Analysis On Smart Charge Scheduling

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I. ABSTRACT

As the population of Electric Vehicles (EV) grows, the demand for electricity will increase drastically. The most popular methods for charging EVs is either charging at home or charging at a public station. For users who decide to charge at home, they often choose to charge the vehicle overnight since that is when the vehicle is not in use. This presents a problem as emission is the highest during the evening since the energy portfolio during the night lacks the renewable resource from solar energy. This becomes an opportunity for EVs to reduce emissions associated with charging, reduce electricity costs, and support a faster transition to renewable energy. We believe that a charging policy can be prescribed to allow the vehicles to charge opportunistically during the times with the lowest emission, and charge only up to state of charge that is needed for the next trip plus some buffer, which can lead to grid load curtailment. As more people adopt electric vehicles, solutions like dynamic charging policies will become increasingly important to ensure a sustainable transition to a low-carbon transportation system.

II. INTRODUCTION

A. Motivation and Background

The adoption of vehicle electrification has been regarded as one of the most important strategies to address the rising concern in energy dependence and to mitigate the effect of climate change in the near future. In the last decade, although empirical data reviews are still suggesting that wide adoption of battery electric vehicles are still difficult to achieve in short-terms, incentives from both the government and OEMs in the form of tax credit and additional packaged technology features are starting to attract and penetrate the early adopting population among the general public.

As more people decide to purchase electrified vehicles, a new concern about energy supply and emissions has emerged. The energy grid currently in service is already strained due to the growing energy demand, and it is projected that this demand will only increase once EV adoption becomes widespread. As of now EV adoption is still held back by the lack of charging infrastructure available, but the growth in charging infrastructure will inevitably accelerate in the upcoming years. The necessity of charging infrastructure can be viewed as two distinct groups, one is the need for more charging stations in public, and the other is the need for chargers at home. This project will focus on the home chargers only, as public charging stations operate on a model where drivers top up as quickly as possible, leaving very little room for optimizing the power delivery curve. This project seeks to minimize the emissions associated with charging at home by opportunistically tuning the charging speed of the charger to charge at the right times to reach just the amount of charge that the user needs but nothing more.

The need for a dynamic charging policy comes from the inherent fact that not every car needs to be charged to 100% the next day. Electricity usage emission is usually the highest during the night, since solar energy which takes up a majority of the clean energy portfolio does not operate at night. So when a person plugs in a charger to charge at night, it is the least environmentally friendly, and also has the highest chance of overloading the power grid.

We will create an optimized charging policy that minimizes the emissions factors and allows for just enough SOC to the battery rather than fully charging the battery. With this objective in mind we will need to obtain both the battery charging model and electricity emission curve. We will derive the charging pattern of users based on a database that logs charging activities in time series.

B. Literature Review

Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles [1]
The paper employs a critical review methodology to analyze the various SOC estimation methods used in EVs. The authors start by identifying the key factors that affect the accuracy of SOC estimation, including the battery model, sensor measurements, and estimation algorithms. They then conduct a thorough literature review, identifying and analyzing the various SOC estimation methods proposed in the literature. Finally a comparative analysis approach is launched to compare and contrast the strengths and weaknesses of each SOC estimation method with the table format to present the findings of their analysis, providing a clear and concise summary of the different methods and their relative advantages and disadvantages.
Forecasting energy demand, wind generation and carbon dioxide emissions in Ireland using evolutionary neural networks
The study used a hybrid model called the Evolutionary Neural Network (ENN) to forecast energy demand, wind generation, and carbon dioxide emissions in Ireland. The ENN model is a combination of two techniques: genetic algorithms and neural networks. The genetic algorithms optimize the weights of the neural network to minimize the error between the predicted

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and actual values, while the neural network captures the complex relationships between the input and output variables. This hybrid approach has been shown to outperform other models, including traditional neural networks, in terms of forecasting accuracy.

DACF: Day-ahead Carbon Intensity Forecasting of Power Grids using Machine Learning [2]

This literature review focuses on the development and evaluation of an Artificial Neural Network (ANN) model that uses day-ahead weather forecasts to improve the prediction accuracy of CO2 emissions in power grids with the hypothesis that this can significantly improve prediction accuracy over current methods. The ANN model is developed considering two types of energy sources: non-renewable and renewable. The model's inputs include historical source production data, hourly historical electricity generation by various sources for each region, and date and time-related features (hour of the day, hour of the year,day of the week). Day-ahead weather forecasts are also included to capture any daily and seasonal trends in the data, as weather conditions affect renewable generation and hence the day-ahead carbon intensity. The model has a Mean Absolute Percentage Error (MAPE) of 6.4% on average across all regions.

