Managing EV Fleets to Deliver Humans, Goods, and Electricity

Osman Yağan (PI) (https://orcid.org/0000-0002-7057-2966)

Mohammad Mohammadi (https://orcid.org/0000-0002-7457-9030)

FINAL RESEARCH REPORT

July 30, 2023

Contract # 69A3551747111

grant from the U.S. Department of Transportation's University Transportation Centers Program. The U.S. Government assumes no liability for the contents or use thereof.

Publications

1. I-C. Lin, O. Yağan, and C. Joe-Wong Evaluating the Optimality of Dynamic Coupling Strategies in Interdependent Network Systems, *IEEE International Conference on Communications (ICC 2023)*, Rome (ITALY), June 2023.

   URL: http://users.ece.cmu.edu/~oyagan/Journals/DynamicCascades.pdf

   ORCID ID's of Contributing Authors:

   - Osman Yağan https://orcid.org/0000-0002-7057-2966
   - Carlee Joe-Wong https://orcid.org/0000-0003-0785-9291
   - I-Cheng Lin

Managing EV Fleets to Deliver Humans, Goods, and Electricity

1 Project Summary

As electric vehicles (EVs) become increasingly popular, efficient and effective charging infrastructure management is essential to ensure the smooth operation of EV fleets. The optimization of EV charging is crucial to reduce energy consumption, minimize operating costs, and improve charging infrastructure utilization. The lack of proper charging management often leads to inefficient charging practices, overloading of the power grid, and increased operating costs. There is a need to develop a decision-making tool that can optimize the charging process for EVs, taking into account the EV fleet's needs, the charging infrastructure capacity, and energy consumption. Such a tool could help reduce operating costs, minimize energy usage, and increase the lifespan of EV batteries, contributing to the sustainable development of the transportation industry. Therefore, there is a pressing need for a comprehensive approach to EV charging optimization, which can efficiently manage charging infrastructure while meeting the EV fleet's energy requirements.

The goal of our project is to lay out the foundations towards developing a tool that assists in managing large electric vehicle fleets. In its fully developed form, we anticipate that the tool will utilize data from sources such as past driving patterns, energy usage, building energy profiles, weather and traffic predictions, and use them to make charging and discharging decisions for both individual vehicles and the fleet as a whole.

During this project, we developed a simpler version of this tool as a proof-of-concept. Namely, we developed a software tool that outputs charging decisions for each vehicle based on the constraints of the EV fleet (e.g., its energy demand) and the instantaneous of price of electricity.

2 Literature Review

Pei Huang (2020) and his team have developed an automated coordination mechanism that enables the grid operator to plan a charging strategy for electric vehicles while maintaining grid capacity constraints. The mechanism includes three main components: a central grid agent, an EV agent, and a request queue. The central grid agent manages energy utilization and sends requests to the grid agent to get feedback on available power and price of energy at each time period. The grid agent then sends this information back to the EV agent, which optimizes the charging strategy for the vehicle for the next planning period.

The optimization process considers factors such as trip details, battery capacity, available energy, electricity price, and charger availability to suggest a charging pattern that ensures the vehicle is charged enough to complete its scheduled trips, while also fulfilling battery state-of-charge constraints and minimizing charging costs. Each charging event is recorded with information about the start time, duration, amount of energy charged, location of charging, and power at which the energy was charged. The research focuses on optimizing the charging strategy to balance energy demand during peak hours and reduce the load on the grid.

In 2022, Saleh Aghajan-Eshkevari published a paper that aims to provide a comprehensive review of control structures of electric vehicles (EVs) in charging stations, objectives of EV management in power systems, and optimization methodologies for charge and discharge management of EVs in energy systems. The paper analyzes the goals that can be achieved with efficient charge and discharge management of EVs, which are divided into three groups: network activity, economic, and environmental goals.

The paper highlights that with optimal EV management, the system operator can reduce the number of power purchases from the upstream network during peak periods, integrate a larger number of renewable resources into the grid, and minimize the cost of starting, shutting down, and fueling generators, ultimately reducing costs. The paper emphasizes the importance of EV management in achieving these goals and highlights the various optimization methodologies that can be used for charge and discharge management of EVs in energy systems. Overall, the paper provides a valuable resource for researchers and practitioners interested in optimizing EV management in power systems.

