging.

- **Variability in the data: missing values, noise and uneven timestamps:**

  Both EV and PV data sets were not only incomplete with missing values, noisy data points and invalid time stamps. The data was heavily pre-processed to downsample and align it prior to being fed into machine-learning models.

- **Weather condition-driven variabilities diminishing the accuracy of PV forecasting:**

  The power that PV generates is strongly weather-dependent: (sun)light variation affects the output, which also depends on irradiance and temperature. It was hard to predict the PV generation exactly because of those irregular changes.

- **Deep learning technique require hyper parameter tuning:**

  The performance of models such as LSTM, GRU, TCN and Transformer,Lightgbm+ LSTM,Random forest,Decision Tree, Gradient Boosting,Linear Regression can be extremely sensitive to hyperparameters including learning rate, sequence length and batch size. Improper tuning often resulted in overfitting and underfitting.

- **Complex feature engineering for EV charging demand forecasting and PV Energy forecasting:**

For both forecasting challenges extensive feature engineering work was performed in the form of temporal encodings, distance-based consumption features and PV-weather related features for boosting model performance.

- **Forecasting, scheduling and cost-optimalization integration:**

  It was the incorporation of EV demand prediction, PV generation forecasting, and a simultaneous use of PV-first scheduling and tariff-based cost optimization into one single entity that introduced substantial algorithmic complexity.

- **Large computation cost for training ML models:**

  It took considerable time and compute resource to train multiple ml models and hybrid models, especially sequence based ones.

Chapter 2

Literature Review

2.1 Preliminaries

This chapter introduces the basic knowledge, models, datasets and evaluation indexes which we need to know in order to understand the proposed EV–PV charging optimization framework. It includes the forecasting models implemented in this work, crucial energy-related concepts and input features that EV demand or solar PV generation prediction should possess. The demand side of EV charging is mainly determined by the distance travelled and energy consumption rate (kWh/km) of electric vehicles (EVs). Furthermore, in this study two parameters are employed, Distance (km), where it is the daily travel distance of a workplace EV and Energy per km (kWh/km), which indicate the vehicle energy efficiency and how much energy is used at each kilometer. Such characteristics impact the charging demand throughout the day, thus enabling machine learning models to identify patterns in charging behavior. Theproduction of solar PV is incumbent on many, varied environmental and meteorological conditions. The renewable database considered for this research is composed of GHI (Global Horizontal Solar Irradiance), which is the total solar energy received by a horizontal surface, and represents the key factor that accounts for available solar energy; Temperature, due to its effect on the efficiency of PV panel operation; RelativeHumidity or Precipitation that influences atmospheric clearness and so PV productivity; DayLength corresponding to hours between sunrise and sunset; SunlightTime indicating actual sunshine duration during each single day. By exploiting these variables, accurate prediction of solar power generation is possible, which is the key condition for PV-first scheduling. We apply a number of machine-learning and deep-learning models in this work. LightGBM (Gradient Boosting Machine) is a fast, distributed, high-performance gradient boosting framework based on decision tree algorithm used for ranking, classification and many other machine learning tasks. The Hybrid LightGBM + LSTM model integrates the capacity of LightGBM in learning non-linear feature interactions with the potential of LSTM to learn time-series patterns and address residual errors, leading to more accurate forecasting for both EV demand and PV generation. LSTM (Long Short-Term Memory) is a popular RNN architecture known to handle long-range correlations in sequential data. GRU (Gated Recurrent Unit), another variant of RNN that is less complex than LSTM in terms of the number of parameters. TCN (Temporal Convolutional Network) adopts causal and dilated convolutions to capture long-regionality patterns in the sequence. The self-attentive Transformer Encoder can capture long-range temporal dependencies without any recurrence. PV forecasting classic ML regressors used were Random Forest, Gradient Boosting, Decision Tree and

Linear Regression. The concepts of energy and tariffs that are necessary for examination in this article are PV, which is an energy method that converts the sun light directly to electric power; LCOE (Levelized cost of Energy) 6), a value representing the life time cost per kWh of PV produced electricity; Flat Rate tariff, by which the charges resulting from power consume- tion do not show variation over course of the day; TOU (Time-of-use) tariff7), a type where costs for power use have differences according to peak hours or off peak hours. For reading comprehension, the following evaluation metrics are reported: - RMSE (Root Mean Squared Error), a measure of the square root of the average squared prediction error - MAE (Mean Absolute Error), measures the average magnitude of prediction errors; and MAPE (Mean Absolute Percent Error) describes Accuracy in percentage format, while R^2 Score (Coefficient of determination) tells how well model explains variance in target. The formulations and models presented in this chapter are fundamental to the EV–PV forecasting and optimization framework proposed in this work. These preliminaries are necessary for interpreting the methods and conclusions in subsequent chapters.

2.2 Review of Existing Research

In this paper [5], these needs are fulfilled by addressing the demand side management (DSM) when integrating EV into charging station (EVCS), of renewable energy systems and to control environmental as well as operating constrains that appears on classical energy methods. The report recognises the requirement to slash greenhouse gas and also notes how growing solar, wind generation, as well as expanding EV penetration can drive CO_2 emissions down by nearly 28% from renewable plant generation only when combined with an increasing portion of global EV trade [5]. There remain serious downsides, such as the high purchase price of EVs and lack of charging network preventing wider penetration. This review paper also examines peak load management with Distributed System Management (DSM) strategies and shows precisely how much their significant improvement could save the energy bill and make grid effective, can reduce energy costs by up to 20%, and could increase grid efficiency by approximately 15% [5]. It also focuses on how the energy storage systems and EV charging are integrated into DSM system so that less traditional power generations are the use.It also responded to how EVCS may benefit the economy and the environment from favoring renewable energy.According to a paper, solar electricity can offer savings of 25% to 30% in operational costs for electric vehicle charging stations. The energy cost reduction strategies are based on the time-of-use pricing, demand response programs and storage integration (Dong et al., 2021) [5] .Overall, peak demand prices were reduced by opting for renewable energy sources instead of the grid, which has played a significant part in this decrease- making EV charging infrastructure more financially viable. Integrating these with EV charging not only generates economic benefits to investors and stakeholders but also boosts the switch to cleaner energy Machine learning algorithms can play a pivotal role in these strategies by providing accurate forecasts of energy demand and enabling dynamic pricing models that reflect real-time energy costs.This paper proposes learning deep LSTM networks for demand and SOC forecasting in EV charging systems using a machine learning approach instead of traditional data-based logic approaches. These models are expected to be able to accommodate the real-time nonlinearities of energy data, which could result in a more accurate load forecast and allow for finer grained optimization power flows within microgrids.The LSTM model achieved an RMSE of 0.49% at estimating SoC, outperforming the VARIMA model that showed a less accurate performance [5] . The model got highest validation accuracy of 99.51% contrasted with 99.13% in VARIMA demonstrate by showing up its superior efficiency for SOC[5].However, the research is limited by no evidence of scalability to large systems and reliance on high-quality real-time data.It is also computationally complex, increases costs and does not completely dealing with practical problems such as hardware compatibility, retrofitting or economic attractiveness. In addition is the issue of renewables being an intermittent resource; not accounting for this could lead to unreliable performance when yield is low due to weather. However, research suggests that intelligent energy management strategies can improve the efficiency of energy distribution and reduce costs in urban settings.

The key motivation of the model proposed in this paper [17] is to optimize a cost function including customer penalties due to node failure, utility costs for upgrading aged-components and power losses as well system reliability improvement utilizing EV smart charging.One of the biggest The paper investigated the impact of uninhibited charging and found it could significantly shorten the life of key grid components.The author [17], developed a linear optimization model on the basis of smart charging algorithms that could reduce load peaks and in this way extend the lifetime of the equipment, and make grid more reliable. Smart charging is a promising method to mitigate some side effects of EV penetration, in which the time and power level when an electrical vehicle (EV) charges can be managed, say by grid operators, interactively with other loads. Studies have shown, for example, that the free running EVs will exacerbate the peak load and the aging failure probability of grid equipment as well as exasperated to operating utility costzhao et al. (2024) [17] projected that smart charging not only reduce peak load but also remarkably lower the probabilities of transformer and cable aging failure. Intelligent charging is beneficial for grid assists in alleviating the load on EVs, it evenly distributes this demand throughout working hours and night periods assists to prolong life time of Electric Vehicle (EV) and decrease its maintenance cost. In this paper, we have developed an optimization model to evaluate the impact of EVs smart charging on the network reliability, minimization cost and aging failure probability in two situations including a 5-bus network model and IEEE 33-bus system[16].As a result, the EV smart charging model shows that discovering this peak load significantly reduces pressures on its network equipment and falls to age failure probabilities for cables(31%) and transformers 6% [17]. This increase in reliability lead to fewer unavailable nodes, and reduced average expected energy not served (EENS) by 21 hours at a rate of 2.5 MWh for the 5-bus network respectively[ ]Solar photovoltaic (PV) systems have also been tied in with EV charging infrastructure as part of an overall move to reduce fossil fuel consumption.Bayram et al. A comprehensive EV charging station design optimization framework, with solar PV systems for self-sufficient energy production is reported . Their studies show that using solar with smart charging algorithms can minimize grid dependence, reduce power losses and decrease payback time of the infrastructure required for charging. Renewable energy in combination with smart charging is not only an ecological gain, but also a financial one.Machine learning (ML) methods have recently come to the forefront of research on optimizing and anticipating the charging needs of electric vehicles. Researchers have incorporated machine learning into electric vehicle charging management to make real-time adjustments to PV system designs for optimum energy consumption and cost savings, based on real-time solar forecasts.The model employs NHTS databases and eliminates the EVs with driving range greater than 250 miles to reflect average usage of EV [17]. The parsed dataset was then (randomly) divided into 80% for training, and the rest for testing. So we have the input layer of MLP model, a 3 layered hidden network (each hidden layer having nodes roundaboutly 50)and at last the output layer is trained upto about 100 epochs(batch size=5). of the model The final predictions as well as performance was also obtained (Performance on final test set) :very high R^2 value almost 1.0000 with very less MSE:0.0035 and MAE: 0.0124 means Excellent prediction accuracy of model [17]. These accurate distance predictions enable a model to estimate energy demand for EV charging, which in turn supports the overall optimization model for load balancing and reliability at the power distribution network.The papers addressed innovative approaches for energy management, which take into account the specific capabilities and objectives of Urban Areas as e.g. maximum population density or flexible demand driven (-peak-) load. At the end, though,the paper's easy answer for how to deal with renewables, by assuming away availability(although not in actual life), effectiveness (which should be there) and scale is more than you can bite off at one time if your name is not "most system operators." There are several limitations to the paper. A lot of working with machine learning is based on best real-time data, which can be difficult to keep updated. While in testing on small networks, they work well, we do not know how fully functional they are going to be for larger systems. The up front cost investment for the sets up of PV Solar with smart charging infrastructure is very high and therefore cannot be spread among commoners including those living in developing countries. Because it's intermittent, the customer is dependent on the grid to function throughout the day when sunshine isn't present. Another challenge is that there will be real-world constraints upon hardware-agnosticism, grid infrastructure and long-term costs. It will open the door to developing more realistic load prediction models that take various parts (e.g., decentralized and centralized fast charging) into account. Furthermore, the application of vehicle-_to-grid (V2G) and its impact on reliability optimization could be well investigated.

In [13] omnithine review of ML techniques for optimal energy management in EVs is studied for comparison. The results indicate that the electrical vehicles can contribute a great deal to mitigating air pollution and promoting more environmentally friendly transportation.Machine learning (ML) has been a part of significant breakthroughs in predicting, optimizing and monitoring energy use in electric vehicles the EV sector. And it has successfully solved battery status management, temperature control and energy consumption by using machine learning techniques like supervised, unsupervised and reinforcement learning. This paper introduces the utilization of Real-Time Learning(RL) and DRL in energy management, especially for fierce scenarios such as regenerative braking conditions or EV charging schedule, compared with real-time resource-limited EMS which struggles due to its computational-heavy nature from a high-level perspective(Antonopoulos et al., 2020) [13] .These models may improve the distribution of energy resources by tailoring EMS tactics to user characteristics.The author, Lian et al. (2020) [13] pointed out that without further processing, they are unable to forecast future demand.This paper also claims, that energy demand (apt only to electric vehicle charging) can be well described using predictive load modelling.Therefore one of the way machine learning algorithms which have trained on historical data along with given weather conditions and a user behavior will provide reliable estimate about how power use in future.This predictive ability is essential for managing charging loads of electric vehicles to lower costs while maintaining grid integrity.Author team also discussed about solar photovoltaic (PV) systems optimization.One efficient way to save energy costs is to combine electric vehicle charging infrastructure with solar PV installations. Reduced dependency on grid power and total energy expenditures may be achieved via proper PV system size. To find the best PV installation capacity, many methods have been suggested, one of which being genetic algorithms.When it comes to combining renewable power sources, such as solar panels, with electric vehicle charging stations, algorithms such as Particle Swarm Optimization and Whale Optimization are used to maximize efficiency in the distribution of available resources (Wang et al., 2020) [13] . Hybrids can save money and ease up on the grid.The paper has also discussed economic hardship from charging electric cars. Solar power when maximized greatly reduces the cost for high-cost energy. The emphasis in this paper is laid on the analysis of energy management techniques, and share of self-consumed PV based energy.Moreover,the authors highlight the opportunity and obstacles of integrating machine learning (ML) with renewable energy sources in urban communities. In the research paper, various limitations have been identified in applying machine learning (ML) to optimize energy management for electric vehicles such as data quality and computational complexity issues, safety considerations or high costs of implementation together with real-time processing and integration into existing vehicle systems.The paper also pointed out,V2G solution and federated learning are a few of the promising advances in MLbased EMS developments as discussed before (Pevec et al., 2019). Federated Learning enables doing distributed training on user devices without sending raw data to the server and therefore makes models more scalable and private. Multi-objective optimization frameworks endeavor to balance energy efficiency, battery life and operating costs with one another among the multiple conflicting outcomes. XAI has found as much wider application in the electric vehicle industry especially for generating trust on ML-driven EMS systems mainly due to its transparency of design choice (Zhang et al., 2019) [13] .Overall, this paper exemplifies the importance of different ML models and optimization methodologies in cost management for energy consumption during EV charging. From the advantages and constraints of each method, it is apparent that there is still scope for long-term research towards scale-up with an accuracy of real-time analysis as well as adaptability to growing EV infrastructures.

In this paper the authors [2] show that data-driven approaches can be beneficial to demand prediction, scheduling optimization and operation in EV (electric vehicles) charging infrastructure. Study estimated that ML would allow small systems to save 770,000 annually and large systems around 240 million. Lastly, it underscores the potential of supervised learning (e.g., [support vector machines], ensemble methods) for energy consumption forecasts and unsupervised algorithms (e.g., clustering or density-based techniques) in EV user profiling.There are plenty of deep learning models suggested in literature for Short-term Charging Load Forecasting that take into account the fluctuant EV loads within grid, like RNN and LSTM [2]. LSTM turns out to be very useful in handling time-series data, which is exactly what eases the peak demand stress.The paper mentions that one of the shortcomings about these predictors is that there exist only few high fidelity data on the charging behavior for EV, which are available to being trained also it's possible limited to generalize them. Fast interpolation of data attributes on open access databases, the real time scheduling problem for reinforcement learning and high-dimensional blending integration of behavioral predictions. Although different kind of clustering approaches such as K-means, Gaussian Mixture Models etc., can be used to cluster similar EV charging behaviors but we require effective peak demand prediction (i.e., user's onerous condition reports both electricity use and generation) for assisting electric grid managers When high resource levels are needed accurate management of peak demand on the supply side. Model features -such as ARIMA and LSTM assist to achieve efficient scheduling,reduces the grid reliance on fulfillable energies. Study highlights the barriers of EV infrastructure planning including data availability and model dimensionality. Furthermore, his research will focus on reinforcement learning for adaptive scheduling and employment of high-dimensional big data for advanced EV behavior prediction, such as appropriately forecasting future EV behaviors to achieve costoptimal, sustainable, or energy justice targets. It has been reported in the literature that the site and design of charging stations greatly influence energy requirements and operational expenses. The demand for charging in commercial use case situation can be also varying, thus it is important the tuning of charging stations capacity (Bayram et al., 2021) [2].

In this article, author Mostafa Shibl [3] goes further than merely presenting the fact of the increasing number of electric cars (EVs) and headaches they give to power distribution systems.Hence, issues of overloaded transformers, voltage drop or rise as well as energy management will be increasingly sensitive with the increase of EV penetration. The author emphasizes the significance of challenging EV charge control strategies, taking into account the inclusion with renewable energy sources and optimal use of existing infrastructure.The work uses different ML techniques to enhance charge and pathway administration of electric vehicles. Such algorithms are Decision Tree (DT) that provides fast decision with a tree structure; Random Forests (RF) that is a decision tree-based method that increases precision; Support Vector Machine (SVM), useful for classification and regression analysis. Also, as a result of its ability to classify data based on distance from training examples, KNearest Neighbours (KNN) is applied. The study also applies Deep Neural Networks (DNN) which can represent patterns over many layers and Long Short-Term Memory (LSTM) which performs well with time-series data and long term dependencies. The comparison of the performance of various algorithms has been made and LSTM, which has given the maximum accuracy for the EV management tasks has been identified as an integral part of the proposed optimization system. This paper has some limitations, one of which is the existence of the highly unpredictable nature of its algorithm outcomes inherent to a number of ML architectures results in fluctuations in assessment point of guesswork. Each time the algorithms are run and hence it becomes hard to forecast with utmost precision.. Another disadvantage is the nature of the dataset where the ML models are trained as high reliability as the outcome depends on the quality of that data. In conclusion, the paper shows that by employing machine learning (ML) algorithms, this paper seeks to illustrate an improvement in the management of electric vehicle (EV) chargers to overcome challenges like transformer overloads, power losses, and voltage fluctuations.

In this paper Yasin Mohammed [12] highlights the necessity to optimize the charging service of electric vehicles in conditions of fluctuating power prices and immense unpredictable consumer interest.. It also explains the development of the information system where the data is examined with the help of machine learning methods in several sources. This technology is intended to understand and decide about electrical vehicle charging based on specific patterns in real-time. It also points to the use of many kinds of data including historical power prices, energy consumption, and local climate, as well as transport behavior. Here, technique for featuring the expense of charging an electric vehicle (EV) is an entire pitch that involves the gathering of several details energy costs, power utilization, and drive habits that are available to the public domain. To apply this data, missing values are handled and characteristics are normalized, as well as univariate statistical analysis and multivariate analysis. Predicting the best times for charging is attained by applying two approaches: deep reinforcement learning (DRL) and deep neural networks (DNN). A decision-making model is developed for the purpose of managing the charging costs – in terms of power price and the like. The approach makes use of Random Forest Regressor for accurate predictions, Deep Reinforcement Learning (DRL) for adaptive decision-making, and Deep Neural Networks (DNNs) for data pattern recognition. Q-Learning is also used to improve charging procedures using reinforcement learning techniques. There are several disadvantages associated with the proposed optimization method for electric vehicle (EV) charging. A major issue is the requirement for high-quality and suitable training data, otherwise, poor or even irrelevant data will lead to wrong predictions and thus counterproductive pricing strategies. However, dynamic programming gives the best solution which might be computationally expensive and hence not appropriate for real-time systems. Since some of the reinforcement learning techniques such as Q-Learning may take considerable time for training and computer power and therefore are not scalable. In closing, the analysis of the electric vehicle charging processes using machine learning and reinforcement learning shows a possibility of enhancing the processes and decreasing the cost. However, these systems' efficiency is highly dependent on data quality, available computing power, and dynamic responses in real-time. It is therefore important to address these restrictions in order to achieve proper deployment and expansion of such systems into real life situations.

In this article the author Neerja B [4] focuses on the importance of energy efficiency and management in achieving carbon neutrality and sustainable energy especially in the use of electric vehicles. It underlines the importance of investing in charging infrastructure and EVs as a process in the application of V2G technology, which offers economic benefits for EV owners and inducements for contractors. The paper presents a case of V2G deployment on college campuses and outlines a machine learning-based method for predicting future energy consumption and price, and the model accuracy is presented. The methodology presented in the article uses a systematic approach to building a vehicle-to-grid (V2G) system that utilizes machine learning techniques to predict energy demand and charging costs for electric vehicles (EVs). It begins with collecting up-to-date data on energy consumption and prices which is followed by analysis to develop a prediction model employing various methods of machine learning. The model is built on previous data to predict future energy demands in given conditions, for example, peak and off-peak periods. The paper aims at exploring the uses of various machine learning methods to develop a prediction model for energy consumption and costs related to charging of electric vehicles (EV). Some of the mentioned algorithms are feedforward neural networks for its ability to identify complex correlation between data and multiple linear regression for a simple way of understanding linear relationship between variables. Moreover, the use of support vector machines is applied for classification of any type inside the dataset. The author recognizes several issues with the machine learning model and the vehicle-to-grid (V2G) technology.. There is one significant restriction which is changes in power consumption patterns, meaning there could be big margins of error in the projection, especially if this is in one particular month. For instance, the model had an error margin of up to 32% in some months to indicate that some factors like weather and user activity might affect the forecasts. Moreover, it also has a limitation of not incorporating future trends of energy consumption or future advancements in technology of EVs. The availability of more complete data is also recognized as another improvement opportunity, that requires new factors connected to V2G price and energy supply. In conclusion, the work has shown how machine learning can be exploited to improve energy consumption and charging costs for EV by exploiting V2G technology. Overall, the proposed predictive model provides a means to predict energy consumption and cost, with opportunities for considerable potential savings and Co2 reductions. So the results further imply that continuous improvement of data collection and model refinement are highly desirable to overcome the current constraints so as to improve overall performance of the system in real-world.