C. Focus of this Study

Our project aims to address the potential conflict between the growing electric vehicle population and the stranded renewable energy development. The methods to be explored will include optimizing charge schedules of home charging. The project objective is to promote a sustainable energy system.

III. Technical Description

This section includes three parts, the prediction of emission curve, the battery modeling and description of the charging session data. These three parts will be integrated in the optimization part.

A. Prediction of Emission Curve

To accurate predict the emission curve on a daily basis, we needed to find data related to how much emission is being outputted in a time-series data format. The dataset that we chose to use was the CAISO North Marginal Operating Emissions Rate (MOER) data provided by querying the Watttime API. This dataset has a comprehensive time-series data of CO2 lbs/MWh every 5 minutes which is representative of the pollution associated with power generation daily in the northern California region. This dataset can be interpreted as at what time of the day is the cost of emission associated with power generation the highest. We have obtained data for an entire year of MOER that can be later used to train the model for our emission prediction.

Additionally we obtained data from other sources including the daily sunset, sunrise, and average temperature data for each day of the year. But the data did not prove useful in improving the accuracy of the model.

In our endeavor to predict the Marginal Operating Emission Rate (MOER), we confronted several challenges. One of the significant obstacles was the unpredictability of spikes in the data. The spikes represent the time when renewable energies are widely used leading to a considerably low amount of CO2 emissions. These spikes occur on a daily basis but the magnitude of difference from nearly 1000 lbs/MWh to almost 0 lbs/MWh proves difficult to model.

During the Summer, those spikes are relatively easy to predict since the weather is almost the same every day and solar energy can be used almost the whole day. However, during the winter, the spikes appear 'randomly' every day. The window when renewable energies are able to provide a correct amount of energy is not the same every day and can happen whenever during the day. We suspect that is due to the less consistent weather in northern California during the winter as a result of rainfall and snow.

Besides, it's important to note that energy consumption isn't solely attributed to Electric Vehicle (EV) charging, adding another layer of complexity to our model. We are essentially working with a black box since we do not know how much of the daily energy consumption comes from EV charging, but it is safe to assume that the usage of EV charging is going to be very similar to people's habits of using residential electricity.

To effectively evaluate the accuracy of our model without significant impact from the issue of data spikes, we employed the Huber loss function. This choice was driven by its distinctive ability to accurately predict spikes. Unlike other loss functions, the Huber loss function applies a smaller penalty to minor errors while imposing a linear penalty on substantial errors. This unique characteristic makes it less prone to outliers and more capable of managing data with extreme values or sudden spikes.

The Huber loss function is defined mathematically as follows:

$$L_\delta(y, f(x)) = \begin{cases} \frac{1}{2}(y - f(x))^2 & \text{for } |y - f(x)| \leq \delta, \\ \delta \cdot |y - f(x)| - \frac{1}{2}\delta^2 & \text{otherwise.} \end{cases}$$

In this formula, y denotes the true value, $f(x)$ the predicted value, and δ is a hyperparameter that determines the transition point between the quadratic and linear regions of the function. We used δ=1 in our two models.

1) Feedforward neural network using values from the past: Our initial approach involved developing a feed forward neural network, composed of eight hidden layers, and utilizing Rectified Linear Unit (ReLU) and linear activation functions.

The model was designed to predict the next 288 values based on the previous 1000 data points. This design choice was motivated by the optimization phase, which required a full day's worth of data. Given that each data point corresponds to a 5-minute interval, we needed to forecast 288 values ahead of time to cover a complete 24-hour period.

Accurately identifying the timing of the spikes is crucial for the success of this project. And with an FFNN, the model lacks the precise prediction of daily spikes due to a lack of consistency in the data. Therefore, we sought to develop a new model capable of predicting the precise timing of daily spikes with greater accuracy. While the exact values predicted may not be entirely accurate, the primary goal is to determine when these spikes occur. To address this need, we introduce the improved model detailed in the following section.

2) Time Series Forecasting using a RNN (LSTM):

Compared to feed forward neural networks (FFNNs), recurrent neural networks (RNNs) are better suited for processing sequential data because they have the ability to capture temporal dependencies in the data. Unlike FFNNs, which only process a fixed input size, RNNs can take variable-length inputs and use their internal memory to process sequential data in a dynamic and adaptive manner.