In 2015, Junjie Hu published a paper that provides a review and classification of methods for smart charging, including power to vehicle and vehicle-to-grid charging of electric vehicles for fleet operators. The paper presents three control strategies: centralized control, transactive control, and price control.Centralized control refers to the fleet operators directly scheduling and controlling the charging of electric vehicles. Transactive control is a market-based control method that aims to reach equilibriums by exchanging information concerning generation, loads, constraints, and responsive assets over dynamic, real-time forecasting periods using economic incentive signals. Transactive control typically requires two-way communication, where information regarding the price and power schedule is exchanged. Price control, on the other hand, uses one-way communication and broadcasts price signals with a regularly updated frequency to the demand-side resources. The paper emphasizes that each control strategy has its advantages and limitations, and that the choice of strategy depends on the specific requirements of the fleet operator.

3 Problem Formulation

3.1 Notations

t: current time slot

N_v: number of the vehicles

$x_v(t)$: power that vehicle v receives during time slot t

c(t): price of electricity in every time slot

L: total power for the entire day and all vehicles

L(t): total power our vehicles are charged at time slot t

D_v: total power that vehicle v demands, i.e., needs to be charged

3.2 Formulation

$$L(t) = \sum_{v=1}^{N_v} x_v(t)$$

$$L = \sum_{t=0}^{T} L(t)$$

$$C = \sum_{t=0}^{T} c(t)L(t)$$

$$Minimize\ aC^2 + bC$$

$$subject\ to \sum_{t=0}^{T} x_v(t) \geq D_v \quad for\ all\ v = 1, \dots, N_v$$

4 Project Results

Below, we present the project results in several stages corresponding to the project progress over the 12 months. In particular, at different stages of the project, we have modified the formulation by adding more complexities, e.g., adding a cost for unavailability of an EV, to make the results more useful in applications.

4.1 Stage 1:

- Divided 24 hours of the day into the 96 time slot which mean every time slot equals 15 minutes
- Infrastructure charging rate is from zero to 2 kWh
- This optimization done for 5 cars
- We consider the spot price of electricity as follows: From 12 a.m. to 6 a.m. and 12 p.m. to 6 p.m. are the times when the price is lower than the rest of the times.

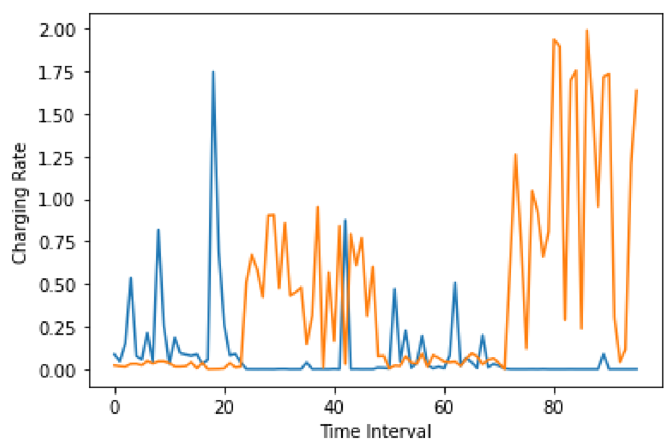


Figure 1:

4.2 Stage 2:

- Adjusted constant cost for different times and varied peak price times
- Applied optimization for different number of the EVs
- The plots below show how our optimization framework adjusts the charging of the EVs based on instantaneous electricity prices, for 10, 20, and 30-vehicle fleets

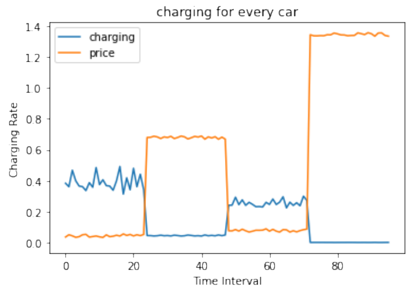


Figure 4: 10 EVs

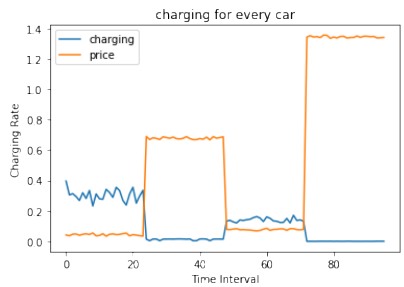


Figure 3: 20 EVs

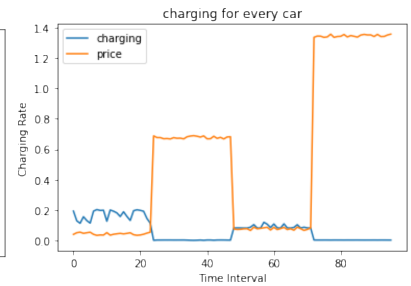


Figure 2: 30 EVs

4.3 Stage 3:

- Limit the charging time duration to 2.5 hours
- Limit the charging need of the cars
- Charging Rate range is: [0,2]