In this paper Muhammad Zulqarnain Zeb [1] discusses the challenges with rising demand for electric vehicle (EV) charging by keeping in view the high power factor of level 3 fast chargers. The solution indicates the deployment of various level charging points, (level 1, level 2 and level 3) in order to decrease the installation cost and loss of power as well control loads on transformers. This work adjusts EV customers behaviour ambiguity through stochastic modelling, and based on Particle Swarm Optimisation identifies the optimal location for the chargers. The performance of the method is experimented in a real distribution system with the simulations conducted on Pakistan National University of Sciences and Technology (NUST) actual distribution system. The results show that an appropriate combination of chargers can reduce cost and loss with potential to maximize the efficiency Power of the distribution system for power distribution system integrated with PV energy. The research methodology is 'siting' and 'sizing" of EV charging station in an active distribution network.To estimate the load of EVs with high accuracy, the data were gathered from 300 EV users about their arrival and departure times, and trip distance. This data was used to build probabilistic models, which estimate the variability of EV charging demand over the day. In this paper, the key algorithm utilized is Particle Swarm Optimisation (PSO) for identifying the location and size of EV charging stations. It identifies the best one by altering the possible solutions in regard to how efficiently they function in the presence of the other. In this regard, PSO is used to solve the nonlinear stochastic problem of placing different types of chargers (level 1, 2, and 3) in an active distribution network with low installation costs, minimum system losses, and satisfying constraints including voltage stability, and heat constraints. The PSO technique is programmed in MATLAB and linked with the OpenDSS platform for numerous power flow and distribution system analysis. Among other limitations in this article one of them is that the stochastic model is developed using survey data from only one site, NUST, Pakistan; therefore, the real behaviors of the EV users in other areas may not be accurately captured by the study, thus limiting the external validity. Two issues are associated with PSO: one is the computing cost, especially for repeated performing to avoid local optima. This increases the computing overhead, which is not suitable for the strategy when implemented in larger or complex distribution networks that may not have large processing power. In conclusion, this study reveals that integrating an optimal combination of several types of EV chargers may significantly reduce fixed costs and system losses in an active distribution network while ensuring efficient charging of electric vehicles. The solution improves the voltage profile and reduces the transformer overloading through photovoltaic (PV) production and smart deployment under Particle Swarm Optimisation (PSO).

In this paper the context is about how Plug-In Electric Vehicles (PEVs) are becoming more popular and how hard it is to keep track of their State-of-Charge (SOC).In order to assess the State-of-Charge (SOC) of plug-in electric vehicles (PEVs), the authors Jajna Prasad Sahoo and S.Sivabusubramanil [7] proposes an ANN-based investigation. Additionally, the study demonstrates how machine learning techniques may accurately determine state-of-charge (SOC), a crucial parameter for improving charging procedures and, consequently, the overall efficiency of electric cars. An ANN model was developed for SOC prediction with the data collected from different PEVs. 20% Training and 80% Testing The performance of the model was benchmarked by metrics MAE, MSE, RMSE and PCC. The error values are also quite low: the percentage of predicted errors in this range was 1 2% but average were around 98 99% between test durations. Table 3 lists the accuracy of the predictions with MAE values in each scenario between 0.0041125 and 0.0077267, which shows a high prediction rate.According to the outcome of study ANN outperforms traditional methods when it comes to speed and computational efficiency. This rise can also be observed in the field of SOC prediction, where there is growing interest for machine learning methods. The review highlights the necessity of reliable SOC estimation, in order to control the complexities involving increasing PEV penetration in power systems. To enhance SOC forecast accuracy in the future, the authors suggest investigating different machine learning techniques as well as optimisation strategies.But while the ANN model may perform well on the training dataset, it might struggle to generalize to new, unseen data, especially if the new data significantly differs from the training set. To sum up, the study demonstrates how ANNs can improve PEV SOC estimates leading to more efficient energy management and charging processes in the emerging electric vehicle industry .

As the world is transitioning towards electric vehicles (EVs), this trend reveals a series of opportunities and challenges for power distribution, in particular with respect to charging infrastructure requirements.In order to solve these issues, Fenil Ramoliya [14] introduces a machine learning based approach to enhance energy distribution efficiency in smart grid settings. The paper is devoted to the development of a smart grid-based framework for electric vehicle (EV) and charging station analysis in a perspective of energy consumption with application of machine learning.In transportation meanwhile, the introduction of electric vehicles (EVs) offers one practical issue and multiple opportunities: energy demand and thus charging infrastructure. With the rise of electric vehicles (EVs) as an alternative to traditional gasoline or diesel based cars, there is a raised interest in stable and comfortable charging infrastructure (CS). We are including that by bringing artistic thinking to how energy is distributed in a smart grid. The work is significant due to the fact that dealing with this critical problem of energy management optimization in a meaningful way for large scale deployments of the EV infrastructure. Specifically, in this paper we conduct a study that relies upon fine grained analysis, based on a large-scale and well-prepared dataset consisting of 3395 high resolution EV charging sessions with 24 energy-related features. The information was then filtered and processed by the authors through statistical analysis and machine learning, relying on patterns of energy use relative to closer established factors. The study clearly pushes forward the smart grid development and addresses issues and challenges in EV energy utilization. Their findings become more acceptable due to the strong methodology used for data analysis and their validation over real-world datasets. Insights obtained can also be indicative of the charging infrastructure design and planning. A limitation of the study is that it relies on the data set that comes from particular types of users and places, which can be biased, and thus might not reflect overall EV usage behavior. The analysis also does not factor in these externalities that influence the consumption of energy in other ways, like the weather or differences in how people consume it. Moreover, the work can also be extended to investigate how machine learning models (e.g., deep learning) may be integrated for enhancing the predictability of EV energy management. Last but not least, it proposes a system framework for optimization of energy distribution in smart grids and exhibits the power consumption characteristics of electric vehicle. It makes a great deal of interesting conversation, especially if electric cars continue to gain traction. A Data set which explains 24 classes of energy feature information that fundamentally includes the complete data set of 3,395 high-resolution EV charging events. They then cast this data as statistical and machine learning questions around energy consumption across many dimensions, and therefore apply it in order to discover temporal trends within it. The evidence is further strong as a result of the robust methodological approach that was applied in examining data from real world data sources. The research is also biased from the dataset point of view, since it relies in a subset of user and places and so does not necessarily prescribe to more general EV usage profiled behaviour/attitudes. The study also does not account for additional externalities that may increase energy use. More research into how external drivers — such as weather and changes in behavior when using energy — might explain the rest. Moreover, it would be exciting to see if state-of-the-art machine learning algorithms (e.g., deep learning) could also be employed into the prediction stage of EV energy management. Summary The paper provides a valuable tool to control energy allocation between elements in smart grids, and some clues on the consumption of electrical energy relative to vehicle use. It sounds very modern, in that electric cars are the future of driving, though there's that.

The major aim of the work [8] is establishing the framework for energy consumption and EVs and charging stations analysis in a smart grid view using machine learning. Specifically, in the context of transport, introducing new energy-based services like Electric Vehicles (EV) results on one hand EV- specific proposition gains and on the other managing power consumption and demand aims over corresponding charging points. The necessity of efficient and dependable charging stations CSs has become prevalent owing to the inclining trend of adopts Electric vehicles EVs as an alternate source for fuel dependent vehicle. And that is going to involve getting pretty inventive about how energy is shunted around in so-called smart grid environments. The contribution is driven by the urgent need for energy management optimization which serves as one of a very significant concern to be addressed towards sustainable deployment of EV infrastructure. The experiment is conducted with extensive data pre-processing of a dataset consisting 3395 high-resolution EV charging sessions and 24 energy features. The data was examined by the authors through utilization of statistical and data mining methods in an effort to identify patterns in the energy consumption relative to different attributes. It is evident that the research has a significant influence not only on smart grid but also on relevant issues and challenges in EV energy use. These findings are also reliable, due to the careful induction mechanism employed in data analysis, as well as the nature of a real-world dataset. This improved knowledge also has great potential in the design and planning of charging infrastructure. One drawback of this work is that the dataset is obtained from a subsets of users and locations, it may not be general EV usage behavior due to selection bias. The valuation also does not reflect those external factors that may cause energy consumption to deviate in both positive and negative ways from the unremarkable class, e.g., ambient temperature or shifts in consumer choice. The work can also be used to explore how we can apply machine learning methods (e.g., deep learning) in more detail to improve the prediction accuracy of electric vehicle energy management. Lastly, the paper introduces a system architecture for optimizing energy distribution of smart grid and lists some performance features of electric vehicle's energy application. It doesn't contribute all that much to the discussion, especially in an age when electric cars are becoming more common place. A 24-d-parameter general energy-based data with all tickets for 3395 high-resolution EV charging. The authors then analyze increasing energy usage. Further investigation into how far outside forces — weather and shifts in behavior when it comes to power consumption — might explain the rest. energy consumption on multiple factors using statistical and machine learning approaches, so that one then may derive some trends. The strength of the findings includes quasi-experiment design and real data used for analysis. The findings of this study are limited by the bias of its dataset in that it only includes certain user groups and regions, which may not be generally representative of EV use. It also does not consider the ecological damage that comes withFurthermore, future works could investigate the possibility to apply state-of-the-art machine learning methods including deep learning for investigating EV energy management prediction. Overall The study presents an interesting approach to being able to manage the energy distribution for smart networks, however it also offered some insights into how electric energy is consumed in connection with car usage. Electric vehicles are all the rage, so this is a very timely addition to the collection.

The paper details the work on electric vehicle (EV) charging and routing optimization from S Prabhakar Karthikeyan, Polly Thomas [15] stating that although lot of industrial pressure is against up-taking EVs, recent trend in electric vehicles are favoring environmental needs for a greener transport solution. The criticality of the two processes and associated uncertainties is what motivates this paper, to study optimization methods and algorithms for EV charging and routing with a focus on robustness. This paper is on top of an literature outline approach, which looked into some other papers and EV scheduling algorithms. We classified a set of optimization techniques, such as dynamic programming, machine learning methods and metaheuristics when assessing their ability to support real-time tasks. The investigation finds that, although some of the algorithms employed permit reductions to both total cost and energy demand levels, they're often accompanied by factors such as increased computational complexity or an inability to adjust in real time. The authors state that "In order to fully exploit these antecedents, and hence enhance the predictive capacity of scheduling algorithms, designs which are user-centric should be combined with machine learning techniques." Classifying and evaluating various algorithms being a sound methodological basis in the applied sense for practitioners as well as in logic for researchers. One weakness of the present paper is that there could be some kind of selection bias regarding the articles that were due for review and this might not represent all existing studies. Even more so, by focusing only on existing published research prospective works will fail to take into account new methodologies and technologies that can support additional improvements in EV scheduling. However, the study also addresses some limitations like application of some algorithms not suitable for real-time environment and were not capable for predicting accurately. We take into consideration The existing state of operation areas and Noticeable adaptive algorithms in contribution to advancement in the field of electric vehicle optimization. It is a very valuable reference for any academia that desires to grow and explore new directions in EV scheduling and optimization. Fill the gaps identified above could be on the other hand addressed in future research work by investigating how state-of-the-art machine learning methods and blockchain technologies can be combined for electric vehicle scheduling. Research may also turn to case studies and actual deployments that can validate the algorithms, methods. In general, It is a good review paper on the current states-of-the-art in EV charging and routing optimization. That's not a small thing, and it's also a welcome addition to the literature on some of the challenges, as well as opportunities, facing that business.

Qinglin Meng [11] presents a Monte Carlo based simulation for modeling EV charging loads considering parameters like daily driven distance and duration of time in hours required to charge the vehicle. In this, the 'green power' billing option where an ordered EV charging according to a scheduled charge could be pulled in is presented and the BSP function of an adoption for PV production-dependent time-of-use pricing is studied. The proposed Ant Lion Optimizer (IALO) algorithm is employed for charging schedules optimization, and it compared to Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO). The simulation studies done with disordered and orderly charging modes display the efficiency of IALO in stabilizing grid power quality, reducing load variation due to EV charger operation and further promoting the coordinated development relationship between EV charge/discharge behavior and PV utilization level.The main research results reveal that the introduced enhanced Ant Lion Optimizer (IALO) algorithm improves to a great extent economic and environmental results of electric vehicle charge combined with photovoltaic systems. A proposed IALO algorithm showed a total revenue increase of 16.8% and 12.8%, respectively, when compared to Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). Moreover, the consumption of PV energy was more with an increase of 162.3% and 37.1% while carbon released decreased by approximately 159.6% and 31.6% under IALO compared to PSO and GWO. The neat charging mode with utilizing the green In order to accurately model the load of electric vehicle (EV) charging, simulation-based methods using Monte Carlo are proposed in literature by taking into account daily driving range and EV starting time for charge as well as charge duration. In this work, we use a 'green electricity' charging scheme to incentivize the EV users with their load shifting in order to match both PV generation and grid capabilities; A sequential mechanism is developed for such a type of tariff based on different pricing levels. An improved Ant Lion Optimizer (IALO) algorithm with a combination of differential evolution features is presented in the study for schedule optimization to maximize revenue and reduce emissions at load aggregators.Then, the performance between Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO) and IALO is compared for quality of results. Simulation results have shown that under both disorder type & order type of charging-modes transformation processes, the method proposed could not only contribute to steady system lines but it also could smooth the total charging load profile and further for PV integration with EVs electricity billing method was able to transform consumption loads into iness' varying k a model compared without using we introduced a smooth curve) Grid power stability (the mean—magnitude percentage of deviation) heels 90 from total d 33 Mean square: error percentage of motion charges by reducing an entire as more iterations higher voltage rrg rg are less;and Voltage fluctuations declining conditions The testingew updated values were g sured against simulation based on —state iterstions whereindly robustnso our case stt c amm.crobustness result evencies over T4(x-axis is time), By applying an energy s form. Results showed the potential for both EVs and PV to be utilized in such a way that grid performance can be improved, costs reduced at the same time as sustainable energy management is promoted. This study is subject to several limitations. Firstly, it ignores the differences of charging behaviour and system performance among electric vehicle (EV) brands and models with varying battery sizes. Additionally, all outcomes were based on the provided effort-specific simulation in a single park scenario and cannot be generalized to other places or realistic conditions where energy demands are not similar. Lastly, the Monte Carlo prediction is modelled based on certain assumptions around user activities and driving patterns which may not describe well the variance in EV usage over time that impacts estimates of load reliability. The intermediate control with solar (PV) could integrate better supply and demand for electric vehicles (EV) visiting the charging station and facilitate grid stabilization. Some parameters and the applicability of our model to a real sense environment can be studied.

The work of Padmavathy R, Jeya Prakash K [6] presents a machine learning enabled prediction and charging scheduling of electric vehicle's energy consumption. The growing market penetration of Electric Vehicles (EV) is a key solution for mitigating environmental pressures and decreasing the use of fossil fuels. Machine learning for energy: How to make machines help electric cars performance and sustainability better. It uses a comprehensive approach involving collecting data on vehicle characteristics, traffic conditions, driving behavior and environmental factors in order to predict the energy consumption of the vehicle and determine how best to use the energy, considering some variables that will have an impact such as battery state, congestion patterns (mirror effect) and weather. Feature engineering isolates relevant data points and model learning through suitable ML approaches is performed next. Simulation and field experiment results are presented to verify the model performance with respect to some well-known methodologies for energy optimization. Consequently, the proposed method can improve energy efficiency by about 10-20%, which can substantially increase driving distances of EVs compared to conventional methods. The paper s contributions are rigorous methodology application and holistic approach for integration of numerous factors in the energy management, leading towards tailor made solution to be a cost-effective solution. The limitations of this work are as follows: Bias in data collection might lead to model accuracy and generalization for different driving environments. Some human-like driving behaviors are not considered in this study, thus the model may not be practical. Secondly, there is a potential for large computational resources to make the system work so scalability and practical use in electric car applications may not be possible.The subsequent study shall validate the model in a wide variety of driving conditions, possibly including renewable sources of energy to ensure environmental viability.

The author Tayarani [9] applies machine learning (BLSTM network) to anticipate when and where electric vehicles will charge, so as to reduce range anxiety and inform which charges are initiated. The paper designed a model based on Bidirectional Long Short-Term Memory (BLSTM) network for predicting the State of Power (SoP), Long-Short Term Memory (LSTM) to improve future prediction accuracy in time series data, Recurrent Neural Networks(RNNs) for future forecasting relating with temporal dependencies. We use a subset of the eVMT project dataset (real-world trip, and charging data from multiple BEVs) that was collected over a 5 year period (2015–2020). By processing real-time inputs and historical trip data, the models are trained to predict when you plug in your vehicle, what trip you're likely to take next, and when you'll return home. In addition, the study rates LSTM and R-NN models and compares their performance through accuracy, F1 score and Mean Squared Error (MSE) metrics. Beyond this, the methodology is grounded in a stochastic modeling framework which captures randomness (unpredictability) surrounding driving and charging behavior such that models evolve with time-dependent behaviors. This will ideally reduce the number of unnecessary charging sessions and would mean lower costs for BEV owners, longer battery life but also some actionable insights to make range anxiety less of an issue for drivers. In this paper, the authors compare the performance of BLSTM networks with traditional methodologies as ARIMA, Support Vector Machines (SVM) and conventional neural networks (C-NNs). Though ARIMA is powerful for time-series forecasting, the nonlinear patterns and sharp spikes common among electric vehicle usage stymie it. SVMs and C-NNs are also very good at classification but not so good at handling large datasets or behaviors that are more challenging to learn. On the other hand, BLSTM networks deal well with high-dimensional and dynamic data giving improved predictions by learning from past and future information.The results show that the proposed BLSTM model is more effective than deterministic models and it can, on average, save unnecessary charging between 15% to 22%. In this sense, the exploitation of real BEV data in research is one strength for that not only increases implement ability but also improves precision of model. However, BLSTM model is very expensive. First, it requires a lot of high-quality training data, something that can be difficult to obtain if electric vehicles aren't common in an area. The computational complexity of using deep learning models like BLSTM is another big drawback as it would mean substantial amount of processing power to train and run such kind of models for all the users. Finally, even after the model updated to may not change its mind so quickly in order to account for sudden changes of driving behaviour and charging infrastructure in view of potential future predictions. These limitations emphasize the significance of further research to improve and simplify the model process.

Shahriar and Movahedi [16] showed how machine learning for charging patterns optimization is also shaping up to be a more worthwhile approach as well, for minimization of electricity cost in EVs when treated previously as an application. Electricity demand from residential power systems for vehicle charging at homes is rapidly increasing due to widespread deployment in electric vehicles (EV) and negatively impacts the residential environment. With the increase of number of electric vehicles (EVs) penetration, it is eye-catching to think about its associated effects on electricity consumption profiles, grid security and domestic energy cost. This paper seeks to design and appraise controlled EV charging strategies that minimize the cost at household level while addressing the problems caused by uncoordinated EV load on the power system. This work is primarily aimed to lower the price of electricity for EV owners under time-of-use rate structures, in which charging activity takes place off-peak. It seeks to look at how varying charging behaviors and the inclusion of community-level changing management can work in favor of grid stability and proficiency. To address this limitation, rather than existing works that only show these patterns as mere properties or using an estimated (simulated) household load data, we aim to deliver actionable results based on real-world household power consumption and up-to-date analysis methods – decisions that could be the base for responsible electric power use and saving money not only with other stakeholders (such as utility companies but also possibly EV drivers). The study approach applies k-means clustering for primary data mining model to explore domestic electricity consumption behavior and journey pattern in reciprocation by those households who owned electric vehicles

(EVs). This is a way of unsupervised learning that can aid in the identification of the profiles found throughout one day in energy consumption and know on what terms time and amount an EV could be charging. We illustrate the effectiveness of our proposed clustering technique by incorporating data-driven insights from it into a convex optimization problem that minimizes the electricity tariff in presence of an EV charging based on real-time time-of-use prices, under two scenarios — AFAP charging and ALAP charging. The optimization problem is formulated within the constraints in terms of battery-capacity, power-envelope and user-flexibility. The approach is further supported by a data driven comparison between controlled and uncontrolled charging signatures to analyze the utility of different charging patterns in terms of household electricity cost reduction under grid stability mandate. Taken together, these methods serve as a complete toolbox to further develop the theoretical basis of residential EV charging. The managed EV charging programs analyzed in the study could result in "substantial" savings on household electric bills, saving potentially more than 30%, researchers determined. K-means clustering model were used to discover house energy consumption prediction patterns that have an average accuracy up around 85% on the pattern discovery. Costs were also lower if delayed Rated Energy charging plan hours are used relative to Peak Demand charge plan fast-charging hours. As for its merits, it is not without drawbacks. There could also be additional biases introduced by the specific dataset used that might not generalize well to all residential environments. Additionally, the household travel and charging profiles derived estimate might not be locally adapted to all scenarios. Methodological matters, including the realistic modeling of charging patterns, can also induce some influences on the results. The paper offers an interesting perspective on issues and opportunities in the domain of EV charging management. To bridge the gap, in future studies it would be interesting to investigate how household characteristics affect charging behavior and its costs.