An RNN processes data by maintaining a hidden state that is updated at each time step as it processes the sequence. The output at each time step depends not only on the current input but also on the previous hidden state. This hidden state serves as a form of memory that allows the network to capture information from previous time steps and use it to make predictions about future steps.

The model that we developed uses Long Short-Term Memory (LSTM) which is a type of RNN that was specifically designed to address the vanishing gradient problem, which can occur in traditional RNNs when gradients become too small to propagate through time. The LSTM architecture includes a set of gating mechanisms that control the flow of information through the network, allowing it to selectively remember or forget information from previous time steps.

In this study, we decided to use an LSTM to forecast the emissions. In particular, we focused on forecasting one day in Summer and one day in Winter. We pre-processed the data by scaling it using the DART library and creating co-variate series for day and month. A co-variate refers to an external variable that may have an impact on the charging behavior of the system. In our case, we used the day of the week and the month of the year as additional variables to help predict the charging behavior. Here, the day series is turned into a set of numbers representing each day, and the month series is a continuous numerical variable.

Then we trained the LSTM on a training dataset of 25 days to predict one full day, with a training length of 20 values, over 10 epochs (no significant improvement after that number of epochs).

B. Battery Modeling

EV battery pack has a limit of power during charging and discharging process. To have an accurate limit of power constraint in optimization problem, we need a battery model to derive a mathematical expression of power limit. Due to battery's electrochemistry nature, the terminal voltage is not constant during either charging or discharging process. If the charging current is constant, the terminal voltage increases rapidly in the ranges of 0-20% SOC and 90-100% SOC. In contrast, the voltage doesn't increase much during the middle range SOC. Also, the charging process and discharging process doesn't share the same power-SOC curve. The charging voltage is higher than discharging voltage when the current is the same. Once the upper cut-off voltage is reached, the current doesn't instantly go to zero. Instead, the terminal voltage is held constant at the upper cut-off voltage and the current will steadily drop from the set charging current to zero. Combining the three factors above, SOC state, current state, and charging or discharging state together lead to a corresponding battery pack terminal voltage and power limit. There are also other factors, for instance environment temperature and battery's life cycle, that can affect the power limit. Because these two factors are not recorded in the charging demand dataset, this project will neglect their impact. Therefore, the battery modeling will have one model for charging and one model for discharging. Each model will have an expression of power in term of SOC.

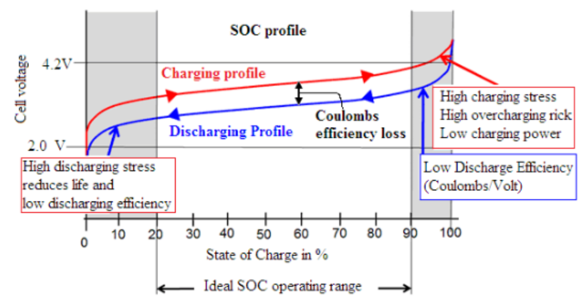

Fig. 1: Battery Cell Behavior: Charging and Discharging [3]

Due to lack of high-quality EV battery charging and discharging dataset that specifies the states above with high granularity, the data for modeling will be generated from PyBamm, a python library with widely recognized battery cell models. By modifying cell parameters of pybamm's single particle model, this model can simulate the development of battery states needed for the project on cell level. Then, the cell level data can be scaled up to the battery pack level, to resemble the SOC and voltage states in charging and discharging behaviors of EV. And the high granularity of data points will be suitable for modeling.

C. Charging Dataset

With the objective to implement our RL-based charging control method, a real-world residential EV charging dataset is obtained from a data article [4]. After initial cleaning, a total of 6,844 charging sessions registered by 96 user IDs, from December 2018 to January 2020, is recorded from a large housing cooperative with 1,113 apartments in Norway.

	User_ID	Start_plugin	Start_plugin_hour	End_plugout	End_plugout_hour	El_kWh	Duration_hours	month_plugin	weekdays_plugin
0	AdO3-4	2018-12-21 10:20:00	10	2018-12-21 10:23:00	10.0	0.30	0.050000	Dec	Friday
1	AdO3-4	2018-12-21 10:24:00	10	2018-12-21 10:32:00	10.0	0.87	0.133333	Dec	Friday
2	AdO3-4	2018-12-21 11:33:00	11	2018-12-21 19:46:00	19.0	29.87	8.216667	Dec	Friday
3	AdO3-2	2018-12-22 16:15:00	16	2018-12-23 16:40:00	16.0	15.56	24.416667	Dec	Saturday
4	AdO3-2	2018-12-24 22:03:00	22	2018-12-24 23:02:00	23.0	3.62	0.983333	Dec	Monday

Fig. 2: charging session data

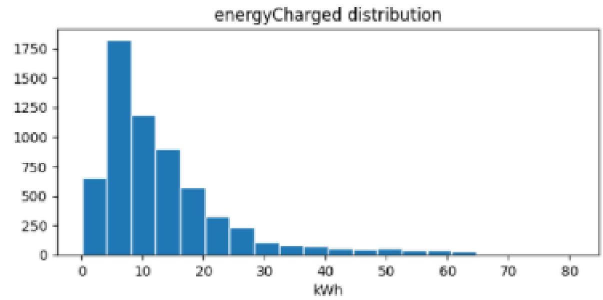

Fig. 3: Distribution of Amount of Session for Energy Charged

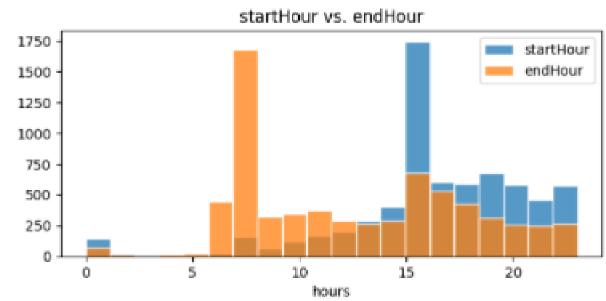

Fig. 4: start and end hour of the charge

Instead of simulating the driving and charging of PEVs based on national household travel surveys, this dataset provides actual historical residential charging behavior to use as our optimization constraints. Each session is recorded with the plug-in, plug-out time, amount of energy charged (kWh), and some other user identifiable attributes.

In this residential charging dataset, a session has an average plug-in duration of 11.85 hours, and an average energy charged of 15.58 kWh, with most frequent plug-in time at 4pm and plug-out time at 7am local time.

D. Charging strategies

- **Baseline Charging**
  The normal way for charging, namely starting charging at the moment of plug in and stop charging whenever the battery reaches 100% or plug out.
- **Shift Charging**
  The shift charging is to choose the proper time for charging during the whole charging session. To be more specific, the vehicle will charge when the emission index is low.
- **Vehicle-to-Grid (V2G) Charging**
  Vehicle to grid allows the vehicle to give back the electricity when the marginal emission index is high and charge when the emission index is low.

E. Optimization Formulation

Using the emission curve, battery modeling and empirical charging session data, we formulated an optimization problem that minimizes the amount of emission resulting from EV charging and obtain the resulting optimal charging policy. The objective function of the optimization problem is defined mathematically as follows:

$$\min_{P,I,SOC} f_{emission} = \sum Emission(t) * P(t)$$

$Emission(t)$ is the marginal emission index as given by the emission curve, and $P(t)$ the charging power is the optimization variable.

Shift Charging

The objective function above is subject to the following constraints when taking the strategy of shift charging.

$$SOC(t+1) = SOC(t) + \frac{I(t)}{Q}\Delta t \tag{1}$$

$$P(t) \geq V \cdot I(t) + C \cdot I(t) \tag{2}$$

$$0 \leq P(t) \leq P_{charging}(SOC) \leq P_{limit} \tag{3}$$

$$SOC(t=0) = SOC_{start} \tag{4}$$

$$SOC(t=t_f) \geq SOC_{target} \tag{5}$$

$$\sum I(t)\Delta t \geq Q * (SOC(t=t_f) - (SOC(t=0)) \tag{6}$$

Below is the physical meaning of each symbols and their assumed values:

Symbols	Description	Value (Unit)
$P_{charging}$	Max charging power at different SOC	Determined from battery model
P_{limit}	Power limit delivered by specific charger	9.6kW
$SOC(t)$	Battery state of charge	0 - 100%
SOC_{start}	Initial state-of-charge at $t = t_0$	From charging data
SOC_{target}	Target state-of-charge at $t = t_f$	From charging data
V	Charging voltage	240V
$I(t)$	Charging current	0 - 40A
Q	Pack capacity	250Ah
C	Proportional loss coefficient	36

TABLE I: Nomenclature and values

Back to Grid charging

In terms of Back to grid strategy, the constraint 3 need to be modified as the following formula so that back to grid operation is feasible.

$$P_{discharging}(SOC) \leq P(t) \leq P_{charging}(SOC) \leq P_{limit}$$

$P_{discharging}(SOC)$ is negative, representing the limit for the amount of power that can be sent back to the grid unit time.