The article by the title Machine Learning in Electric Vehicle Charging Optimization [18] defines the main gaps in the current EV charging schemes including the lack of real-time optimization, the inconsistency of renewable energy sources, and the lack of adaptability based on data. To provide solutions to them, it discusses different machine learning solutions: supervised models (predicting loads: regression, random forests) to forecast loads, unsupervised models (K-means, anomaly detection) to analyze behaviors, reinforcement learning to schedule dynamically, and deep learning models (LSTM, RNN) to predict demand at times. The approach will be to gather and preprocess multi-source data of charging stations, grids, and users to train ML models to predict demand, optimize the charging schedule, and ensure grid stability. The data is conceptual, non-homogeneous (time-series and behavioral data, e.g., energy consumption, user preferences, grid load) and the study lacks experimental outcomes or model accuracy values and instead concentrates on theoretical advantages. The results indicate that optimizing the charging system with the assistance of ML can reduce the charges, stabilize grid load, improve renewable integration, and improve user experience- showing the potential of intelligent and data-driven EV charging systems in spite of the lack of quantitative indicators of performance.

The paper [19] focuses on the key issue of the design of sustainable ultra-fast electric vehicle charging stations (UFCS) which are characterized by high short-term power loads and heavy reliance on the grid. Past studies had mostly used the conventional approaches to demand or slow-moving or unrealistic forecasting approaches, but without incorporating realistic weekday weekend EV demand patterns, deep learning-powered solar forecasting, and techno-economic optimization. In order to address this gap, the paper suggests a hybrid architecture that integrates Gated Recurrent Unit (GRU) deep learning in solar photovoltaic (PV) output prediction with Genetic Algorithm (GA) in the optimization of the sizing of PV and battery energy storage systems (BESS) to optimize Net Present Value (NPV). GRU and LSTM models were compared with GRU having higher forecasting and convergence. The methodology involves the modeling of EV arrival based on probabilistic data of the Italian National Road Authority, charging curves of Fastned, and solar irradiance of the National Solar Radiation Database (NSRDB). The state-of-charge of the EV battery at arrival was simulated using the Weibull distribution and the GA optimization took into account technical constraints (SOC limits, energy balance) as well as financial ones (CAPEX, OPEX, replacement cost).The dataset consisted of time-series solar irradiance, temperature, EV traffic probabilities, charging profiles and cost data. GRU model was used to predict the PV generation that was utilized by GA to design the optimum PV and battery capacities in various conditions. A 20-year horizon was used to test three configurations, namely, grid-only, PV-only and PV+BESS. The findings indicate that grid-only systems obtained an NPV of 27.29 million Euro, PV-only integration brought up to 33.48 million additional (33.97M), and BESS added to the value again, making the total 33.97 million (33.68M). As the cost of PV and battery material was estimated to be cut down, the NPV increased to 34.05 million. To sum up, the current study has shown that a combination of a deep learning-based GRU forecasting system with Genetic Algorithm optimization will make it possible to size PVBESS systems efficiently in order to serve ultra-fast EV charging stations. The hybrid model increases the stability of energy, decreases grid reliance, and elevates the economic profitability that creates a constructive, scalable and intelligent model of future charging infrastructure that operates on renewable power.

2.3 Summary of Key Findings

Ref	Objective of Study	Models	Accuracy	EV Control	PV Sizing	Others/Features
[1]	To lower the total cost of installation and the power losses in the circuit by maximizing the placement and scale of several types of EV chargers	Particle Swarm Optimization (PSO), Stochastic modeling	N/A	No	Yes	Particle Swarm Optimisation (PSO)
[2]	Test energy and economic performance and help in reduction of cost.	SVM, DT, K-NN, RF, XGBoost, LSTM, GRU	SVM 2.85%, DT 54%, RF 12.8%, SVR 21.1%, LSTM/GRU provided	Yes	Yes	N/A

Ref	Objective of Study	Models	Accuracy	EV Control	PV Sizing	Others/Features
[3]	Optimizes the operation of the distribution grid	DNNs, SVMs, KNNs, TBRs, DP	DT (94%), RF (95%), SVM (30%), KNN (42%), DNN (78%), LSTM (95%)	Yes	Yes	N/A
[4]	To forecast energy consumption and EV charging costs.	BPNN, SVM, MLR, HW-RLM	MAPE 93–97%	Yes	No	V2G integration
[5]	Maximize self-consumption, minimize cost, reduce CO2 emissions.	LSTM	LSTM 99.51%, VARIMA 99.30%	Yes	Yes	DR, ESS, DSM, real-time forecasting, dynamic battery
[6]	Optimize EV charging schedules to lower cost and increase renewable use	SVM, ANN, SmartEV	SVM (75–84%), ANN (76–81%), SmartEV (89–97%)	Yes	Yes	N/A
[7]	Improve SOC prediction accuracy for PEVs	ANN, RF, SVM, CNN, VARMA, LSTM	ANN achieves 98–99% PCC	No	No	SOC prediction focus
[8]	Forecast EV charging behavior	SVM, RF, XGBoost, CatBoost	RF 87.55%, SVM 89.33%, XGBoost 92.89%, CatBoost 98.37%	No	No	Charging session + weather-based modeling
[9]	Predictive charging optimization for BEVs	RNN, LSTM, BLSTM	N/A	No	Yes	Predictive neural network model
[11]	Optimize EV charging scheduling using green electricity pricing	PSO, GWO, IALO	IALO 88.5%	Yes	Yes	N/A
[12]	Real-time optimization of EV charging cost using ML	DT, RF, DNN, KNN, SVM, LSTM	DNN 95%	Yes	Yes	DP, Q-Learning
[13]	Techno-economic feasibility, profit maximization, CO2 reduction	RL, DRL, supervised	N/A	Yes	No	N/A
[14]	Optimize energy distribution in smart grids using ML	N/A	N/A	No	No	N/A
[15]	Optimize EV routing and charging	GA, ACO, MAPSO, HA, DT	N/A	Yes	Yes	BESS integration

Ref	Objective of Study	Models	Accuracy	EV Control	PV Sizing	Others/Features
[16]	Improve energy consumption	K-means, Convex optimization	85%	Yes	Yes	AFAP, ALAP, peak shaving, valley filling
[17]	Minimize cost and improve reliability	MIQCP	$R^2 = 1$, MSE = 0.0035, MAE = 0.0124	Yes	Yes	Piecewise linear grid model
[18]	To optimize electric vehicle (EV) charging using machine learning for improved grid stability, cost efficiency, and integration with renewable energy sources. Focused on demand forecasting, load balancing, and dynamic pricing.	Regression, Random Forests, K-Means, DBSCAN, Isolation Forest, RL, RNN, LSTM, CNN	N/A	Yes	No	Adaptive real-time control using RL. Integration with renewable energy and V2G.
[19]	To develop an intelligent optimization framework integrating deep learning–based solar forecasting.	GRU, LSTM, GA	N/A	Yes	Yes	N/A

2.3.1 Research Gap

There are still gaps in the literature for EV charging and solar PV integration. In the literature, most of the studies either account for EV charging demand alone or PV generation only, and both uncertainties are not always modelled simultaneously. Real-world EV operation like arrival departure times, daily distance and energy-per-km usage may often be dismissed and limit the usability of historical models. In the same vein, PV forecasting applications typically fail to model the strong long-term variability of solar output and fail to couple it with EV load changes. Many of these studies also have limited financial assessment, failing to include flat vs TOU rates or Levelized Cost of Energy (LCOE). While a few works study the forecasting problem of ML/DL methodologies, little to no work employed a hybrid architecture of gradient-boosting models and sequence-learning network in order to exploit the advantages of non-linear extracted features and temporal dependencies. Finally, the approach of prioritizing solar as an input to charging while resolving conflicts between vehicles (PV-first smart scheduling) is rarely employed. Most importantly, such a unified framework is not yet available in literature which involves integration of:

- EV demand forecasting
- PV generation prediction
- conflict-aware PV-first scheduling

- More realistic and practical case of optimising cost under a set of tariff conditions.

This leads to a substantial need for an end-to-end intelligent EV–PV coordination system which drives cost reduction and optimizessolar penetration while minimizing grid dependence in the environment of workplace charging.

Chapter 3

Requirements, Impacts and Constraints

3.1 Final Specifications and Requirements

The development of the proposed EV–PV integrated charging cost-optimization framework required both technical and methodological resources. The system was implemented in Python 3.10 using TensorFlow and Keras for deep learning architectures, Scikit-learn for machine-learning regressors, and Pandas/NumPy for data processing. Matplotlib and Seaborn were used for visualization. Training was performed on a high-performance workstation equipped with GPU acceleration (NVIDIA), a multi-core CPU, and at least 16 GB RAM to support computationally intensive deep learning models. Two datasets were utilized: (i) an EV dataset containing historical driving distance and energy-per-kilometer patterns of workplace vehicles, used to forecast daily energy demand; and (ii) a solar PV dataset containing timestamped PV energy generation values, used to model daily renewable availability.Preprocessing involved train–test split (80/20), feature scaling (StandardScaler/RobustScaler, label encoding for categorical fields and cyclic temporal encoding for time features. Deep learning models (LSTM, GRU, TCN, Transformer Encoder, Hybrid LightGBM–LSTM) were trained for EV demand forecasting, while machine-learning regressors (Random Forest, Gradient Boosting, LightGBM, Decision Tree,LSTM,TCN,GRU,Transformer Encoder and LightGBM-LSTM) were used for PV forecasting. Grid cost assumptions included Flat Rate tariffs (0.25 AUD/kWh) and Time-of-Use (TOU) pricing, while the Levelized Cost of Energy (LCOE) for solar PV was fixed at 0.05 AUD/kWh. Accuracy of all models was evaluated using RMSE, MAE, MAPE, and R^2 before integration into the PV-first cost optimization module.

Creating the proposed EV–PV integrated charging cost-optimization model was based on technical and conceptual resources. The system is developed in Python 3.10 using TensorFlow and Keras for deep learning architectures, Scikit-learn for machine-learning regressors and Pandas/NumPy for data manipulation. Visualization was done through Matplotlib and Seaborn. Training took place in a high-performance workstation with GPU acceleration (NVIDIA), a multicore CPU and at least 16 GB RAM for computationally expensive deep learning models.

Two sets of data were employed: (i) an EV dataset regarding historical energy demand and vehicle-by-vehicle energy-per-kilometre profiles, in order to predict daily electric load; and (ii) a solar PV dataset with the as-recorded time-stamped measurements of solar generation on a daily basis, for modelling daily renewable availability. Pre-processing steps were train-test split (80/20), feature scaling: (StandardScaler,/RobustScaler/min-max scaler), label-encoding of categorical fields, and cyclic temporal encoding for time-based features. LSTM, GRU, TCN and Transformer Encoder as well as Hybrid Light-GBM– LSTM were learned for EV demand forecasting whereas Random Forest(ec) (RF), Gradient Boosting Machine (GBM), Tree-based Methods,, LightGBM, Decision TreeP(LS[K¶[were developed for PV forecasting. Grid cost assumptions were based on Flat Rate (0.25 AUD/kWh) and Time-of-Use (TOU) price plans, whereas solar PV Levelized Cost of Energy (LCOE) was constant at 0.05 AUD/kWh. The performance of all the above models was examined in terms of RMSE, MAE, MAPE and R^2 before they are embed into the PV-first cost optimization module.

3.2 Societal Impact

The project has a great positive impact for the development of the society in electric mobility, renewable energy integration and smart utilisation of energy. By using machine learning to predict the demand of EV charging and PV availability, the system enables low-cost reliable workplace charging that is optimal for users who want to own an EV. It reduces dependence on fossil-fuel-generated grid energy, which decreases urban air pollution and makes for healthier cities industry actors, policy makers and utilities to derive informed decisions. The model helps raise awareness for the category of sustainable energy solutions, and demonstrate what's being done with smart analytics to shape tomorrow's urban mobility. The proposed architecture aligns with SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action), helps to reach the global clean-energy goals, and accelerates society's transition to low-carbon mobility systems and energy systems.

3.3 Environmental Impact

The utilization of solar PV energy in EV charging not only helps to reduce carbon emissions by reducing the dependence on grid electricity generated with fossil fuels. 1 shows that the PV-first will discharge renewable energy whenever required, in order to make sure the environmental impact of EV charging activities is reduced. Integration of LCOE allows the environmental and economic performance of solar to be assessed over the long term, spurring investment in clean, low-carbon power.

Anatomically describes a model in which neither an oversizing nor an under-use of the PV plant is apparent and wastage energy does not take place, contributing to the responsible management of resources. Allowing renewable-based charging, the framework contributes to eco-friendly Workplace hubs and is in coherence with national renewable energy policies and international climate targets. The result is a more eco-efficient, stable and sustainable EV charging system.

3.4 Standards - if applicable

The envisioned system complies with global standards for smart energy and EV charging infrastructures. The design principles conform to the most relevant parts of IEEE 2030.7 for the standardisation of smart EV-charging systems and ISO 50001 regarding energy management best practices. Furthermore, the alignment with the Sustainable Development Goals (SDG 7 and SDG 13) also conforms to a global clean-energy and climate-protection context. These guidelines help ensure system inter-operability, operational reliability and long term scalability.

3.5 Project Management Plan

The development was accomplished in a phased approach with defined milestones. First, the data were collected, cleaned, feature engineered and explored to ready EV and PV datasets for machine learning. The second task was to develop and evaluate multiple ML/DL models for both EV demand and PV generation forecasts, along with being accelerated by using GPUs. Hyperparameter tuning, optimizer selection and early stopping strategies were used to achieve stable and accurate models. The third stage incorporated the best forecasting models in a PV-first schedule by scheduling charging of EVs through six 4-h long time slots with emphasis to renewable energy consumption rather than grid. The last stage performed scenario-based economic analysis for a Flat Rate and TOU tariff considering LCOE of solar power. Frequent progress monitoring and resource monitoring allowed early intervention, leading to the timely delivery of the work and successful achievement of project goals related to cost saving, renewable integration and sustainability.

3.6 Risk Management

There were several principal threats to validity when developing the EV–PV optimization framework in this study. Data discrepancies (i.e., missing, noise, and nonhomogenous timestamped data in both EVs and PVs) presented accuracy threats that were mitigated by comprehensive preprocessing and feature extraction. Model overfitting was also a key concern for all forecasting models applied on EV demand (LSTM, GRU, TCN, Transformer and Hybrid LightGBM+LSTM) and PV generation (Random Forest, Gradient Boosting, Decision Tree, Linear Regression, LSTM, GRU, TCN and Hybrid LightGBM+LSTM). This was counteracted through dropout, batch normalization and early stopping, in combination with a careful grid search on hyperparameters. Computational challenges (e.g., long training times, hardware constraints) were addressed with GPU acceleration and specialized training pipelines. Lastly, integration risks – due to the inclusion of EV forecasting, PV forecasting, PV-first scheduling and cost optimization based on a control at the tariff – were minimized with a modular architecture flexible for rigorous testing that helped guarantee stable behavior over time.

3.7 Economic Analysis

The sensitivity analysis shows that the developed EV–PV charging re-scheduling model gives practical real-world cost savings by minimizing the cost of routine workplace EV charging. Using very accurate predictions of EV charging demand and solar PV availability, the system will schedule charging sessions to optimise usage of low-cost solar energy and minimise use of grid electricity that is costlier. This predict-first PV-first approach results in significant short-term economic benefit, with 17–41% cost reduction for both flat and TOU tariffs. In real-world environments, such as offices, university campuses and corporate fleets, this reduces operating costs without the need to make any changes to existing infrastructure. The system also decreases onsite reliance on peak-hour grid electricity, enabling businesses to avoid costly TOU charges and take advantage of cheaper off-peak rates. The framework strikes a balance between utility due to time-shifting of renewable energy when possible and preventing wasteful spending through load-leveling. In summary, the scheme offers these economic benefits in a simple and efficient manner thus making it an attractive, deployable solution for EV charging in practice.

Chapter 4

Proposed Methodology

4.1 Design Process or Methodology Overview

The approach of this work is based on a systematic dual forecasting pipeline for prediction of EV charging load and solar PV generation with integrated PV first smart charging scheduling. Following extensive preprocessing and feature engineering such as including distance travelled, historical energy per km visitations and daily driving patterns in EV datasets and irradiance, temperature, wind speed and atmospheric heat changes in PV dataset. Many machine learning models were experimented for EV charging demand and PV generation forecasting. For EV charging demand prediction, we have experimented LSTM, GRU, TCN, Transformer Encoder and a hybrid LightGBM + residual LSTM model. For solar PV energy forecasting we experimented with Gradient Boosting, Decision Tree, LightGBM, Linear Regression, XGBoost and Random Forest along with the hybrid method of LightGBM with residual LSTM. Based on the comparison, we proposed the hybrid LightGBM with residual LSTM model for both EV and PV prediction as it leverage strength of LightGBM in capturing complex non-linear interactions with that of learning long range temporal dependency by LSTM leading to stable and accurate predictions. Subsequently, the forecasted EV demand and PV availability fed into a PV first smart charging scheduling algorithm based on a greedy allocation scheme. Behaviours regarding arrival and departure times were also examined to find how useful charging periods might be identified, or if charging windows can be matched with the availability of solar irradiation for example. With the use of this scheduling method, vehicles are allocated to six different four hour charging slots that are spread on four main chargers and one master charger. One important rule to follow is those vehicles which have highest predicted charging demand should have early priority and the user's most energy demanding cars are scheduled during the times of maximum predicted PV generation. The master charger serves vehicles with very low charging demands, so that small ones can be charged efficiently without affecting the scheduling strategy. This priority scheme enhances EV demand and PV available power matching, alleviates the dependence upon grid energy supply and mitigates charger usage fairness. Finally, the cost module compares under TOU, flat and LCOE prices in order to measure total cost savings. We believe that this comprehensive pipeline consisting model comparisons, hybrid forecast model adoption, demand aware PV-first scheduling and cost analysis is a well-optimized framework to manage EV & PV energy in an intelligent manner.

Figure 4.1: Proposed Data Preprocessing Workflow

4.2 Preliminary Design (Architecture) Specification

Two forecasting architectures were designed in this dissertation, one for EV demand forecasting and one for PV energy forecasting. For the EV demand forecast, the following machine learning/deep learning models were implemented: Random Forest, Gradient Boosting, Decision Tree, LightGBM, LSTM, GRU, TCN, and a combined hybrid LightGBM-LSTM architecture. The models trained on a 1-year dataset of travel distance, energy/km and temporal elements extracted from 50 EVs. The dataset was cleaned, standardized, had features constructed and subsequently split into 365-day sequences per car to align with its personal behavioral and temporal dependencies. The core of the final system was the Hybrid LSTM architecture, which relied upon sequentially trained features to make daily predictions with residual correction from the tree-based model. Similarly, the PV energy forecast relied upon a machine learning and data-driven statistical modeling approach by evaluating machines for Energy based on environmental variables (GHI, temperature, wind speed, pressure, sunlight hours, daylength): Random Forest Regressor, Gradient Boosting Regressor, LightGBM Regressor, LSTM while also implementing a seasonal sinusoidal solar-irradiance generation model to predict realistic sunrise-peak-sunset behavior across 96 intervals per day. This hybrid approach relies upon physically known patterns of solar output paired with trained learned distributions that can achieve higher resolution (15 minutes) than the stated intervals. Both architectures trained and validated through comparisons led to an optimized dual-model system for energy demand and generation prediction with the architectural visualizations found in the methodology shown in Figure 4.2:

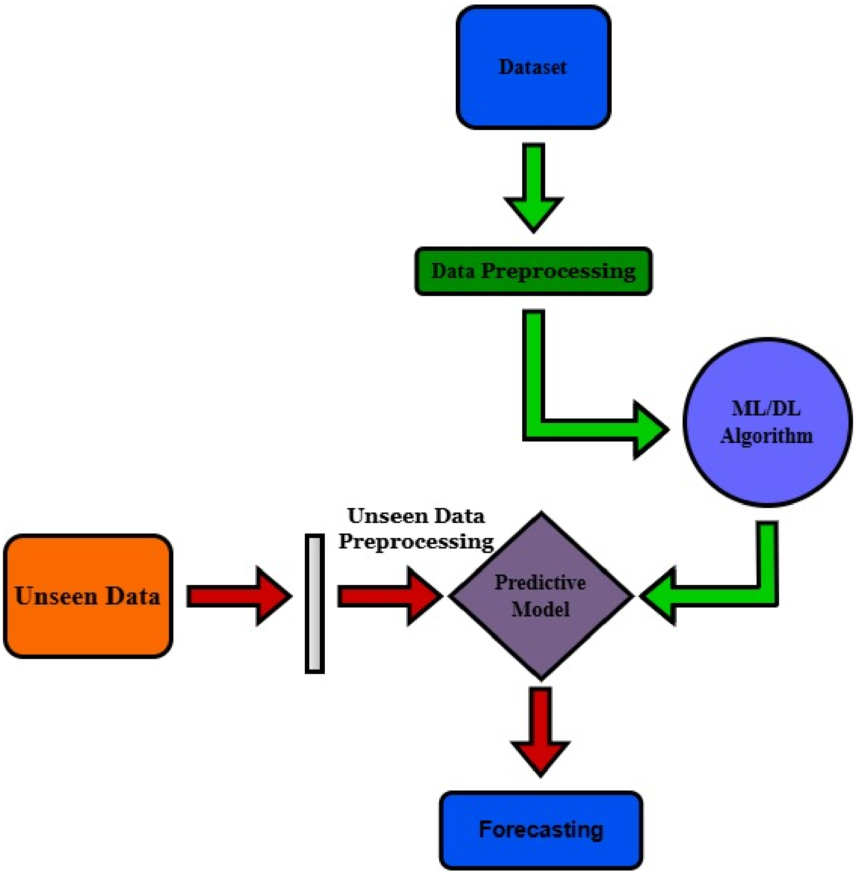

Figure 4.2: Proposed Methodology of Architecture

4.3 Dataset

4.3.1 Data Collection and Overview

4.3.1.1 EV Dataset

This dataset is generated by merging three of EV data sources - daily driving distances, workplace arrival slots and workplace departure slots each with 874 vehicles and 365 days of records in wide format. First, these wide tables were converted to long format so that each row now represents a single vehicle on a given day. Upon melting the datasets, in turn, these 3 long tables were joined together into one daily operational dataset with distance traveled and coded arrival/departure slots for every vehicle-day. Next, the slot numbers that correspond to 30-minute slots were translated into real clock times (in HH:MM format) for easy interpretation of data. Then these fine-grained data were matched with technical parameters of 50 electric vehicles in the CARS. xlsx we constructed based on [] that contains battery capacities, energy consumption rates, and driving ranges.This enhanced operation dataset was translated into 50 technical specifications of EVs sampled from CARS. xlsx, containing battery size, energy consumption per km and range. Assignment of the 50 EV models to the 874 vehicle indexes was achieved via a systematic matching process using real drive profiles. Maximum and average daily distances per vehicle, were estimated and used to estimate the daily energy demand of the vehicle based on the energy-per-kilometers rates. Every demand model from C was then contrasted against these estimated demands and the ”best” model was assigned to the vehicle whose average demand most closely matched its battery capacity. This reduced the gap between needed energy and accessible energy, so that for each specification model we could link it to a vehicle type where its actual use was plausible. A final mapping file contains matched vehicle ID, daily distances, estimated demand and battery difference match percentage for each of the 50 models. Then we calculated our EV charging demand using these equations. [10]

$$\text{EV Demand} = \text{Distance} \times \text{Energy per km}, \tag{4.1}$$

$$\text{Charging Demand} = \text{EV Demand} \times 0.9. \tag{4.2}$$

Using Distance to represent how many kilometers a vehicle travels each day (Distance) multiplied by the amount of energy consumed for every kilometer (Energy per km), as determined by the manufacturer's specifications; this computes the daily hours of usage for each vehicle (Total Daily Usage). Finally, this information (including the arrival time, departure time, and energy efficiency) provides the final dataset, which includes the total amount of energy required to charge each electric vehicle and is used in the energy optimization and/or charging strategy process.