Also another constraint needs to be added to take the loss into consideration when carrying out the action of discharge.

$$P(t) \geq V \cdot I(t) - C \cdot I(t)$$

C is a constant which is used to represent the 15% of loss during the charging and discharging behavior.
Considering the value needs to be negative when the discharging happens, the upper constraint is added.

The above optimization problem is solved using CVXPY in Python and the results are illustrated in the following section.

F. Results

In this section, we firstly show the results of the predicted emission curves during winter and summer with the methods of FFNN and LSTM.

Then we displayed the power limit for charging and discharging which are used as constraints in the optimization formulation.

Finally by integrating the predicted emission curves (summer and winter), the battery model and the real charging data. We took three different strategies, baseline, shifting and back to grid charging and compared the average emission output for each session.

1) Emission Curve Prediction Results:

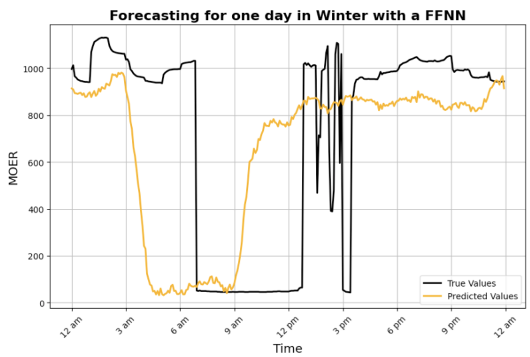

Fig. 5: MOER prediction for one day in Winter with FFNN

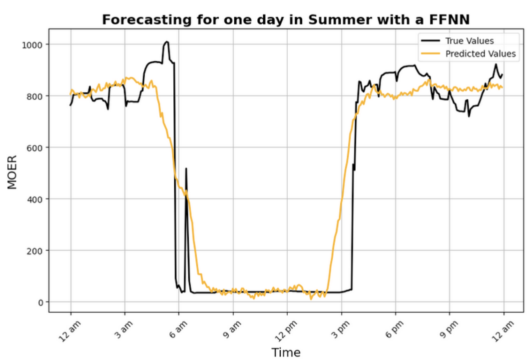

Fig. 6: MOER prediction for one day in Summer with FFNN

Figures 5 and 6 display the outcomes of our predictions for two distinct days, one in summer and another in winter. The Huber loss values for these two instances are 77.8 for summer and 320.6 for winter. As anticipated, our model accurately predicts the daily pattern in summer, given that the pattern remains relatively consistent throughout the season. This allows us to predict the spikes in energy usage effectively during the day. On the other hand, our model's accuracy is somewhat diminished for the winter day. Although we can still predict a spike in energy usage, there is an error of 4 hours in this specific prediction. This inaccuracy in the prediction of time of the daily spike is what motivated us to approach this emission curve differently as a RNN model.