4.3.1.2 PV Dataset

The second major component of this study, and therefore an integral part of the forecasting of renewable energy availability for supporting cost effective EV charging, is the Photovoltaic (PV) dataset. Due to the variability of solar energy output as a result of varying atmospheric and environmental conditions, detailed time series data must accurately reflect the effects of these constantly changing conditions on solar generation outputs. Consequently, time series data of weather changes, sunlight availability, and irradiance levels is included in the PV dataset used in this research. The dataset for PV was collected from Kaggle, combining Renewable Power Generation and Weather Conditions datasets , covering 196,776 observations at a frequency of 15 minutes. This extensive temporal coverage encompasses several seasonal cycles, weather patterns, and diurnal variations to build robust forecasting models. One important variable in this dataset is Energy delta [Wh], which represents the amount of solar energy produced over relatively short time periods (e.g. 15 minute intervals). This gives the model a fine-grained modeling of solar production and allows it to identify very short term changes in solar production, such as when clouds suddenly cover the sun or the amount of sunshine hits a specific surface area increases. The GHI (Global Horizontal Irradiance) variable is also included in this dataset. GHI is the biggest determinant of the amount of solar PV output produced from solar energy since it measures the total solar radiation received at a horizontal surface and directly correlates with generating capability.

4.3.2 Data Preprocessing

The first step in preparing Data for Deep learning is to prepare the Data through Process Data Pre-Processing, which includes the refinement of un-prepared Data (refining of Data) until it is ready for Analysis(s) or Model(s) training. To keep Models valid and accurate, Data Quality should be prioritized because Data Quality has a very large effect on how well the Model(s) perform. By Organizing Data for Analysis or Machine Learning (ML), you will increase the quality and relevance of results produced from your Model. In Figure 4.3, you will see the Simulation Approach to Data Preparation.

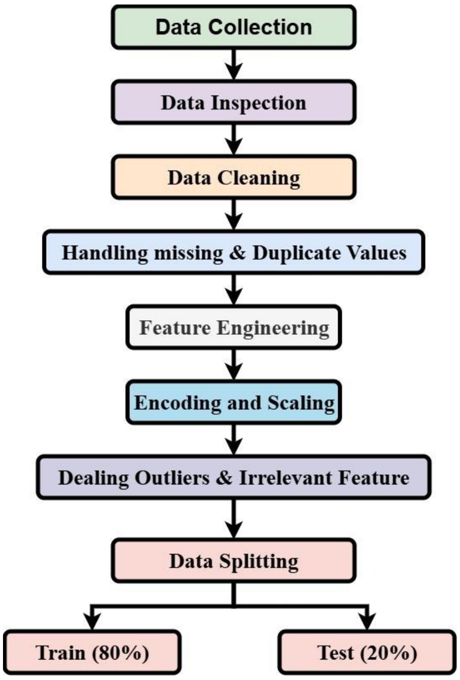

Figure 4.3: Proposed Data Preprocessing Workflow

4.3.3 Data Loading and Initial Exploration

Loading the dataset into memory is one of the first steps in preparing a dataset for future analysis, known as pre-processing the dataset. This step is foundational because it allows you to perform additional analyses and feature engineering based on the loaded dataset. The dataset used for this research is named Final.csv, and it contains extensive data regarding electric vehicle (EV) charging demand and many of the features that relate to it. The features included within the dataset include vehicle-specific information, the total daily charging demand, energy consumption associated with EV charging, all of the times associated with charging. All of the items listed above are important for developing strategies that will optimize the amount of energy used for EV charging. After loading the dataset into memory, the next step is to perform an exploratory data analysis (EDA) of the dataset. Conducting an EDA helps the reader to understand the structure and components of the dataset to gain insight into its potential problems. The exploration also enables you to identify any motivations and justified reasons for any dataset deficiencies (missing or incomplete data), any inconsistencies within the dataset, or the presence of extreme values (outliers) that may impact your modelling performance as you build your models using the dataset. The first step to performing an EDA is to observe the shape of the dataset (i.e., how many rows and columns), which provides us with a general idea of how much information (data) is contained in the dataset. Each row typically represents an individual data point, and each column corresponds to a specific feature or variable. The shape provides a first glance at how large the dataset is and how many attributes (or features) we are working with. It also allows us to confirm whether the dataset aligns with expectations, especially in terms of dimensions. Figures 4.4 and 4.5 depict an overview of the dataset.

```
                         Car_model   Days  Distance arrival_time  \
0  Lucid Gravity Grand Touring (MY26)   Day1        25        08:30
1  Lucid Gravity Grand Touring (MY26)   Day2        10        08:00
2  Lucid Gravity Grand Touring (MY26)   Day3        10        08:30
3  Lucid Gravity Grand Touring (MY26)   Day4        40        10:00
4  Lucid Gravity Grand Touring (MY26)   Day5        15        06:30
5  Lucid Gravity Grand Touring (MY26)   Day6        70        08:30
6  Lucid Gravity Grand Touring (MY26)   Day7        10        09:00
7  Lucid Gravity Grand Touring (MY26)   Day8        30        10:00
8  Lucid Gravity Grand Touring (MY26)   Day9        10        08:30
9  Lucid Gravity Grand Touring (MY26)  Day10        85        06:30

  departure_time  Energy_per_km_(kWh/km)  EV_demand  Charging_demand
0          09:00                  0.1968      4.920         5.466667
1          09:00                  0.1968      1.968         2.186667
2          17:30                  0.1968      1.968         2.186667
3          16:30                  0.1968      7.872         8.746667
4          15:00                  0.1968      2.952         3.280000
5          17:00                  0.1968     13.776        15.306667
6          09:30                  0.1968      1.968         2.186667
7          16:30                  0.1968      5.904         6.560000
```

Figure 4.4: EV Dataset

Time	Energy del	GHI	temp	pressure	humidity	wind_spee	rain_1h	snow_1h	clouds_all	isSun	sunlightTir	dayLength	SunlightTir	weather_t	hour	month
########	0	0	1.6	1021	100	4.9	0	0	100	0	0	450	0	4	0	1
########	0	0	1.6	1021	100	4.9	0	0	100	0	0	450	0	4	0	1
########	0	0	1.6	1021	100	4.9	0	0	100	0	0	450	0	4	0	1
########	0	0	1.6	1021	100	4.9	0	0	100	0	0	450	0	4	0	1
########	0	0	1.7	1020	100	5.2	0	0	100	0	0	450	0	4	1	1
########	0	0	1.7	1020	100	5.2	0	0	100	0	0	450	0	4	1	1
########	0	0	1.7	1020	100	5.2	0	0	100	0	0	450	0	4	1	1
########	0	0	1.7	1020	100	5.2	0	0	100	0	0	450	0	4	1	1
########	0	0	1.9	1020	100	5.5	0	0	100	0	0	450	0	4	2	1

Figure 4.5: PV Dataset

4.3.4 Data Cleaning, Handling Missing Duplicate Values

One of the techniques used in data cleaning was the filling of missing values. As an example, media was utilized to fill in continuous variables like price and units sold so that a missing value would not cause the loss of non-existent values. In the case of categorical variables such as region and car model, mode was used to represent the common variables. Besides that, values were changed with the car model or days, which should not have had any negative impact on the relationship. Both the dups were detected and removed not only by deleting the duplicate but also by combining it with that part of the context which contributes to the numerical values (e.g., mean or sum) and replacing nominal values with those that occur most frequently. The primary goal at this stage was to ensure that the data remained unbiased, thus becoming more friendly to the machine learning models Moreover, encoding together with feature scaling was also performed to increase the scaling of the features of the numerical data. Categorical variables in machine learning models, such as ca model, can be better utilized after they have been encoded.

4.3.5 Feature Engineering

Feature engineering is one of the most important data preprocessing steps in developing machine learning models. In feature engineering, the aim is to create new features from the ones that are already in the dataset, which gives better insights and improves the predictive ability of the model. In the context of this project on energy cost minimization for EV charging, feature engineering is crucial to prepare the dataset for time-based and cyclical information, as well as seasonal variability. Below, I describe how new features are derived from the existing dataset and the mathematical transformations of these features to improve the model's understanding of the data.

4.3.5.1 Time-Related Features

The dataset consists of all vital time-based details, including the arrival and departure times of each EV at the charging station. However, the raw time data is not in a favorable form for machine learning models, which prefer numbers; therefore, in the form of hours and minutes, it is not directly useful. Then, the machine takes these time-related features and transforms them into more meaningful and computationally friendly formats.

- Splitting Time into Hours and Minutes: Arrival and departure times, which are in "HH:MM" format, are separated into two columns showing hours and minutes. Granular representation of time enables the machine model to work with both aspects of time.

- Conversion to Total Minutes: After separating the time into hours and minutes, total time for arrival and departure is expressed in minutes. Total minutes are calculated using the following equation 4.3:

  $$\text{Total Time} = (\text{hours} \times 60) + \text{minutes} \tag{4.3}$$

  This converts the time into a continuous variable (in minutes), which is more suitable for machine learning algorithms. As an example, the departure time of "03:30" has been changed to "210 minutes after midnight", so that it is easier for the model to use this information to make predictions about future trips.

- Parking duration: The parking duration is an important variable to consider because it will determine how long the EV will be charged at the charging station. The parking duration can be computed by taking the difference between the departure and arrival times. In most instances,(4.4),

  $$\text{Parking Duration} = \text{Departure Time (total)} - \text{Arrival Time (total)} \tag{4.4}$$

  However, a special case is when the departure time crosses midnight. In such cases, we account for the wrap-around by adding 1440 minutes (equivalent to one full day) to the result if the parking duration is negative. This ensures that the parking duration is always a positive value (4.5).

$$\text{Parking Duration} = \begin{cases} \text{Departure Time (total)} - \text{Arrival Time (total)}, & \text{if positive,} \\ \text{Departure Time (total)} - \text{Arrival Time (total)} + 1440, & \text{if negative.} \end{cases} \tag{4.5}$$

4.3.5.2 Cyclical Features

All time-related features are inherently cyclical, such as the hour of the day representing arrival or departure time. The hour of 23 is closer to 0 than it is to 12, yet all numerical values are treated equally when it comes to machine learning algorithms, therefore failing to capture such a cyclical relationship. To handle these types of features, we apply cyclical encoding using sine and cosine transformations. Using this kind of encoding method, we map the circular data-for example, time, days of the week, etc, into continuous numerical values, making sure the model captures the fact that this is data with a circular relationship.

For instance, for the total arrival time (in minutes), we perform the following transformations 4.6 and 4.7:

$$\text{arrival\_time\_total\_sin} = \sin\left(\frac{2\pi \times \text{arrival\_time\_total}}{1440}\right) \tag{4.6}$$

$$\text{arrival\_time\_total\_cos} = \cos\left(\frac{2\pi \times \text{arrival\_time\_total}}{1440}\right) \tag{4.7}$$

The denominator 1440 represents the total number of minutes in a day (24 hours × 60 minutes). By using these transformations, the model will be able to understand that hour 23 and hour 0 are essentially close to each other, and similarly for other time-related features.

4.3.5.3 Calendar Features

In addition to the direct time-related features, we also derive several calendar-based features to capture the seasonal and weekly variations in charging behavior and energy consumption. These features help the model account for patterns that depend on the time of year, the day of the week, or whether it's a weekend.

- Day of the Week: The day of the week is extracted from the day number (from Day 1 to Day 365). This is represented as a numerical value (0 for Monday, 1 for Tuesday, ..., 6 for Sunday). This helps the model understand weekly charging patterns, as behavior can differ from weekday to weekend (4.8).

  $$\text{day\_of\_week} = (\text{day\_number} - 1)\%7 \tag{4.8}$$

  We also create a binary weekend flag, indicating whether a particular day is a weekend (Saturday or Sunday).

- The week of the year, which is determined by the day number in conjunction with the year, indicates which week of the year this observation falls within, and will help identify patterns or trends occurring over multiple weeks that may be impacted by changes from one week to another (4.9).

$$\text{week\_of\_year} = \left\lfloor \frac{\text{day\_number} - 1}{7} \right\rfloor + 1 \tag{4.9}$$

- Month of the Year: The month feature is derived from the day number, where months are mapped to the appropriate days in a non-leap year. For example, Day 1 to Day 31 would fall in January, and Day 32 to Day 59 would correspond to February. The conversion of day number to month is calculated using the cumulative sum of days in each month (4.10).

$$\text{month} = \text{np.searchsorted}(\text{cum\_days},\ \text{day\_number}) + 1 \tag{4.10}$$

- Quarter: The quarter of the year is determined based on the month. For example, months 1-3 represent Q1, months 4-6 represent Q2, and so on (4.11).

$$\text{quarter} = \left\lfloor \frac{\text{month} - 1}{3} \right\rfloor + 1 \tag{4.11}$$

- Season: Based on the month, we can categorize the data into seasons: Winter (December, January, February), Spring (March, April, May), Summer (June, July, August), and Autumn (September, October, November). This can be encoded using the following function 4.12:

$$\text{Season Encoded} = \begin{cases} 0, & \text{for Winter,} \\ 1, & \text{for Spring,} \\ 2, & \text{for Summer,} \\ 3, & \text{for Autumn.} \end{cases} \tag{4.12}$$

4.3.5.4 Cyclical Calendar Features

Much like time-related data, calendar features like day of the week, month, and season exhibit cyclical behavior. For instance, month 12 (December) is closer to month 1 (January) than it is to month 6 (June). To account for this cyclical nature, we use sine and cosine transformations for calendar features as well, similar to how we handled time-related features.

For example, for day of the week, we apply equtions 4.13 and 4.14 :

$$\text{dow\_sin} = \sin\left(\frac{2\pi \times \text{day\_week}}{7}\right), \tag{4.13}$$

$$\text{dow\_cos} = \cos\left(\frac{2\pi \times \text{day\_week}}{7}\right). \tag{4.14}$$

4.3.6 Categorical Encoding

This step is aimed at encoding the categorical variables that are present in the dataset. The vehicle model column is one of the categorical variables that represent the identification of each vehicle. However, the numerical machine learning models require all categorical variables be converted into numbers, especially the models that rely on numerical data. Therefore, the car characteristic is a nominal one and necessitates coding in a manner that is acceptable to machine learning. Actually, the label encoding method is very simple, and that is what we are doing right now. In label encoding, all the categories are assigned a number. To clarify the example, let's say we take a situation of 50 car models, then label coding will be 0 to 49 to represent each of the 50 car models. The nature of such encoding not only places the individual models under different categories, it also tells the machine learning model of the difference when two models are compared in terms of numbers. The car model labeling system converts the various car models into numbers that can be easily fed into the machine learning algorithm. During the transition, the data is assimilated by the model, which starts processing the car model as one of the input factors along with the others.

4.3.7 Dealing With Outliers & Irrelevant Features

The outliers' factors and redundant column factors are also important factors that should be taken into account in the research and introduction of the model, respectively. Strict outliers cannot be eliminated by merely disregarding them but put into perspective to make one conscious of their position as a plausible variation, errors or abnormal yet informative events. This can be accomplished through the following processes, such as transformations, strong scaling or capping (winsorizing) in such a way that the outliers would not affect the analysis but they would be a picture of the exceptional cases to some extent. Equally, the domain knowledge, as well as the algorithm of the feature selection that encompasses the association analysis, mutual information, and recursive feature removal, are also applied to detect the inapplicable features. It is also possible to offer such techniques as PCA that will allow achieving this dimensionality reduction, to keep the important variables and drop the insignificant ones. Having a suitable control mechanism of the outliers and the irrelevant columns, we reduce the noise of the data, the easily interpretable predictive model, and the overall performance of the modeling. In Figure 4.6 depicts correlation heatmap of features.

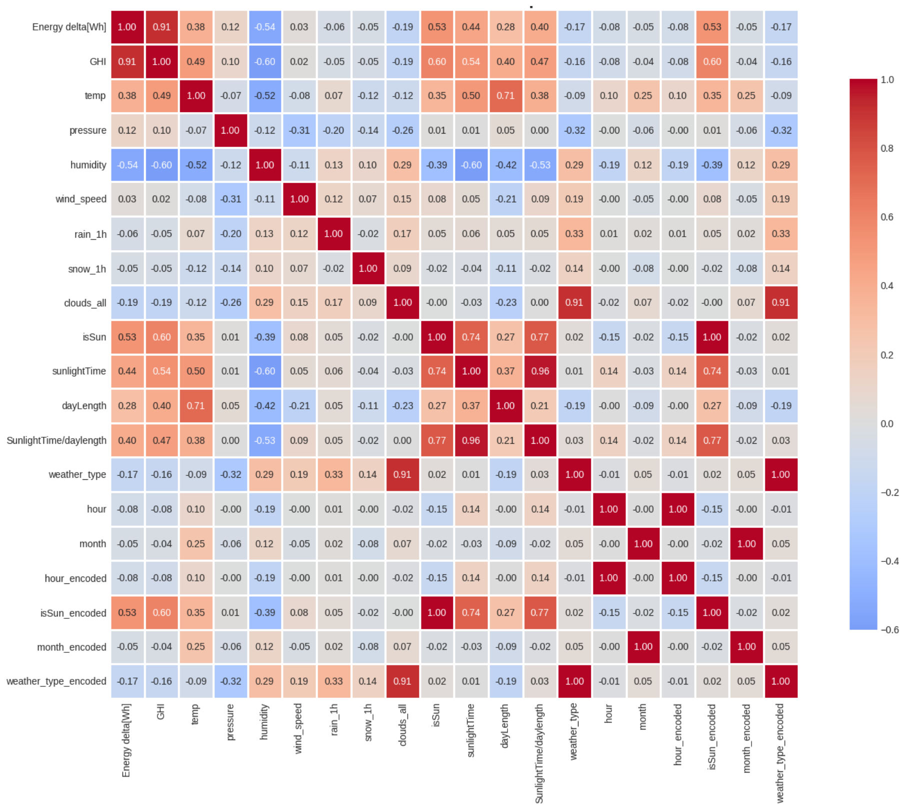

Figure 4.6: Correlation Heatmap of Features

4.3.8 Feature Scaling

Scaling the data is an important process in getting the dataset in shape to train a machine learning mode, which are scale-sensitive to the input features. The features are scaled to a range of 0 to 1 through Min-Max scaling so that the fluctuations are maintained uniform across features. Scaling is done so that all features have a similar impact on the learning of the model. With the order of magnitude difference in trading volumes and stock prices, not scaling the features would result in problems where features with larger numeric values overwhelm learning and end up building a biased model. Scaling all the features to the same range normalizes them, and this enhances the model's performance, accelerates convergence during training, and protects against problems caused by gradients. There are certain standardization techniques provided in the Standard Scalar of the library scikit-learn.
The Z-score is defined as equation 4.15:

$$z = \frac{x - \mu}{\sigma} \tag{4.15}$$

where z is the standardized value (Z-score), x is the individual data point, μ is the mean of the data, and σ is the standard deviation.

The mean μ is given by equation 4.16:

$$\mu = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{4.16}$$

where μ is the average of the data, N is the number of data points, and x_i represents each individual data value.

The standard deviation σ is given by equation 4.17:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{4.17}$$

where σ is the standard deviation, x_i is each data point, μ is the mean, and N is the total number of data points.

4.3.9 Data Splitting for Model Training

Before training a machine learning model, it is essential to split the dataset into training and testing sets. This ensures that the model is trained on one portion of the data and evaluated on another portion that it hasn't seen during training. The splitting is done randomly, with 80% of the data used for training and 20% reserved for testing. This step helps in evaluating the model's generalizability and ensures that the model does not overfit the data. In Figure 4.7 depicts data distribution.

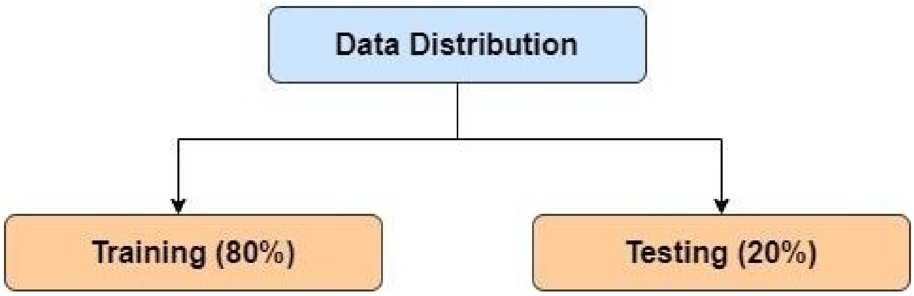

Figure 4.7: Data Distribution

4.4 Model Architecture

4.5 Hybrid Model

4.5.1 Overview

The proposed hybrid LightGBM-LSTM model represents the most robust and accurate forecasting framework established in this research work. This hybrid framework is mutually enhancing in nature due to the excellence of both competent learning approaches. On the one hand, LightGBM excels at feature-oriented complex non-linear characteristics extraction; on the other, LSTM shows tremendous strength for temporal dynamics of sequential modeling. For this hybrid structure, the first learner is LightGBM, operating as a feature-oriented local characteristic extractor. It learns the complex interactions between quasi-static features and engineered features that are a combination of vehicular usage features, temporally driven features, and spatial features. Therefore, the LightGBM output will represent an early baseline prediction, effectively capturing many considerable non-linearities but, as a single model, may still not capture significant sequenced structures over time. To compensate for this limitation, a secondary learner LSTM is learned as a residual on top of the predicted error from LightGBM. The secondary LSTM learns on the temporal development of the remaining residuals. Thus, it learns minor long-range events and temporally driven dynamics that tree-based approaches cannot. Therefore, the hybrid model becomes a unified prediction solution where LightGBM learns and predicts based on feature-driven dynamics. Still, LSTM supplements its accuracy by learning from a temporal perspective. For EV demand and solar PV energy forecasting, this two-stage approach will achieve the highest levels of prediction accuracy with the least prediction residual variabilities over time because it can effectively predict both through the non-linearity driven characteristics and the patterned sequential behavior.

4.5.2 Model Setup

Training the Hybrid workflow begins with the training of LightGBM on the EV dataset to create base predictions. Residuals (True Value - Predicted Value) from the LightGBM model are then trained as targets for the subsequent LSTM residual model. The LSTM residual predictor includes one or more layers with Dropout and Batch Normalization to promote the robustness of learning from the error structure. The final prediction is created by summing the predictions from the LightGBM and the corrected predictions from the LSTM residual model. The use of a two-stage architecture promotes both higher accuracy and better model stability.

4.5.3 Architecture

The Hybrid LightGBM–LSTM model used in this study is a two-stage forecasting architecture that leverages the strengths of tree-based boosting algorithms with deep recurrent neural networks toward highly accurate predictions for both EV charging demand and PV energy. First, the architecture consists of a LightGBM base learner modeling the nonlinear relationships among static and engineered features such as distance driven, energy-per-km and environmental attributes. LightGBM constructs an ensemble of decision trees through gradient boosting whereby each tree tries to minimize residual error of the previous tree. Mathematically, LightGBM optimizes an objective function as shown in equation 4.18:

$$L = \sum_{i=1}^{N} l\Big(y_i, \hat{y}_i^{(t-1)}\Big) + f_t(x_i) + \Omega(f_t) \tag{4.18}$$

where $l(\cdot)$ is the loss function (MSE), f_t is the newly added tree at iteration t, and Ω is the regularization term penalizing model complexity. After LightGBM is fully trained, the model generates initial predictions $\hat{y}_{\text{LGBM}}$ and computes the corresponding residual errors as shown in eqation 4.19.

$$r_i = y_i - \hat{y}_{\text{LGBM},i} \tag{4.19}$$

The residuals represent the time-series aspects not recognized by LightGBM: the very long-term shifts in time and the dependencies between the sampled points in the sequence. To remedy such mistakes, a Residual LSTM Network is proposed at the second level of the hybrid architecture that is specifically trained to become acquainted with the residual structure as time goes by. The LSTM part consists of three recurrent layers stacked one above the other with 256, 128, and 64 units respectively, with each layer subjected to Batch Normalization and Dropout (0.3) as a regularization technique that maintains the stability of the training process and helps fight overfitting. The core gating equations for the respective LSTM layers are as follows from eaquation 4.20 to 4.25:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i), \tag{4.20}$$
$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \tag{4.21}$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), \tag{4.22}$$
$$\tilde{C}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c), \tag{4.23}$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, \tag{4.24}$$
$$h_t = o_t \odot \tanh(C_t). \tag{4.25}$$

where i_t, f_t, and o_t denote the input, forget, and output gates; C_t is the cell state; and h_t is the hidden state. These equations allow the LSTM to retain long-range temporal information— a capability absent in tree-based methods. The final LSTM output is passed through a Dense layer with linear activation to predict the corrected residual sequence $\hat{r}_t$.

The final hybrid prediction is computed as shown in equation 4.26 :

$$\hat{y}_{\text{Hybrid}} = \hat{y}_{\text{LGBM}} + \hat{r}_{\text{LSTM}} \tag{4.26}$$

Thus, this additive merger enables the LSTM to adjust for LightGBM's predictions by modeling some temporal dependencies (charging behavior over days, seasonal variations in PV and cyclic patterns) that a boosting model cannot learn.

In the EV charging demand forecasting process, LightGBM uses more static and engineered features (distance, energy consumed per km), whereas the LSTM adjusts for sequential patterns. The PV prediction setup utilizes LightGBM to model the complex relationship between weather variables and energy production (e.g., GHI, temperature, pressure, wind speed) and an LSTM to capture solar cycles on a day-by-day basis as well as transition from sunrise to sunset and the periodic changes of irradiance throughout each season; together these architectures produce a model that is very robust and have lower variance than single architectures for predicting energy production for previously unseen days. The hybridization avoids the main disadvantages of each model when alone; LightGBM compensates for the computational expenses and scaling sensitivity of LSTM whilst LSTM compensates for the sequential structure learning deficit of LightGBM. Thus, the Hybrid LightGBM+LSTM is superior to all machine learning and deep learning models implemented in this research, as it is the strongest forecasting model for EV demand forecasting and PV energy generation. Figure 4.8 shows the Hybrid model architecture.

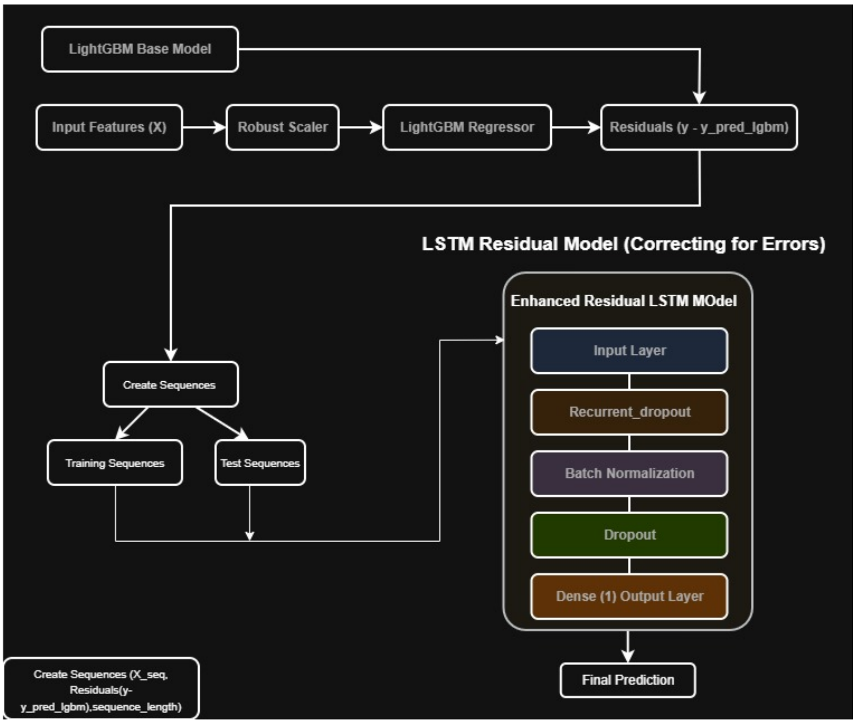

Figure 4.8: Architecture of Hybrid Model

4.5.4 Advantages Disadvantages

The Hybrid Models greatest benefit is the combined learning capabilities it has, i.e., LightGBM's ability to model non-linearity and LSTM's ability to capture temporal dependency. The two-stage nature of the model helps to reduce both over-fitting and underfitting, resulting in significant improvement in prediction accuracy. The Hybrid Model performs extremely well on EV datasets and also performs well for PV forecasting dataset. A disadvantage of the Hybrid Model is that it is more complicated than single-stage architectures and requires careful training in each stage. In addition, the Hybrid Model is slower to train than traditional machine learning models; however, it is significantly more accurate and stable when predicting sequences of varying lengths.

4.6 Implementation of Selected Design

This operational EV-PV integrated charging system has been developed by following a series of successful multi-layered implementations using a combination of predictive analytics, renewable energy forecasts, and smart scheduling as the foundation for all aspects of the system, in order to provide a single interface through which to dynamically match the anticipated generated solar energy to the anticipated daily rechargeable amount of energy required on a daily basis for each electric vehicle in the entire fleet, therefore decreasing both dependence on grid electricity and allowing for timely deliveries of every electric vehicle based on expected timelines.

The process of developing the system took place over a number of interdependent phases: the initial phase included the design/development of a fully functional predictive model

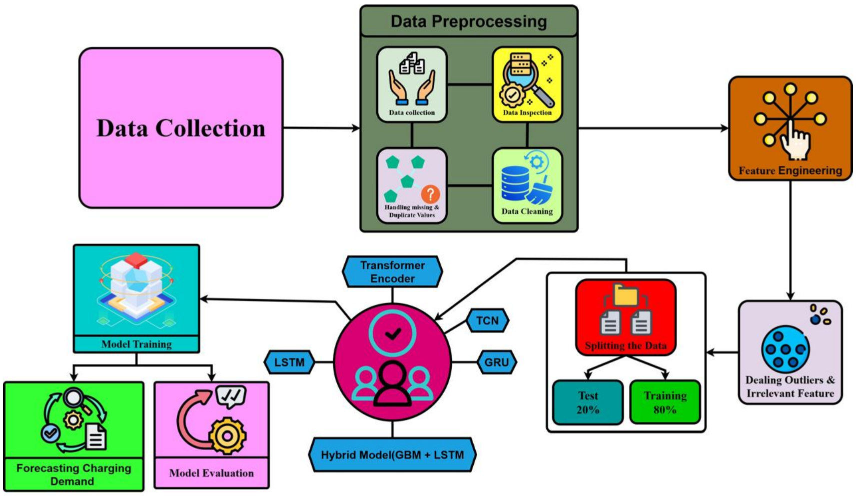

Figure 4.9: EV charging demand forecasting workflow

that would accurately forecast the amount of demand placed on the electric vehicle charging market for an electric vehicle charging station. Once completed, the predictive model served as the basis for all subsequent phases of the implementation process, including the design/development of a complete suite of advanced deep learning algorithms, such as Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU), Temporal Convolutional Network (TCN), Transformer Encoder, and Hybrid Model, which were thoroughly trained and tested to identify which algorithm would yield the most accurate electric vehicle charging demand forecasts. The LightGBM + LSTM architecture was the best performing out of all the different machine learning models tested using a sliding window forecasting methodology. It was able to capture long-term dependencies and recurring daily patterns of behavior better than the other architectures due to its gated mechanisms to uniquely store the previous state of the model. It also had the lowest RMSE, MSE, and R-squared compared to the other models tested, making it the best performing forecasting engine in the system.

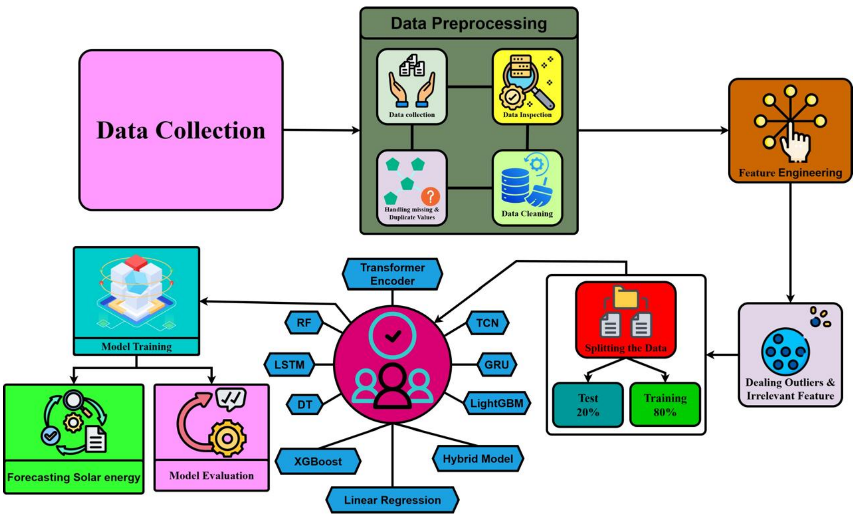

Figure 4.10: Solar PV energy forecasting workflow

A parallel forecasting engine was developed to predict solar PV output because it is an important input for solar-priority charging. The data input required for the solar generation prediction was obtained by testing a number of machine learning models on how to best model the relationship between several environmental factors (GHI, temperature, and wind speed) and the amount of energy produced. We have used multiple models for solar PV energy forecasting such as Decision Tree, Random Forest, XGBoost, Linear Regression, LSTM, TCN, GRU. And then the Hybrid Model was selected due to its ability to accurately generalize across different types of weather and the fact that it did not show signs of overfitting when tested using an extensive amount of data. By generating 15 minute timeframes of solar energy predictions, this model supplied critical data for the scheduling algorithm to allocate charging sessions at peak times of renewable energy generation. The Conflict-Aware PV First Charging Scheduler was at the heart of the system's intelligence and was the "brain" of day-to-day operations for converting forecasts into chargeable or discharging plans. It was a combined tool that used the day be fore's forecasts for EV charging needs and solar power production for a day. During the comparison of forecasts of solar energy provided for a fifteen-minute time segment, the scheduler verified whether the predicted level of solar energy was capable of achieving the changing needs of the EVs. The first step was to schedule charging sessions to maximize solar usage during times of abundant solar power. The algorithm was developed to account for various factors affecting charging sessions including the conflictual constraints of the number of charging stations and specific arrival-departure times. When conflicts emerged as a result of concurrent EVs wanting to charge during periods of abundant solar power, fairness and use-maximized approaches to scheduling were employed to develop equitable results for distribution of PV. The system took into account when forecasts predicted a shortfall in solar generation and blended PV energy with grid power for periods of time on days that were forecasted for shortfalls of solar generation. When necessary, including overnight charge times, vehicles were recharged solely from the grid, provided that the time that the vehicle would be parked was within the available window. This allowed for an accurate determination of the level of dependency on grid power for the next 24 hours. The complete cost analysis module was created to calculate the total economic impact of all of the scheduling decisions made in this process. This module took the final charging schedule and mapped back through each scheduling period to identify the energy sources of each vehicle's charging for each of the identified time periods as divided between solar energy and grid energy. The cost of solar energy was based on the levelized cost of solar energy, while grid energy cost was determined based on time of day using the TOU structure of electricity pricing. The analysis of the total cost to operate the vehicles demonstrated that by implementing a PV-first strategy and using intelligent scheduling software to match charging loads to solar production, the total electricity cost would be significantly less than if the vehicle had been charged uncontrolled from the grid without matching to a baseline scenario of total grid energy consumption. To summaries this section of the report, the design has brought together methodology and operational policies into a cohesive system to yield a practical solution to implementing smart charge infrastructure (real-world convergence), one that is also economically viable and environmentally friendly, providing a scalable model for future implementation.

Chapter 5

Result Analysis

5.1 Comparative Analysis

The overall comparison of all the models for forecasting both EV Charging Demand and PVEnergy indicates that Hybrid LightGBM-LSTM gives balanced and reliable performance in all scenarios. The other single models, including LSTM, GRU, TCN, and Transformer, show great learning capacity, but their behaviors with respect to overfitting, stability, and generalization vary. The traditional machine learning models, including LightGBM, Random Forest, Gradient Boosting, Decision Tree, and Linear Regression, often report competitive performance by R-squared but higher MSE/RMSE and are less robust against noisy or highly nonlinear temporal patterns. For example, in forecasting EV charging demand, most deep learning models, such as LSTM, GRU, and TCN, have smoother learning curves; they provide proper capturing of temporal dependencies. The Hybrid LightGBM–LSTM model combines LightGBM's strengths in modeling nonlinear feature interactions with the strengths of LSTM in correcting residual temporal errors. It balances the bias-variance tradeoff with no significant overfitting, a very stable residual distribution, and better interpretability. Besides, hybrid LightGBM–LSTM achieved 99.6% coverage in the Confidence Band Analysis, and the Q-Q plot-residuals confirmed the normality of the error distribution with reduced structural bias. Although its accuracy is only slightly better than classical models, its robustness and error-correction capability make it the most reliable one for operational demand forecasting. In addition to PV, there are other similar hybrid modeling approaches that have been used in the solar energy/research domain. The hybrid models in each domain appear to allow for much greater adaptability compared to LSTM, GRU and TCN. While the LSTM and GRU models can provide a reasonable level of prediction accuracy, they also appear to have more variability with respect to their predictions due to the inherent unpredictability caused by weather. Regarding classical models, the performance of Random Forest and Gradient Boosting was strong according to the R^2 metric, while the MSE and RMSE were larger because they failed to capture the sequential temporal pattern. In contrast, the Hybrid LightGBM–LSTM model provides the most optimized and stable forecasts with residuals being more structured and narrower prediction intervals. Extreme error occurrences are also reduced. Residuals within a confidence interval analysis and Q-Q plot evidence well-behaved residuals without heavy-tail deviation, which confirms excellent generalization on unseen environmental conditions. Within both forecasting domains, the Hybrid LightGBM–LSTM shows the best balance between predictive accuracy, reliability, computational efficiency, and interpretability. It avoids overfitting tendencies of deep neural networks while mitigating the bias and rigidity of more traditional ML models. This turns it into the most effective, optimized, and operationally suitable model in real-world EV-PV integrated energy management systems. In Figures 5.1 and 5.2 show all model comparisons.