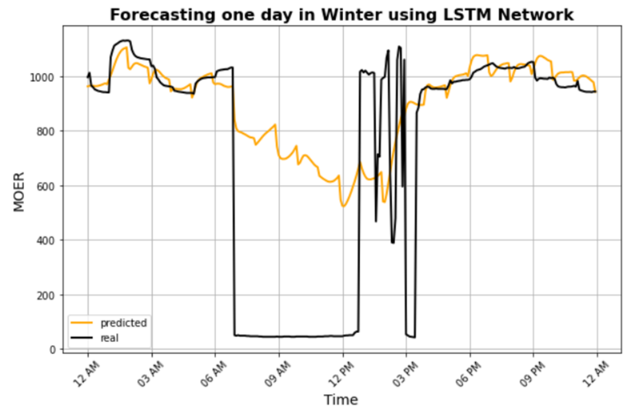

Fig. 7: MOER prediction for one day in Winter with LSTM

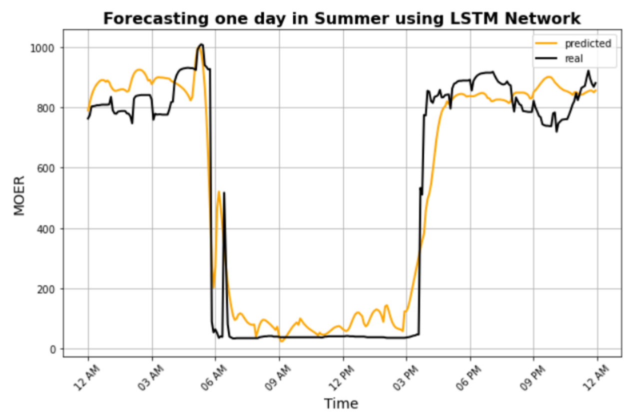

Fig. 8: MOER prediction for one day in Summer with LSTM

Figures 7 and 8 display the outcomes of our predictions for two distinct days using a LSTM network instead, one in summer and another in winter. The Huber loss values for these two instances are 78.6 for summer and 231.9 for winter. As for the FFNN, our model accurately predicts the daily pattern in summer, given that the pattern remains relatively consistent throughout the season. This allows us to predict the spikes in energy usage effectively during the day. There is no improvement for that part, the results are both consistent using FFNN or RNN.

On the other hand, our model's accuracy is better performing for the winter day than the previous model. It is identifying the timing of the spikes with a good precision, although there is still a lack of precision concerning the value of the emissions. All in all, we obtained convincing results with this LSTM model. We will use these predictions in the following parts of that paper.

2) Battery Modeling Result:

The model subject is Tesla Model 3 Long Range battery pack consisting of 4416 pcs of Tesla/Panasonic 2170 cells.

These cells are arranged in 96 groups in series, each group as 46 cells in parallel. By matching the cell parameters of PyBamm Single Particle Model to electrical parameters of Tesla/Panasonic 2170 cell in the table below, the PyBamm simulation can return very similar battery cell behaviors to the actual cells.

TABLE II: Parameters of Tesla/Panasonic 2170 cell and PyBamm Cell Model

Parameters	Cell 2170	PyBamm Cell Model
Capacity (Ah)	4.8	4.73
Lower Voltage Cutoff (V)	2.5	2.6
Upper Voltage Cutoff (V)	4.2	4.1

For each SOC step, the battery pack's current and voltage are 46 times and 96 times of the battery cell's current and voltage results respectively. The power of battery pack are the product of the current and the voltage. By trying fitting the Power-SOC curve with several convex mathematical expression, it could be found that logarithmic equation fits the best for the discharging process and for the first 95% SOC steps of the charging process. These last 5% SOC steps is best fitted by a straight line. Thus, the battery modeling is concluded with one expression for discharging and two expressions for charging.

Charge Model (7)

$$P(SOC) = \begin{cases} 142.8log(SOC) + 8755.4 & \text{for } SOC \in [0, 0.95], \\ -175107.3SOC + 175107.3 & \text{for } SOC \in (0.95, 1] \end{cases}$$

Discharge Model (8)

$$P(SOC) = 306.3log(SOC) + 8838.8$$

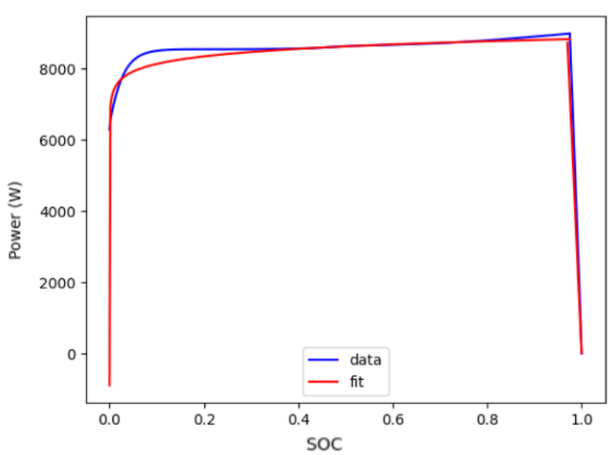

Fig. 9: Charge Model of Battery Pack

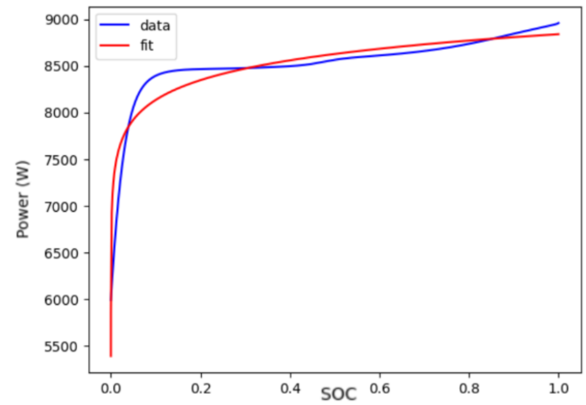

Fig. 10: Discharge Model of Battery Pack

3) The Effectiveness of Shift Charging:

Firstly, we compare the average marginal CO2 emission by taking the strategies of baseline charging and shift charging.

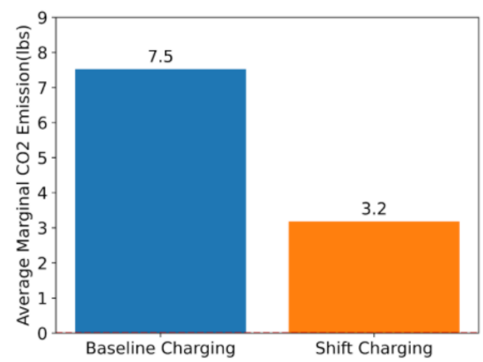

Fig. 11: Average CO2 Emission

As shown in Figure 11, there is a significant difference of average marginal CO2 emission between the strategy of baseline charging and shift charging. By taking the strategy of shift charging, 57% of emission can be saved.

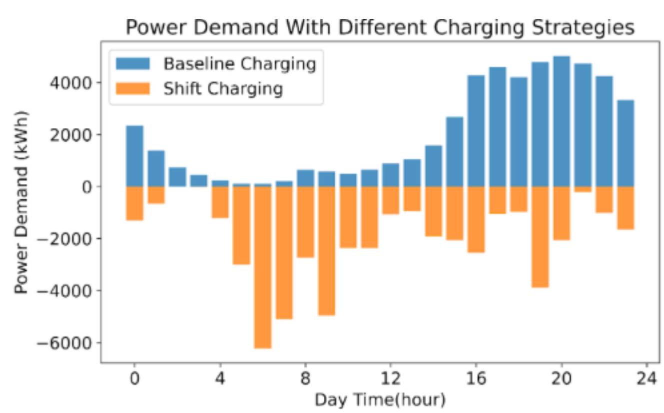

Fig. 12: Power Demand For Two Strategies

Figure 12 shows the average power demand with baseline charging and shift charging. It is common that the demand is very high during peak hours usually from 5 to 10pm. However, 65% of the power demand this period can be shifted to idle time during the day, making the electricity load balanced within the whole day.

4) The Effectiveness of Vehicle-to-Grid:

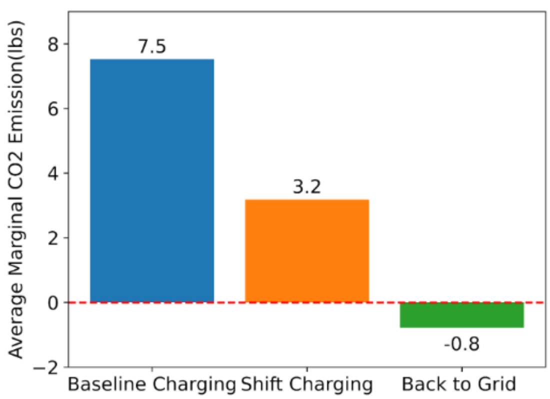

Fig. 13: Average CO2 Emission

Figure 13 shows the average marginal CO2 emission with three strategies. We assume that charging represents giving out emission and discharging is saving emission. The negative value of back to grid represents that earning money by taking the strategy of back to grid. The emission can be saved at the same time with the vehicles charged. By analyzing the result in detail, 68% of the charging sessions can attain negative emission volumes.

IV. Discussion

The charging emission curve was predicted with good accuracy for the summer season, with Huber Loss less than 100. However the issue rises from the prediction of winter curves as the Huber Loss is often higher than 100. While we were able to accurately predict the time at which this spike occurs now, we still lack in the ability to determine the magnitude of the spike. As seen in Figure 6, not all spikes drastically decrease, and our prediction was not able to fully capture that which leads to a higher Huber Loss value. However this prediction is accurate enough that the impact of such model should have minimal impact on the overall policy prescription of the model. We believe that with additional parameters we should be able to further increase the accuracy of our model.