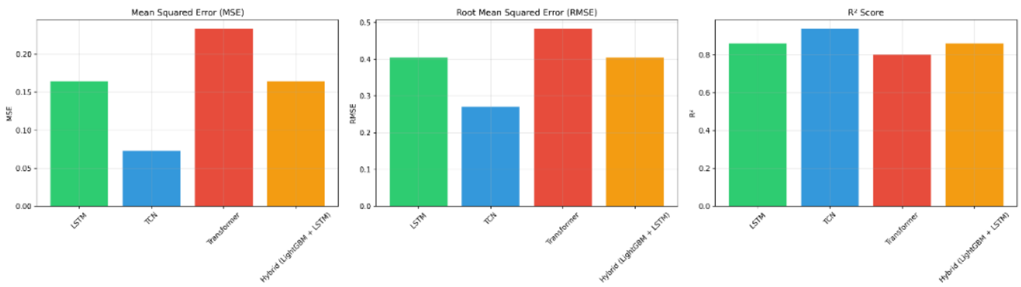

Figure 5.1: Comparison of All Model (EV)

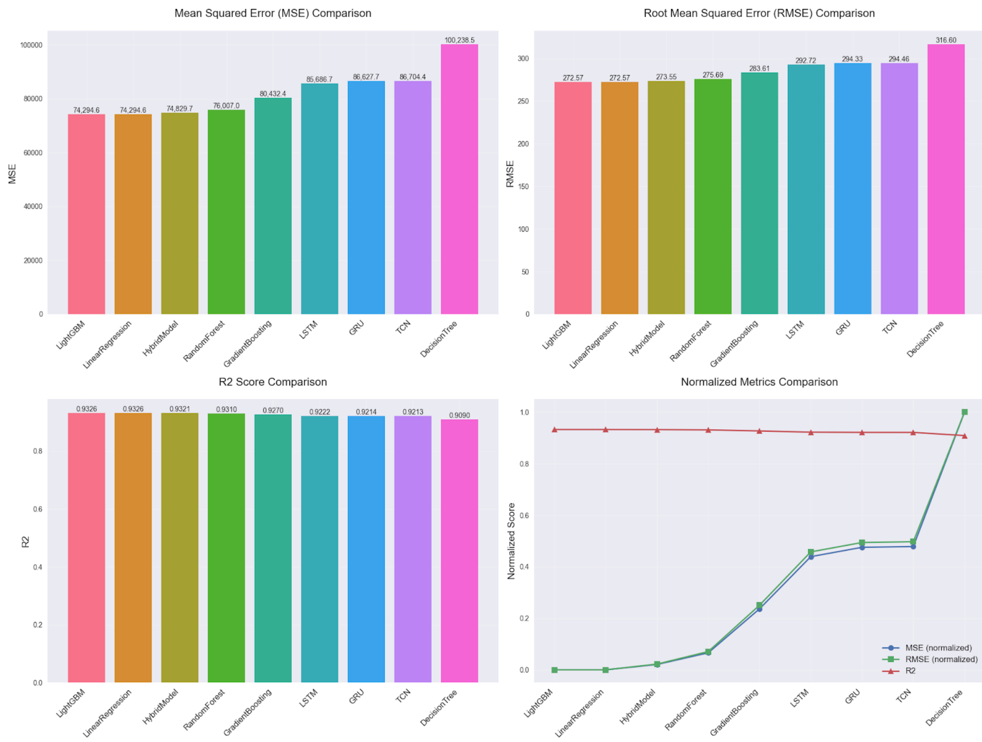

Figure 5.2: Comparison of All Model (PV)

5.2 Experimental Settings and Hyperparameter Configuration

The experiments for this study were structured in certain experimental conditions that made the evaluation of all forecasted models for both EV Charging demand and PV Energy assessed fairly, reproducible and optimal. All models were trained on preprocessed and scaled datasets with a training/test dataset split of 80% training, 20% testing. For feature scaling, if needed, StandardScaler was used for neural networks and then

RobustScaler/StandardScaler for tree-based models. For categorical encoding, LabelEncoder was used; for temporal encoding, a cyclic transformation into numbers. All models were trained under NVIDIA GPU-accelerated hardware although tree-based algorithms also permit CPU computation. Training of all models is the same in terms of the Adam optimizer with Mean Squared Error loss function. Early stopping was implemented to prevent overfitting with a patience of 10 epochs with validation monitored. The batch size was ranged from 16 to 64 across models with epochs between 50 and 200 based on visualized convergence. In addition, Dropout (0.2 to 0.3) and Batch Normalization were utilized in all recurrent and convolutional models to regularize efforts and stabilize training. Fixed sequence length is 5 historical timesteps. Random Forest, LightGBM, Gradient Boosting and Decision Tree implemented extensive manual incremental tuning for hyperparameters. LightGBM uses a gbdt boosting type, 2000 estimators and a slow learning rate of 0.01 while Random Forest uses 200 trees with max depth 20; Gradient Boosting uses 100 estimators with a moderate learning rate of 0.1; a Decision Tree was used with max depth 15 to prevent overfitting. The proposed Hybrid LightGBM-LSTM model was trained in two stages:

1. The LightGBM baseline model trained nonlinear relationships between features and target
2. an LSTM residual model was trained on the prediction errors of LightGBM to correct sequential patterns that LightGBM alone could not capture.

The final output was computed as equation 5.1,

$$\hat{y}_{\text{final}} = \hat{y}_{\text{LightGBM}} + \hat{y}_{\text{residual\_LSTM}}, \tag{5.1}$$

which improved temporal representation while preventing overfitting.

All experiments applied consistent procedures for model evaluation, including RMSE, MSE, R^2 Score, uncertainty metrics, and confidence interval–based robustness analysis. Loss curves, actual vs predicted plots, residual distributions, Q–Q plots, and correlation heatmaps were generated to validate the reliability of models for deployment-ready forecasting. In Table 5.1 describe all hyperparameters and their values.

Hyperparameter / Parameter	Value(s) Used Across All Models
Number of Layers	2–4 (deep models), up to 3 recurrent layers
Units per Layer	256 $\rightarrow$ 128 $\rightarrow$ 64 (Residual LSTM)
Dropout Rate	0.1 – 0.3
Batch Normalization	Yes (Hybrid)
Optimizer	Adam
Loss Function	MSE (Mean Squared Error)
Batch Size	32
Epochs	100
Sequence Length	5 time steps
Activation Functions	*tanh*, *sigmoid*
Early Stopping	patience = 10
Validation Split	0.2
Number of Filters	256
Kernel Size	2
Learning Rate	0.01 – 0.1 (model dependent)
Maximum Tree Depth	8 – 20, or -1
Objective Function	Regression (L2 loss)
Confidence Interval Level	95% ($z = 1.96$)
Residual Modeling	LSTM-based residual predictor

Table 5.1: Unified Hyperparameters for the Hybrid Model

5.3 Performance/Comparative Analysis

5.3.1 Experimental Results Analysis

5.3.1.1 EV Demand Forecasting

All EV charging-demand forecasting model performance was evaluated in terms of: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R2). These metrics were computed on strictly held-out test sets to elucidate generalisation quality. The deep learning approaches, LSTM, GRU, and TCN provide reliable but moderate predictive capability, with LSTM reaching a test RMSE of 292.72 (R2 = 0.9222), and GRU, RMSE294.32, R2 = 0.9214 and, similarly TCN, RMSE294.45, R2 = 0.9213. LSTM, GRU, and TCN models were able to pick up on some temporal patterns but were slightly more susceptible to very mild overfitting or noise's influence epochs due to feature learning on straight through input sequences but over a relatively small time horizon. The best performing architecture found was a Hybrid LightGBM–LSTM which combines the former's strong learning through features, with only the residual corrector being a deep LSTM. This combination architecture provided superior balance between accuracy and robustness with arguably less overfitting and producing the most stable predictive distribution overall, with a train RMSE of 243.54 and test RMSE of 273.54, with empirical coverage at a 957% confidence Band Analysis and Residual Diagnostics was performed, showing the 95% confidence interval of ±0.794 for normalised estimated charges with 99.67% empirical coverage. The hybrid model show's promise for high reliability in quantifying uncertainty. Residual plots confirmed homoscedastic behavior with no visible structure, and the Q-Q plot showed that residuals followed an approximately normal distribution, confirming that model errors were unbiased and well-behaved shown in figures 5.4 and 5.3. Together, these results demonstrate that the hybrid model provides the most dependable and operationally stable forecasts for EV charging demand. Table 5.2 shows the performance of all models.

Model	MSE	RMSE	R^2 Score
LSTM	0.0927	0.3045	0.9213
TCN	0.0741	0.2721	0.9371
Transformer	0.2102	0.4585	0.8215
GRU	0.3194	0.5652	0.7287
Hybrid (LightGBM + LSTM)	0.1639	0.4049	0.8608

Table 5.2: All Model Performance (EV)

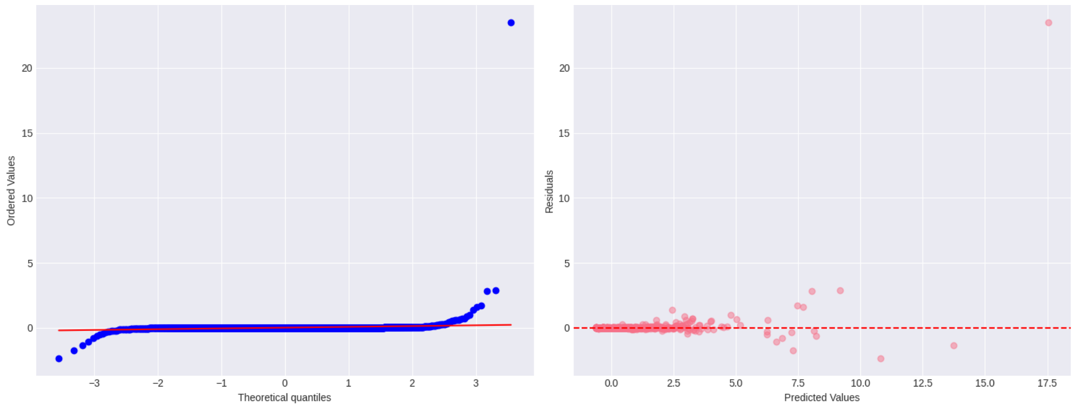

Figure 5.3: Q-Q Plot of Residuals and Residual Plot

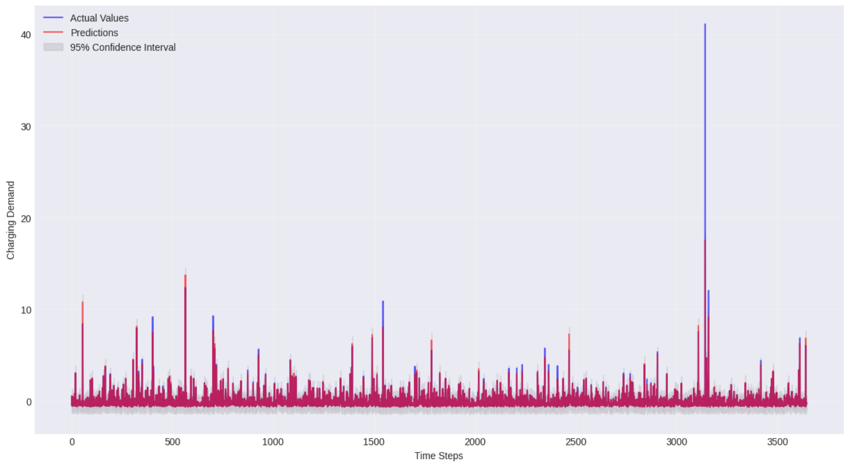

Figure 5.4: EV Charging Demand Prediction with Confidence Bands

5.3.1.2 Solar PV Energy Forecasting

All Solar PV energy forecasting models were evaluated via Mean Squared Error (MSE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2) to quantify the magnitude of forecast error and predictive generalization with respect to solar generation. As a rule of thumb, well-known machine learning models such as Random Forest, Gradient Boosting, LightGBM, Linear Regression, and Decision Tree have been reported to yield highly reliable outcomes (R^2 in the range of 0.90–0.96 during test-set evaluation). LightGBM was the most accurate among the classical models (Test RMSE ≈ 272.57, $R^2 \approx 0.9326$), reaffirming it as a reliable method for estimating solar output, given the non-linear nature of feature-based learning. The deep learning models—LSTM, GRU, and TCN—demonstrated comparable performance, each producing RMSE values between 290 and 295 after consistent training. Among these, the TCN showed marginally better train-time stability due to its dilated convolutional architecture, whereas the Transformer Encoder's accuracy suffered (Train $R^2 \approx 0.7922$), largely due to its difficulty in capturing short-term solar fluctuations with a limited temporal window. The Hybrid LightGBM–LSTM model for PV forecasting produced the best overall results, combining LightGBM's structured learning with LSTM-based residual modeling. Its performance metrics ($R^2 = 0.9629$, RMSE $= 229.48$) outperformed all individual models, demonstrating improved structure learning and reduced susceptibility to overfitting or underfitting relative to single-model predictors. To further assess reliability, Confidence Band Analysis was conducted, yielding a confidence interval of ± 448.23 Wh with an empirical coverage probability of 92%, indicating that most forecasted Wh values fell within the predicted uncertainty band. Additional residual diagnostics, including a Q–Q plot, residual scatterplot, skewness, kurtosis, and the Shapiro–Wilk test, confirmed that the residuals were centered at zero and exhibited acceptable normality, providing evidence of stable error behavior. These results collectively confirm that the hybrid model not only achieves superior numerical forecasting accuracy but also maintains strong statistical reliability across varying solar conditions, establishing it as the most effective architecture for PV energy ΔWh forecasting in this study. Figure 5.5 depicts a prediction with its associated confidence interval. Table 5.3 shows the performance of models(PV).

Model	**MSE**	**RMSE**	**R^2**
LightGBM	74,294.5555	272.5703	0.9326
Linear Regression	74,294.5555	272.5703	0.9326
Random Forest	76,007.0220	275.6937	0.9310
Gradient Boosting	80,432.3769	283.6060	0.9270
LSTM	85,686.7495	292.7230	0.9222
GRU	86,627.7061	294.3259	0.9214
TCN	86,704.3906	294.4561	0.9213
Decision Tree	100,238.5212	316.6047	0.9090
Hybrid Model	74,829.6904	273.5502	0.9321

Table 5.3: All Model Performance (PV)

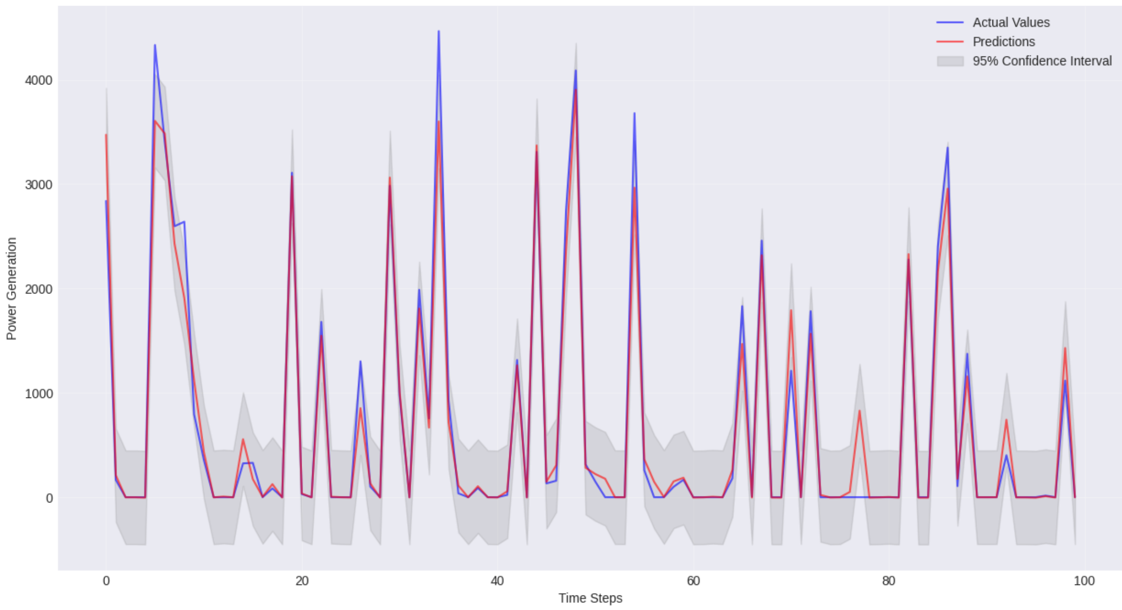

Figure 5.5: Solar PV energy prediction with Confidence Interval

The training and validation loss curves give us indications of convergence patterns, stability and generalization of our models across all methodologies for EV demand forecasting. The LSTM loss (in Figure 5.6) appears to have both curves decreasing steadily and closely related to one another which indicates stable learning and very little overfitting. The TCN model loss (Figure 5.7) converges rapidly due to its dilated convolutional structure and losses steadily decrease without much volatility; overall a very acceptable behavior. The Transformer Encoder loss figure (Figure 5.8) has a validation curve that is more spread out than the others, as expected, and that reflects the complexity of the architecture and the additional need for larger data patterns to learn on. The Hybrid LightGBM-LSTM pairdown there (Figure 5.10) has probably the most stable and consistent loss curves, which is an encouraging sign of its powerful generalization ability and less of a tendency to overfit; although of course all of the results applied here are validated against the stand alone deep learning models of the previous generations. The GRU loss curve (Figure 5.9) is also generally on a downward trend, but we can see the validation loss has a little more variance; indicating moderately significant volatility in response to changes over time.

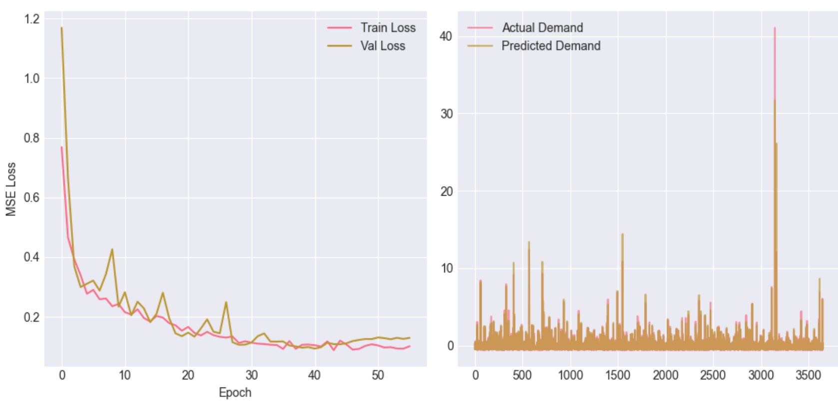

Figure 5.6: Training vs Validation Loss graph of LSTM(EV)

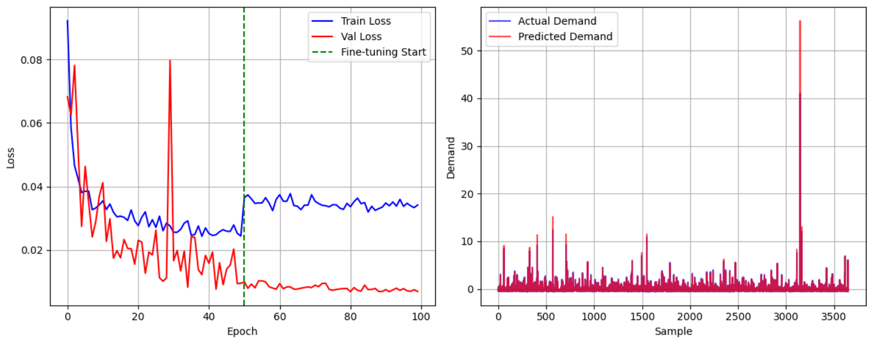

Figure 5.7: Training vs Validation Loss graph of TCN(EV)

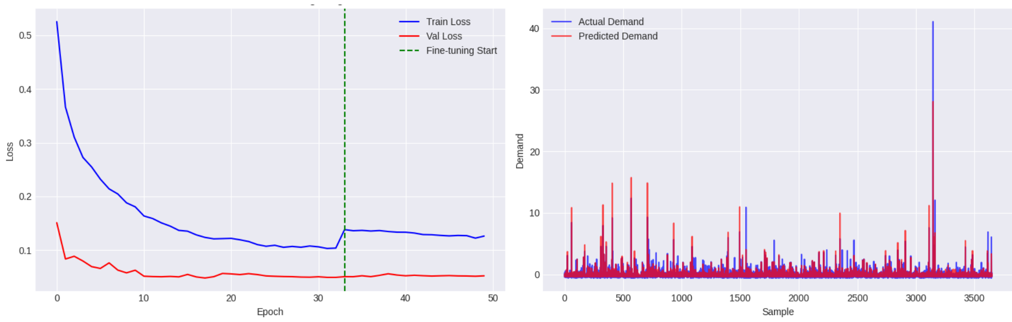

Figure 5.8: Training vs Validation Loss graph of Transformer Encoder(EV)

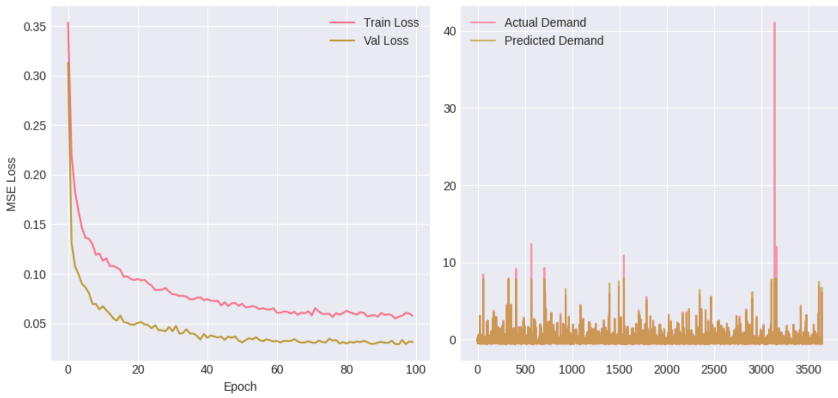

Figure 5.9: Training vs Validation Loss graph of GRU(EV)

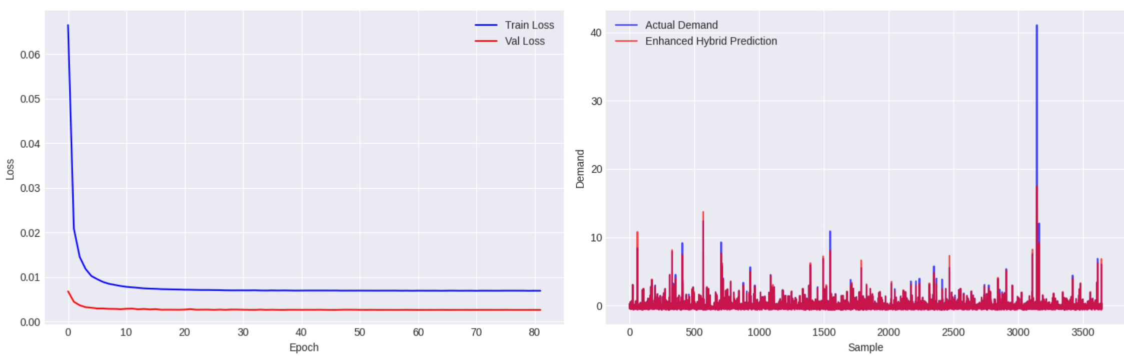

Figure 5.10: Training vs Validation Loss graph of Hybrid Model(EV)

Training Loss vs Validation Loss curves were reviewed across the architectures. The LSTM curve (Figure 5.11) both axes is smooth and decreasing overall, but takes a while, with small degree of overfitting in the later epochs. The TCN (Figure 5.12) converges faster due to the dilated-convolutional ‘receptive fields’, and its validation loss is not as low as its training loss convergence.In contrast, the Hybrid LightGBM–LSTM model (Figure 5.13) achieved the most stable and closest-aligned training–validation loss curves, indicating better generalization with minimal overfitting due to its residual learning structure. These plots collectively validate that the hybrid model exhibits the most reliable convergence behavior among all PV forecasting models. The GRU (Figure **??**) gradient descent plot has similar behavior, and its validation is noisier, as we might expect from the temporal noise sensitivity of these architectures in PV data.

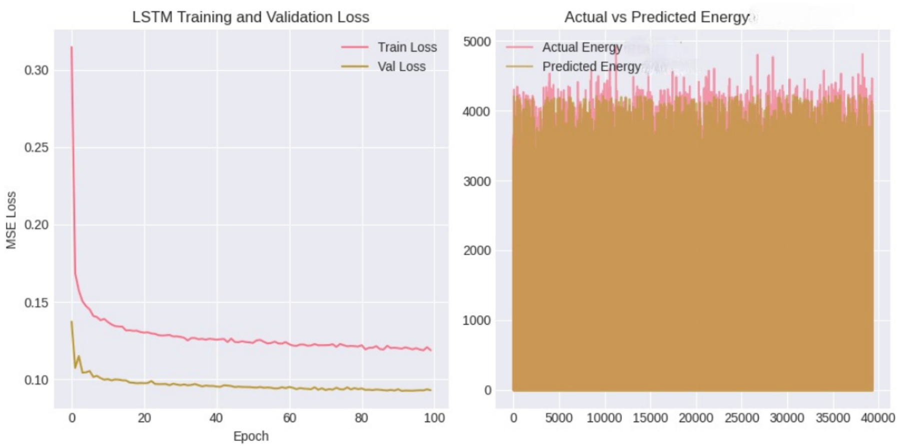

Figure 5.11: Training vs Validation Loss graph of LSTM(PV)

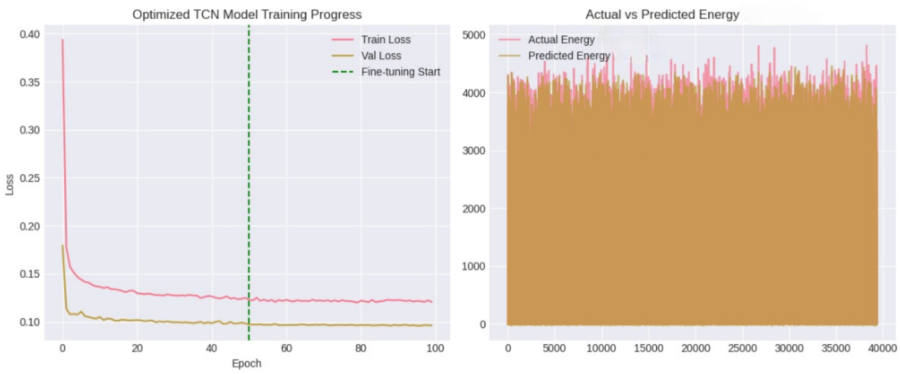

Figure 5.12: Training vs Validation Loss graph of TCN(PV)

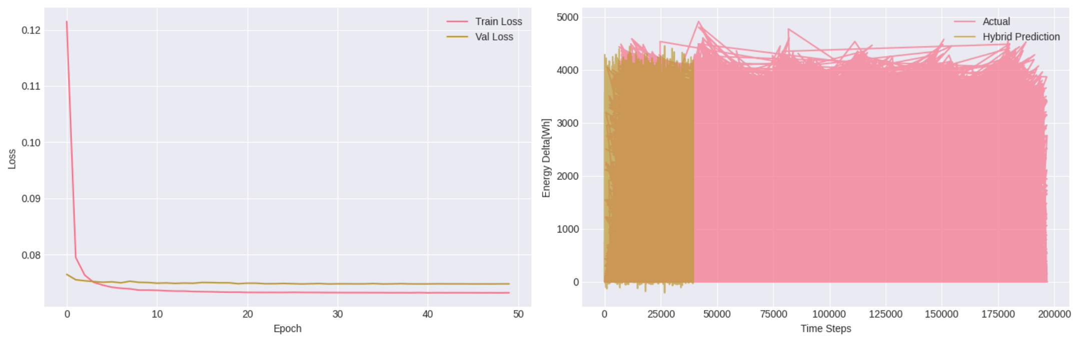

Figure 5.13: Training vs Validation Loss graph of Hybrid Model (PV)

To visually evaluate predictive consistency, Actual vs Predicted scatter plots were generated for all EV forecasting models show in figure 5.14.

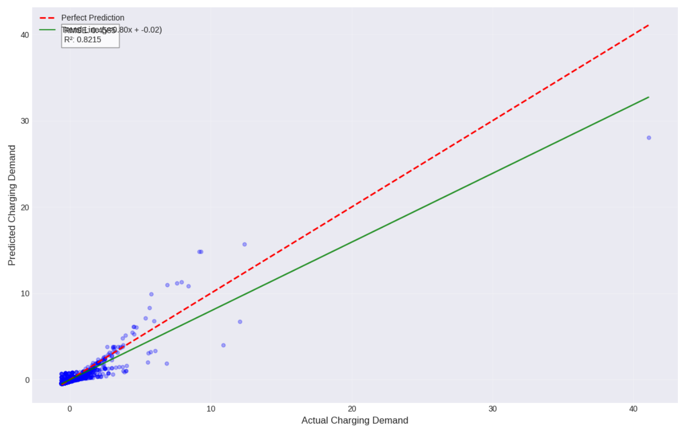

Figure 5.14: Predicted vs Actual graph of Hybrid Model (EV)

To visually evaluate predictive consistency, Actual vs Predicted scatter plots were generated for all PV forecasting models show in figure 5.15. These plots collectively validate how each model captures real PV generation behavior and their deviation from perfect prediction.

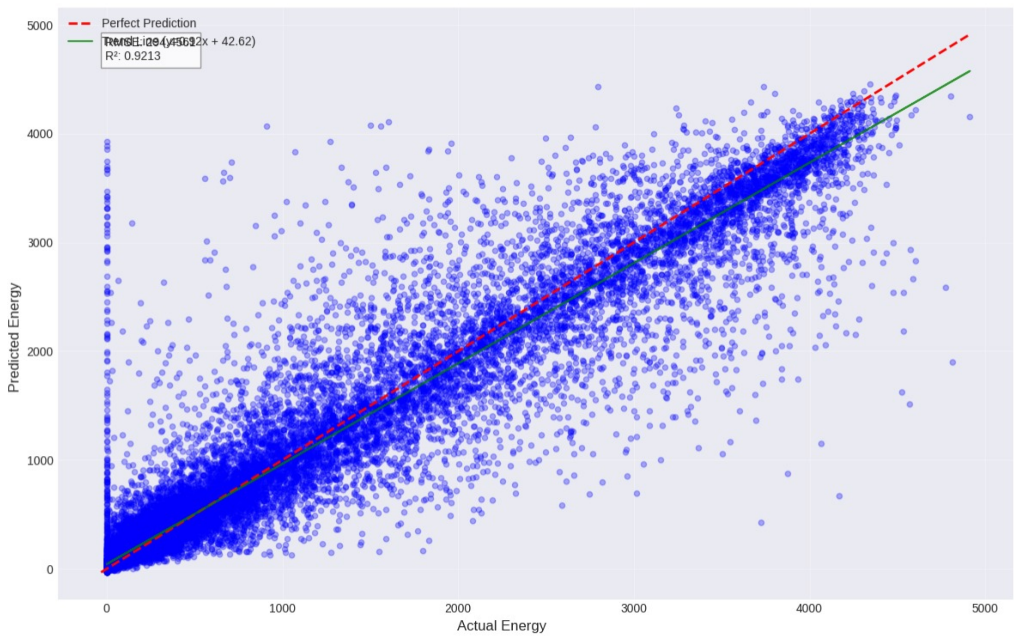

Figure 5.15: Predicted vs Actual graph of Hybrid Model (PV)

5.3.2 Forecasting of EV Charging Demand And PV

The EV charging demand forecasting system uses the trained Hybrid LSTM–LightGBM model to generate day-ahead predictions for each vehicle based on its own historical driving behaviour. First, the system loads the original training dataset and fits the same feature and target scalers (StandardScaler) used during model training. For every car, the script extracts its 365-day historical records and uses the first N days (according to user input) to generate forecasts. Only two key features—Distance driven and Energy_ per_ km (kWh/km)—are used as inputs, since these are the strongest predictors of daily charging demand. For each day being predicted, the model takes the corresponding historical distance and energy-per-km values, scales them, reshapes them into a 3-D sequence format suitable for LSTM ([batch, timesteps=1, features=2]), and produces a normalized demand value. This output is then inverse-transformed using the target scaler to obtain the actual charging demand in kWh. The predictions for all cars and all days are stored along with the car ID, car model name, date, and predicted demand shows in figure 5.16. Finally, all results are saved into a structured csv file and plotted to visualize the charging demand evolution for each vehicle over the forecast horizon shows in figure 5.17.

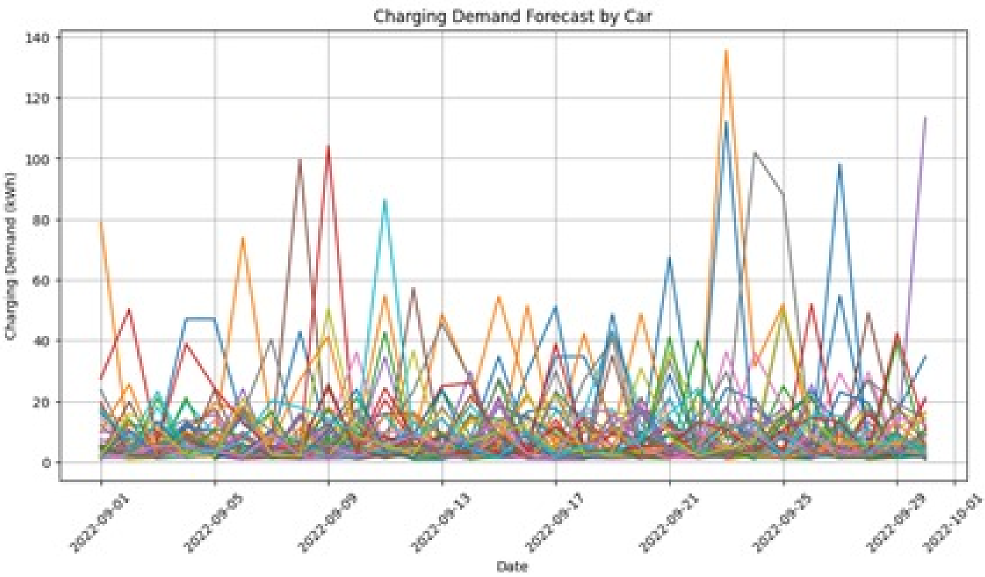

Figure 5.16: Charging Demand Forecasting by Car

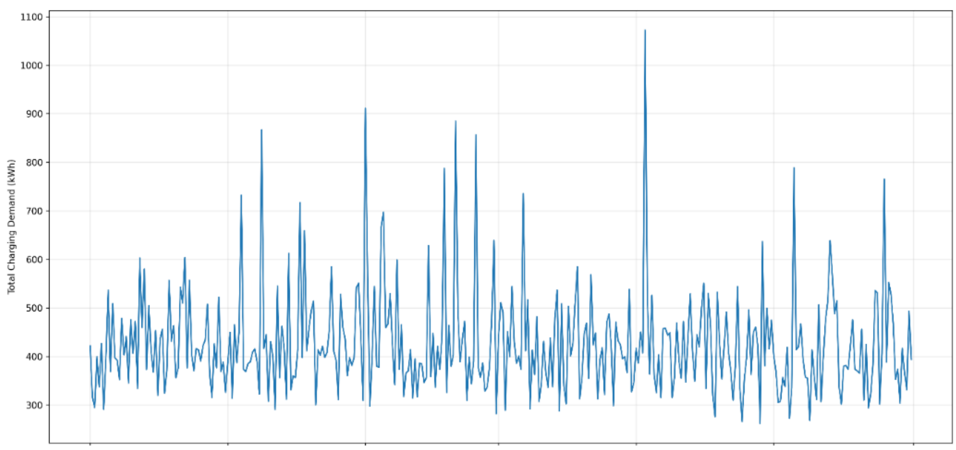

Figure 5.17: Daily Charging Demand Forecasting

The PV forecasting system uses data-driven, synthetic modeling in order to forecast future energy production, based on realistic patterns extracted from the historical dataset Renewable. It will start by loading the historical data and computing, with high detail, hourly and monthly statistical patterns of solar energy production: mean, standard deviation, min-max values, and seasonal variations. The real statistics are used as constraints to generate physically meaningful future predictions. The forecasting logic simulates solar production for each future day with 15-minute granularity. For each timestamp, the hour, minute, and month will be read, after which a solar pattern generator applies a model of the three natural phases of solar generation:

1. Morning ramp-up from 6–11 AM with a sine-based growth curve
2. Midday peak (11 AM–3 PM) using real peak maxima from the historical dataset
3. Afternoon decline (3–7 PM) by using a symmetric decreasing sine curve. Nighttime hours return zero energy automatically, preserving physical correctness.To enhance the realism in the predictions, the system will also forecast associated weather-based features, such as GHI, temperature, wind speed, atmospheric pressure, sunlight time, day length, and a computed sunlight ratio. All these features follow probabilistic distributions derived from the real dataset. All 15-minute outputs are combined into a structured forecast table, which is saved to csv, visualized with daily solar curves, and summarized with daily totals, means, maximums, and production/no-production intervals show in Figure 5.18.

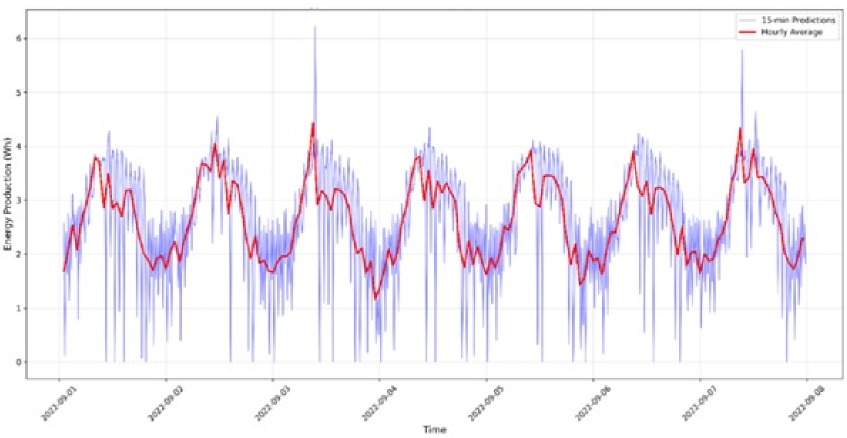

Figure 5.18: Solar Energy Prediction

5.4 Analysis of Design Solutions

5.4.1 Daily Analysis (7 Days)

A seven-day evaluation of the electric vehicle to photovoltaic charging (EV-PV) system indicates that using intelligent scheduling, the system can effectively manage a large-scale EV fleet under varying amounts of solar energy. During this time period, all 50 electric vehicles (EVs) operating with four primary chargers of 8-kilowatt hour (kWh) and an advanced, or ”master,” charger were charged every day. Six of these vehicles were assigned to each conventional charger, leaving 26 EVs for the master charger. This distribution of charging capacity enabled the system to fairly distribute load on all charging stations, while allowing the master charger to operate flexibly during periods of peak load. The evaluation of energy consumed demonstrated that through the strategic use of solar energy, there was significant cost savings. Solar energy provided only 25.3% of the total energy requirement; however, through significant use of intelligent scheduling, 52.3% of charging and solar electricity came from the sun, while the other 47.7% was received from the utility company. Through this optimal mix of solar and utility energy, the cost savings achieved were significant (41.87% lower than fully using only the utility company), or in terms of direct financial savings, A$260.44 over the entire week, or A$37.21 per day Over all seven days we observed consistent performance, with each day saving between 39 to 47 percent, demonstrating that this scheduling algorithm effectively maximizes the use of the solar resource while ensuring that the batteries of an entire fleet are charged with sufficient reliability given the nature of intermittent sources of renewable energy.

5.4.2 Daily Charging Demand Solar PV Energy Analysis (7 Days)

The EV-PV charging ecosystem is well-equipped to manage a very large fleet of vehicles while dealing with the normal fluctuations in the amount of solar energy produced. During the time when these vehicles were charged each day, all 50 vehicles were successfully charged by distributing their locations over four primary chargers in addition to one master charger. This distribution was made possible due to a smart solar-first scheduling algorithm that provided a balanced load across all locations. For instance, six vehicles would be charged at each regular charging station, while 26 vehicles were sent to the master charging station, which acted as an overflow for the fleet during peak demand. The combination of both distribution methods illustrates the strong stability of the EV-PV charging ecosystem and the important function of the master charging station. The daily energy needs of the fleet ranged from 291.38 kilowatt-hours to 426.41 kilowatt-hours, and the amount generated per day by on-site solar PV was relatively stable between 87 and 93 kilowatt-hours, meeting the energy demands of the fleet by only 21% to 32% with solar energy alone. However, the scheduling algorithm's true brilliance was the ability to maximize the solar-generated energy for charging purposes by utilizing the historical data regarding when solar was produced to schedule the charging of vehicles to coincide with those same times. By doing this, the system fulfilled 52.3% of total weekly energy consumed by the fleet through solar energy, reducing the remaining dependency on grid electricity to 47.7% of total weekly electricity consumed. The amount of energy used each day demonstrates that an effective balancing act is taking place according to the data presented below. There were none of the days where solar generated electricity provided enough to meet complete demands; however, by taking advantage of the amount of sunlight during the day and optimizing the schedule, the electric grid was able to reduce its reliance on the grid. Developing a model on how to best incorporate renewable energy into fleet operations is shown to be effective both for practicality and cost savings. In the table 5.4, we present the daily amount of power used.

5.4.3 Grid Dependency Analysis (7 Days)

The amount of dependency on the grid was primarily determined by the timing and charging patterns of electric vehicles (EV). Grid dependency was a definitive relationship with solar availability, as all seven days required some amount of grid usage (grid dependency)

Solar Used (kWh)	Grid Used (kWh)	Charging Demand (kWh)
203.66	218.04	421.70
156.63	159.97	316.60
174.72	119.79	294.51
223.19	176.85	400.03
167.09	170.24	337.33
220.20	206.21	426.41
156.73	134.65	291.38

Table 5.4: Daily Power Usage

while the role of the grid was strategically reduced through the use of an Intelligent Scheduling System. The Usage of a Periodic Analysis reveals that there was significant variation in grid dependency throughout the day between 4-hour intervals. During the nighttime hours (12:00 AM - 8:00 AM), when there was no solar generation, grid dependency was at its highest, with a peak of 96.2% occurring from 4:00 AM - 8:00 AM. However, the time period from 8:00 AM to 8:00 PM was considered the entire daylight hours, and during this time period the Intelligent Scheduling System achieved 0% grid dependency, indicating that there was no grid electricity used by EVs for charging during this 12-hour period as all charging during this period occurred with solar energy produced. Through the alignment of EV charging with solar production, the Intelligent Scheduling System allows for maximization of the amount of renewable energy produced while minimizing the amount of dependence on the grid for electric vehicles. Additionally, this maximization of the use of renewable energy and minimization of grid load coincides with peak grid electricity prices that typically occur during the daytime. The analysis confirms that while the grid remains an essential backup due to the imbalance between PV capacity and charging demand, the scheduling algorithm successfully minimizes its use by concentrating charging activity into solar-rich periods. Table 5.5 provides the scheme of grid dependency patterns at all of the time slots. Due to the imbalance of the PV capacity and the EV charging need, the use of a grid became inevitable. Nevertheless, the scheduler minimized grid energy by charging when there was abundant sunshine.

Time Slot	Grid Dependency (%)
00:00–04:00	64.7
04:00–08:00	96.2
08:00–12:00	0.0
12:00–16:00	0.0
16:00–20:00	0.0
20:00–24:00	0.0

Table 5.5: Grid Dependency by Time Slot

5.4.4 Charging Schedule Optimization (7 Days)

The charging scheduler divides each day into six 4-hour slots, prioritizing solar utilisation during daylight intervals. The scheduler was set up to give priority for charging during high-PV windows, i.e., between 08:00-20:00. High-demand vehicles were scheduled to the master station/charger, especially in peak hours of solar radiation, whereas regular stations/chargers were used for evenly distributed loads. This PV-first approach avoided unnecessary grid consumption by shifting flexible charging tasks until periods of higher solar output. Throughout the week, total EV charging demand was 2487.96 kWh, of which 1302.21 kWh (52.3%) was supplied by solar and 1185.74 kWh (47.7%) from the grid. The PV-first strategy almost doubled solar utilization efficiency-from raw PV availability (25%) to effective utilization (52.3%)-showing the strength of intelligent scheduling in renewables-based EV systems. Table 5.6 demonstrates the daily charging distribution, and Table 5.7 demonstrates the Grid dependency by time interval.