For future work, the battery model could also be improved. A limited amount variables were considered for the modeling and only logarithmic relation of SOC is used. This rudimentary model excels in the purpose of ease of solving optimization problem in the next stage, but certainly lacks in consideration of other potential elements that may affect the battery's performance. If variables like temperature and aging conditions are measurable and controllable inputs, they could also be incorporated in the expression of power. This way, the power in charging and discharging processes can be predicted more accurately. This means a more accurate power limit in optimization formula could be developed and more reliable optimization results could be achieved.

Due to the unavailability of charging session data in California, we substitute with the charging session data that originated from Norway. Because of the difference in geography, there will be an inherent incompatibility between the predicted emission curve and charging session data. Therefore the numerical values related to emissions volume of CO2 are theoretical values, and are potentially prone to producing accurate results. However, conceptually the effectiveness of shift charging and vehicle-to-grid strategies have been proven viable with this study, and we see that there is potential of implementing these two strategies into a concrete charging policy.

V. Summary

Our research was motivated by the desire to develop a smart charging policy that minimizes the environmental impact of high-carbon power generation. By leveraging advanced artificial neural networks, we successfully reduced the average marginal CO2 emissions in comparison to baseline measurements. Our methodology entailed modeling an emission prediction curve utilizing feedforward neural networks (FFNN) and subsequently refining it with a long short-term memory (LSTM) model. Moving forward, we recommend exploring additional variables that may impact emissions for even better results.

To facilitate the optimization of charging protocols, we developed a battery model to simulate the battery cycle of a typical electric vehicle battery. This enabled us to optimize the timing of charging while minimizing associated emissions. Further improvements to the model can be made by incorporating parameters such as battery temperature and electrochemistry. In terms of our existing optimization strategy, we were able to prescribe various charging policies with different charging strategies in mind, but in the future we can explore additional scenarios that could be the result of additional parameters such as the price curve and battery protection from low SOC. In conclusion, our study provides a compelling proof of concept that emissions can be substantially reduced through the strategic implementation of shift charging and vehicle-to-grid technology.

References

[1] R. Xiong, J. Cao, Q. Yu, H. He, and F. Sun, "Critical review on the battery state of charge estimation methods for electric vehicles," *IEEE Access*, vol. 6, pp. 1832–1843, 2018.

[2] Y. Wang, H. Xu, Z. Xu, X. Guo, Y. Li, H. Chen, S. Chen, and J. Chen, "Dacf: Day-ahead carbon intensity forecasting of power grids using machine learning," in *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 2021, pp. 3268–3277.

[3] C. Bharatiraja, S. Padmanaban, P. Siano, K. Ramesh, and R. Selvaraj, "Real time foresting of ev charging station scheduling for smart energy system," *Energies*, vol. 10, 03 2017.

[4] L. Sørensen, K. Lindberg, I. Sartori, and I. Andresen, "Residential electric vehicle charging datasets from apartment buildings," *Data in Brief*, vol. 36, p. 107105, 04 2021.

My Individual Contributions

In this project, I took on the responsibility of forecasting the timeseries data related to the charging behavior of Electric Vehicles (EVs). My contribution played a crucial role in developing an optimized charging policy that minimizes emissions and ensures efficient energy usage.

I undertook the task of forecasting the charging behavior of EVs using various methods and types of recurrent neural networks (RNNs). I experimented with different approaches and evaluated their performance to identify the most effective solution. After thorough analysis, I determined that an LSTM (Long Short-Term Memory) model would best capture the temporal dependencies in the data. To ensure accurate predictions, I performed comprehensive data preprocessing tasks, including scaling the data using the DART library. For the forecasting model, I implemented the LSTM architecture. The resulting model provided valuable insights into the charging patterns of EVs, contributing to the development of an optimized charging policy.

In addition to my technical role, I actively contributed to the project's success through effective communication and participation. I maintained open and constructive communication with team members, sharing my findings, progress, challenges ad explaining concepts that I learnt about RNNs. I actively engaged in discussions during team meetings. I am glad our group created a positive and productive atmosphere for the entire project.

Overall, my individual contributions encompassed the technical aspects of data preprocessing, feature engineering, and implementing an LSTM forecasting model. Additionally, my proactive participation to the project played a crucial role in ensuring a successful outcome for this paper.