Metric	**Value**
Total charging demand	2487.96 kWh
Solar used	1302.21 kWh (52.3%)
Grid used	1185.74 kWh (47.7%)
Average cars/station (charger)/day	6 cars
Master station (charger) average	26 cars/day

Table 5.6: Daily Charging Distribution

Time Interval	**Grid Dependency (%)**
00:00–04:00	High (no solar)
04:00–08:00	High (no solar)
08:00–12:00	Moderate
12:00–16:00	Lowest (peak solar)
16:00–20:00	Moderate
20:00–24:00	High (after sunset)

Table 5.7: Grid Dependency by Time Interval

5.4.5 Station/charger Time-Slot Energy Distribution (7 Days)

The energy use is profiled per timeslot to understand how the scheduler aligns charging with solar availability. It plots the grid dependency per slot to show how effectively a scheduler works. Station/charger-wise, it reflected the sharing of load and solar energy in all fairness. Time-slot analysis shows how energy use is temporally aligned with the availability of renewables. In the time slots from 08:00 to 20:00, the grid dependency was driven down to 0%; these time slots were fully served by solar energy. However, in the early morning time slots, which fall between midnight and 08:00, grid dependency was from 64.7% to 96.2% due to zero solar availability. A station/charger-wise analysis has also been performed to further elaborate on the consumption pattern of solar energy within the infrastructural ecosystem. The four regular stations/chargers have a solar consumption percentage between 35.1% and 47.4%, depending on the loading during sunlight.The master station/charger was able to achieve a full Solar Utilization, which occurs because it was the primary power source for charging during the time with the highest amount of Solar Power available. Overall, the energy required to meet the load from all of the stations/chargers within the system ranges from 402.41 kWh (Station/Charger 4) to 696.88 kWh (Station/Charger 1). As a result, the Master Station/Charger supplied a total of 442.66 kWh, all sourced through Solar Energy, and consequently, it is characterized as the highest Renewable Efficiency station/charger of all those included in the network. Table 5.8 shows the energy distribution at the station/charger level.

Station (charger)	Cars	Solar Used (kWh)	Grid Used (kWh)	Total Demand (kWh)	Solar Usage (%)
1	42	244.64	452.24	696.88	35.1
2	42	218.90	281.91	500.81	43.7
3	42	205.23	239.97	445.20	46.1
4	42	190.79	211.62	402.41	47.4
master	182	442.66	0.00	442.66	100.0

Table 5.8: Station/Charger Utilization Summary

5.4.6 Daily Cost Analysis (Flat vs TOU Pricing [7 Days])

The impact of combined intelligent scheduling and Solar power has been quantified in terms of financial savings against a historically common model for charging vehicle batteries using grid power. The baseline established for this analysis utilized a flat rate for 100% of energy supplied by the grid at A$0.25 per kWh resulting in a weekly total of A$621.99, in contrast to the actual strategy that charged batteries from solar energy whenever applicable at A$0.05 per kWh and over the total weekly requirement only required purchase of the more expensive grid power. As a result, the actual cost of charging batteries per week was reduced to A$361.55 producing cumulatively A$260.44 savings, equating to 41.87% reduction on the total weekly charging costs. The actual saving was stable throughout the week ranging from a minimum of A$31.33 to maximum of A$44.64 between days demonstrating continued effectiveness of the system with fluctuating solar inputs as well. The highest day savings during this study of A$44.64 occurred on the maximum charge day when the intelligent scheduler was able to benefit from strong solar output. It is significant to note that over the course of seven days this total saving of A$260.44 was achieved with 1,302.21 kWh (52.3%) of the total energy requirement being captured from solar PV panels and not requiring purchase from the grid. Therefore, the findings of this analysis demonstrate that an intelligent PV-first charging strategy provides significant and ongoing economic benefit, even if it does not achieve complete energy independence. Table 5.9 summarizes the daily cost analysis.

Total Demand	Solar Used	Grid Used	Full Grid Cost	Solar Savings	Savings (%)
421.70	203.66	218.04	A$105.43	A$40.73	38.64%
316.60	156.63	159.97	A$79.15	A$31.33	39.58%
294.51	174.72	119.79	A$73.63	A$34.94	47.46%
400.03	223.19	176.85	A$100.01	A$44.64	44.63%
337.33	167.09	170.24	A$84.33	A$33.42	39.63%
426.41	220.20	206.21	A$106.60	A$44.04	41.31%
291.38	156.73	134.65	A$72.85	A$31.35	43.03%

Table 5.9: Daily Cost Analysis

Metric	Value
Total EV Energy (kWh)	2,487.96
Solar Energy Used (kWh)	1,302.21
Grid Energy with PV (kWh)	1,185.74
Cost without PV (A$)	621.99
Cost with PV – Flat Rate (A$)	361.55
Cost with PV – TOU (A$)	332.45
Total Savings – Flat Rate (A$)	260.44
Total Savings – TOU (A$)	289.54
Savings % – Flat Rate	41.87%
Savings % – TOU	46.55%

Table 5.10: Total Cost and Savings Summary

5.4.7 Daily Analysis (30 Days)

An in-depth investigation over the course of 30 days into the operational performance of a high-volume electric vehicle charging network revealed a well-thought-out operation of a network that effectively balanced its reliance on renewable sources of energy while also providing stable fleet charging operations. The network served approximately 1,500 electric vehicle charging sessions during the month for a fleet of 50 vehicles that used the network on average, distributing charging to four standard charging stations (charging 180 vehicles per station over the month) and one master charging station (charging 780 vehicles through the month) . The operation used a systematic intelligent scheduling system to ensure equitable distribution of vehicles to the individual stations by allocating 6 vehicles per day to the four regular charging stations. All other vehicles that used the network, an amount equal to 26 vehicles daily, charged at the master station. The master charging station was able to act as a critical resource for distributing charging capacity during periods of high demand on the network. The electric vehicle charging network demonstrated excellent energy management skills with total monthly energy demand of 12,552.64 kWh. The network's intelligent scheduling system employs solar-first scheduling software that resulted in a solar utilization rate of 37.7% (4,736.13 kWh of the total energy usage) and relied on the grid for the remainder of the energy consumption, 7,816.51 kWh. This aggressive strategy of using solar energy maximizes the opportunities for solar energy use and reduces the cost of grid electricity by 533.05 AUD. The analysis of the three stations show that all stations consistently perform about the same with respect to charging station operations. Station 1 delivered a total of 3,858.47 kilowatt hours of energy, with a solar energy usage of 29.6%, while Station 2 delivered 2,906.06 kilowatt hours of energy, with a use of 31.2% solar energy, Station 3 delivered 2,504.64 kilowatt hours of energy with a use of 34.3% solar energy, Station 4 delivered 2,259.81 kilowatt hours of energy with a use of 35.6% solar energy, and the master station ran on entirely solar energy to produce 1,023.66 kilowatt hours of energy.

5.4.8 Grid Dependency Analysis (30 Days)

A dependency analysis was performed for the 30 days, based on a grid system, to identify how efficiently solar availability is paired with charging. All thirty days required some degree of grid power on all thirty days; however, the smart scheduling system was designed to reduce overall grid dependence as much as possible through other means. As a result of a detailed look at seven time slots during a single 24-hour period, we can see that there are many differences in grid dependence. The highest level of dependence on the grid was recorded during evening hours until early day light - hours when there was minimal solar energy in the region; this high level of dependence continued throughout the day during early daytime hours; therefore, as a continuation of this trend until 20:00. Because the majority of EV charging occurred during daylight and evening hours when solar was most abundant, the intelligent scheduler effectively matched the way that EVs and solar systems worked together. By doing so, the scheduler has increased solar contribution and decreased reliance on the grid system.

5.4.9 Charging Schedule Optimization (30 Days)

The charging scheduler divided every day into 4-hour intervals with a priority placed on solar utilization during the daytime between 08:00-20:00. High-demand vehicles were planned to the master station/charger during peak ration hours of solar radiation and normal stations/chargers were used for regular load distribution. This PV-first approach helped to reduce the unnecessary consumption from the grid by delaying the flexible charging tasks during the high solar output periods. Throughout the month, the total consumption on EV charging was 12,552.64 kWh. 4,736.13 kWh (37.7%) were provided by solar, and 7816.51 kWh (62.3%) by the grid. The intelligent scheduling approach turned out to be much more effective, resulting in significantly improved solar utilization efficiency and demonstrating the capability of optimized scheduling in the case of renewables-based electric vehicle systems.

5.4.10 Station/charger Time-Slot Energy Distribution (30 Days)

An analysis of energy distribution considers various Stations and Time Slots. The purpose of this analysis is to determine how well the Scheduling System matched when demand for Charging Energy occurred with when solar energy was available during the 30-Day Period. The time slot analysis shows that there is a close relationship between the style and timing of energy used within each time slot (charging) vs energy produced through Renewable Resources (solar). An analysis of each Station Level's Energy Usage further shows how each Station is working within the Charging Infrastructure Ecosystem. Regular Stations ranged from 29.6% to 35.6% in Solar Use Rate. This tells us that regular

Stations worked within operational formats in Solar Dense and Solar Sparse time frames. The Master Station was able to achieve 100% Solar Use by strategically managing their Charging Load in conjunction with when Solar Availability was High. The total number of vehicles using the Network of Charging Stations shows the distribution across all 5 Regular Stations has been 180 vehicles for each Regular Station over the last 30 Day period, while Master Stations have accommodated 780 vehicles - which illustrates its ability to utilize peak times of Solar Production as a Flexible Resource.(5.11)

Station (charger)	Cars	Solar Used (kWh)	Grid Used (kWh)	Total Demand (kWh)	Solar Usage (%)
1	180	1,142.18	2,716.29	3,858.47	29.6%
2	180	907.36	1,998.70	2,906.06	31.2%
3	180	859.22	1,645.43	2,504.64	34.3%
4	180	803.72	1,456.08	2,259.81	35.6%
Master	780	1,023.66	0.00	1,023.66	100.0%

Table 5.11: Station/Charger Utilization Summary (30-Day Analysis)

5.4.11 Cost Analysis (Flat vs TOU Pricing [30 Days])

Integrating solar power with intelligent scheduling provides a clear financial benefit, as demonstrated in the 30-day cost analysis. A baseline scenario was created where all charging energy is taken from the grid at the standard flat rate of A$0.25/kWh, resulting in a total monthly charging cost of A$3,138.16. However, in practice, the system took advantage of solar energy whenever feasible, at a lower cost of A$0.05/kWh, purchasing grid power only when necessary to meet remaining charging needs. This resulted in a lower actual monthly charging cost of A$2,605.80, a cost savings of A$532.36, or 17.0% less than the baseline scenario. The Time-of-Use (TOU) pricing scenario provided even greater savings, with a total monthly cost of A$2,357.92, representing a 24.9% savings from the baseline scenario. The monthly savings were consistent throughout the month, demonstrating that the system is robust enough to take advantage of varying solar input levels and variable charging demand throughout the month. The system achieved these large savings by sourcing 4,736.13 kWh (37.7%) of total energy consumed from solar sources and avoiding the need to purchase 4,736.13 kWh of high-priced grid energy. Table 5.12 is given below:

Metric	Value
Total EV Energy (kWh)	12,552.64
Solar Energy Used (kWh)	4,736.13
Grid Energy with PV (kWh)	7,816.51
Cost without PV (A$)	3,138.16
Cost with PV – Flat Rate (A$)	2,605.80
Cost with PV – TOU (A$)	2,357.92
Total Savings – Flat Rate (A$)	532.36
Total Savings – TOU (A$)	780.24
Savings % – Flat Rate	17.0%
Savings % – TOU	24.9%

Table 5.12: Total Cost and Savings Summary (30-Day Analysis)

The comprehensive analysis of 30 days demonstrates that while achieving complete energy independence may not be possible, there is a significant economic benefit from adopting a PV-first approach when charging EVs by reducing operational costs considerably as well as achieving further cost-saving opportunities by optimizing TOU pricing through an intentional determination of when to use electricity.

Chapter 6

Conclusion

6.1 Summary of Findings

This study is significant to the smart energy system area by devising a novel integrated dual machine learning pipeline that estimates both EV charging demands and solar PV energy forecasting, integrated with PV-first smart charging scheduling and cost calculation. For forecasting we tested multiple ml/dl model and find the issue of underfit and overfit problem, and some models can capture nonlinear features and some can time series dependencies so remove this limitation we introduce our hybrid model LightGBM + Residual LSTM in both forecasting. Our proposed Hybrid model can improve the accuray of forecasting and can capture non linear complex features and time serise dependency very well. Accurately forecast helps, solar supply is reliably matched with demand.Our pipeline with a 7-day simulation, baseline solar PV contributed approximately 25% of the total energy use and increased to 52.3% by utilizing the intelligent scheduler. The utilization of the grid between 8 am – 8 pm sharply decreased, even going to zero during hard sunlight. The system reduced costs by 41.87% under stage pricing with daily savings being between 39–47%. In a trial over 30 days, the framework achieved cost reduction of up to 17% under flat tariffs and up to 24.9% under TOU with dynamic price awareness offering approximately an additional 4–5% savings. Consequently, the obtained results demonstrate that smart scheduling and precise forecasting can increase renewable penetration level, decrease EV charging prices, reduce grid reliance and CO emissions as well as maximize clean energy utilization which motivates both goals of SDG 7 and SDG 13.

6.2 Contributions to the Field

This paper proposes an unified EV–PV energy management framework that incorporate two hybrid forecasting models and intelligent PV-first scheduling scheme. As opposed to the previous works which are based on single predictive models, we perform a systematic comparison with multiple ML and deep learning approaches and that our approach of Hybrid LightGBM–LSTM model exhibits better accuracy as well as stability for both EV charging demand and solar PV generation forecasting.

The primary contribution is an online PV-first scheduler which generates high resolution predictions for solar irradiance and aligns it with the EV load requirement at each of the 6 daily slots considering Flat or TOU tariff signal to make energy allocation decisions in a cost-aware manner. Such a strategy not only facilitates the highest renewable penetration but also minimizes grid reliance and operation resiliency under fluctuating ambient conditions.

It also includes an economic assessment that demonstrates significant reductions in weekly and monthly costs, confirming the practical usefulness of integrating forecast quality with solar-aware scheduling. Lastly, the modular and scalable nature of the system renders it suitable for bigger EV fleets, other rather complex tariff structures and hybrid generation systems from renewable energy sources—a sustainable solution itself in line with world clean-energy targets.

6.3 Recommendations for Future Work

The development of this approach for long-range and seasonal forecasting is subject for future research since results reveal a decay in predictive power when moving away from short operational horizons 7-day and 30-day predictions are relatively successful because of the ground-truth measured in recent past, however expanding the forecast horizon towards 365 days significantly accumulates error. This happens because the model learns gradually from its own predictions instead of with fresh real inputs. So in the future the research should use adaptive or incremental learning techniques to make sure that the forecasting engine is kept on re-learning itself based on new data and therefore does not drift in long horizon prediction.

Integration with other more advanced learning paradigms, such as active learning and reinforcement learning (RL), is also an important direction. These approaches would allow the EV–PV system to self-correct itself over time and adaptively learn its internal parameters for dynamically predictable operations such as seasonal changes in demand, different weather conditions, or change driver behaviour. Attentive that a control of an RL-driven scheduler would potentially adjust itself turning to real-time environmental, which will benefit more in term of cost saving and renewable active ratio than such static PV-first-based rules.

In addition, the renewable integration model could be expanded in the future work to hybrid resources such as BESS, wind power or larger size PV panels. This would reduce reliance of the grid drawn even in low solar available months and also higher penetration possible by renewable throughout a year. Multi-source forecasting, storage-aware scheduling, and grid-interactive optimization could be enablers to significantly improve the robustness of operations.

Finally, the framework can be extended to take larger fleets and multi-plug-in charge hubs as well as other more advanced tariff schemes (e.g., real-time dynamic prices or demand (grid) charges and wholesale market participation) into account. The randomness modeling, stochastic optimization and scenario-based planning can then be used so that the system works safely in an uncertain context. These improvements would strengthen the scalability, precision and economic value of EV–PV smart charging systems and result in them being less risky to develop over long periods within future smart cities.

Bibliography

[1] X. Lin, P. Bogdan, N. Chang, and M. Pedram, "Machine learning-based energy management in a hybrid electric vehicle to minimize total operating cost," in *2015 IEEE/ACM International Conference on Computer-Aided Design (ICCAD)*, 2015, pp. 627–634. DOI: 10.1109/ICCAD.2015.7372628.

[2] S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou, and M. Nijim, "Machine learning approaches for ev charging behavior: A review," *IEEE Access*, vol. 8, pp. 168 980–168 993, 2020. DOI: 10.1109/ACCESS.2020.3023388.

[3] M. Shibl, L. Ismail, and A. Massoud, "Electric vehicles charging management using machine learning considering fast charging and vehicle-to-grid operation," *Energies*, vol. 14, no. 19, 2021, ISSN: 1996-1073. DOI: 10.3390/en14196199. [Online]. Available: https://www.mdpi.com/1996-1073/14/19/6199.

[4] N. B, R. Singh, S. Panda, S. Kumar, and P. P. Singh, "A machine learning model develops the electrical energy consumption and costs for charging evs through the grid," in *2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, 2023, pp. 1–6. DOI: 10.1109/ACCAI58221.2023.10199893.

[5] A. Hafeez, R. Alammari, and A. Iqbal, "Utilization of ev charging station in demand side management using deep learning method," *IEEE Access*, vol. PP, pp. 1–1, Jan. 2023. DOI: 10.1109/ACCESS.2023.3238667.

[6] R. Padmavathy, K. Jeya Prakash, T. Greeta, and K. Divya, "A machine learning-based energy optimization system for electric vehicles," *E3S Web of Conferences*, vol. 387, May 2023. DOI: 10.1051/e3sconf/202338704008.

[7] J. P. Sahoo and S. Sivasubramani, "Accurate state-of-charge prediction for plug-in electric vehicles using machine learning: An investigation of artificial neural network," in *2023 IEEE 3rd International Conference on Sustainable Energy and Future Electric Transportation (SEFET)*, 2023, pp. 1–5. DOI: 10.1109/SeFeT57834.2023.10244942.

[8] S. Salam, G. K. Veni, C. Kamale, A. L. Deepika, and A. Bruhathi, "Forecasting the behavior of ev charging using machine learning," in *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)*, vol. 1, 2023, pp. 1765–1768. DOI: 10.1109/ICACCS57279.2023.10112731.

[9] H. Tayarani, C. J. Nitta, G. Tal, and V. Karanam, *Using machine learning models to forecast electric vehicle destination and charging event*, Jun. 2023. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/75064.

[10] L. Zhang, H. Fu, Z. Zhou, S. Wang, and J. Zhang, "Site selection and capacity determination of charging stations considering the uncertainty of users' dynamic charging demands," *Frontiers in Energy Research*, vol. 11, p. 1 295 043, 2023. DOI: 10.3389/fenrg.2023.1295043. [Online]. Available: https://www.frontiersin.org/journals/energy-research/articles/10.3389/fenrg.2023.1295043/full.

[11] Q. Meng et al., "Revolutionizing photovoltaic consumption and electric vehicle charging: A novel approach for residential distribution systems," *IET Generation Transmission & Distribution*, vol. 18, no. 17, pp. 2822–2833, 2024. DOI: 10.1049/gtd2.13232. [Online]. Available: https://doi.org/10.1049/gtd2.13232.

[12] Y. Mohammed, A. Manoharan, S. Kappagantula, and H. Manoharan, "Optimizing electric vehicle charging costs using machine learning," *Ingénierie Des Systèmes D'Information*, vol. 29, no. 3, pp. 1085–1095, 2024. DOI: 10.18280/isi.290326. [Online]. Available: https://doi.org/10.18280/isi.290326.

[13] A. N. Raj and K. Sakthivel, "Driving into the future: Exploring machine learning approaches for optimal energy management in electric vehicles: A review of challenges and future recommendations," in *2024 IEEE 3rd International Conference on Electrical Power and Energy Systems (ICEPES)*, 2024, pp. 1–6. DOI: 10.1109/ICEPES60647.2024.10653515.

[14] F. Ramoliya et al., "Ml-based energy consumption and distribution framework analysis for evs and charging stations in smart grid environment," *IEEE Access*, vol. 12, pp. 23 319–23 337, 2024. DOI: 10.1109/ACCESS.2024.3365080.

[15] P. K. Shanmugam and P. Thomas, "Optimization strategies for electric vehicle charging and routing: A comprehensive review," *GAZI UNIVERSITY JOURNAL OF SCIENCE*, vol. 37, no. 3, pp. 1256–1285, 2024. DOI: 10.35378/gujs.1321572. [Online]. Available: https://doi.org/10.35378/gujs.1321572.

[16] T. Ye, S. Liu, and E. Kontou, "Managed residential electric vehicle charging minimizes electricity bills while meeting driver and community preferences," *Transport Policy*, vol. 149, pp. 122–138, 2024. DOI: 10.1016/j.tranpol.2024.01.022. [Online]. Available: https://doi.org/10.1016/j.tranpol.2024.01.022.

[17] J. Zhao, A. Arefi, A. Borghetti, and G. Ledwich, "An optimization model for reliability improvement and cost reduction through ev smart charging," *Journal of Modern Power Systems and Clean Energy*, vol. 12, no. 2, pp. 608–620, 2024. DOI: 10.35833/MPCE.2022.000837.

[18] C. Joshua, M. Jonathan, J. Jude, and U. Ejaz, "Machine learning for electric vehicle charging optimization," 2025, Preprint, ResearchGate. [Online]. Available: https://www.researchgate.net/publication/391482802_Machine_Learning_for_Electric_Vehicle_Charging_Optimization.

[19] K. Lalbiakhlua, S. Deb, K. R. Singh, S. Datta, H. A. Shuaibu, and T. S. Ustun, "Deep learning based solar forecasting for optimal pv bess sizing in ultra fast charging stations," *Scientific Reports*, vol. 15, no. 1, pp. 1–17, 2025. DOI: 10.1038/s41598-025-17408-0. [Online]. Available: https://www.nature.com/articles/s41598-025-17408-0.