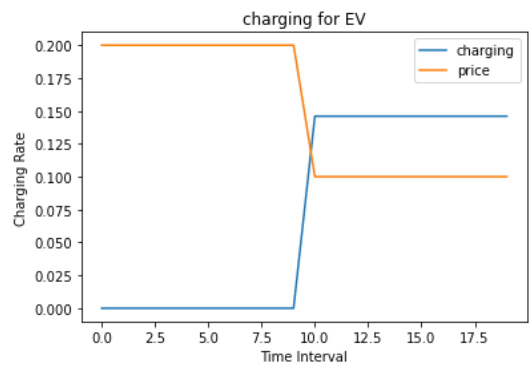


Figure 5

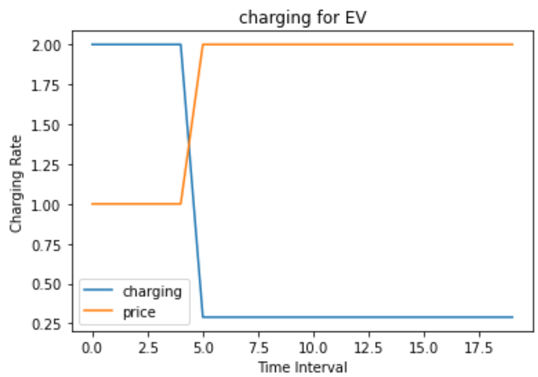
In Figure 5, we see that the our formulation waits until the price of the electricity drops and then charges the vehicle at a constant rate in the time-interval where the price is *low*. Here, the charge rate is zero during the *expensive* time interval since we are able to meet the vehicles' demand by charging only during the *cheap* time.

4.4 Stage 4

- Charging during the expensive times because the Electric Vehicle charging need can't cover during the cheap times.

Next, we test our solution for the case where the energy demand of a vehicle is higher than the previous scenario, so it would not be sufficient to charge the vehicle only during the cheap duration (even with charging at the maximum rate).

We see in Figure 6 that our solution adapts to this scenario well and charges the vehicle during the expensive time interval, although at a relatively low rate, and then starts charging at the maximum rate when the price drops.



Total Charging = 14.33
Cheap time charging = 1.99
Expensive time charging = 0.28
Cheap time slot = [0,5]
Expensive time slot = [6,20]

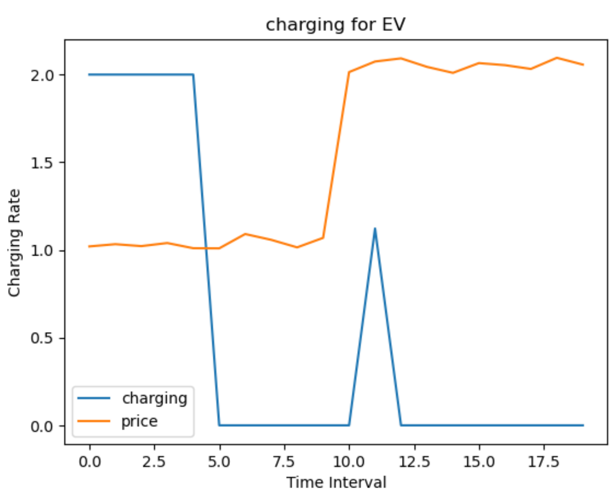
Figure 6

4.5 Stage 5

○ Consider specific available times to charge the EV during the day

Next, we incorporate the fact that a vehicle may not always be available for charging, e.g., when it is actually in use. To this end, we can change our optimization framework to add a constraint that vehicle charge levels should be zero in certain time intervals.

In Figure 7, we see that our solution adapts well to this additional constraint. It charges the vehicle at the maximum rate when the price is cheap, but only until the vehicle starts being unavailable. As soon as the vehicle returns to the base, i.e., becomes available, our solution starts charging it to the desired level.



Available to charge: [0 – 5], Price: $1
Unavailable to charge: [5– 10], Price: $1
Available to charge: [10-15], Price: $2
Unavailable to charge: [15-20], Price: $2

EV Power need: 11.12 Kwh
The prices will fluctuate over $1 and $2

Figure 7

4.6 Stage 6

- o Change the model and add the future demand as a constraint which means we know the amount of charging in the future
- o *2 EVs with Different needs and Unavailable times to charge*

We now consider a scenario where 2 vehicles with different unavailability times and different demand levels in future times. For example, it might be the case that Vehicle 1 will be in use two separate time intervals during the day (e.g., 9am-11am and then 3pm-5pm) with known minimum battery levels needed at the beginning of those unavailability times.

Figures 8 and 9 show how our model adapt to this scenario and optimizes the charging of both vehicles while respecting their unavailability periods and meeting their power demands.

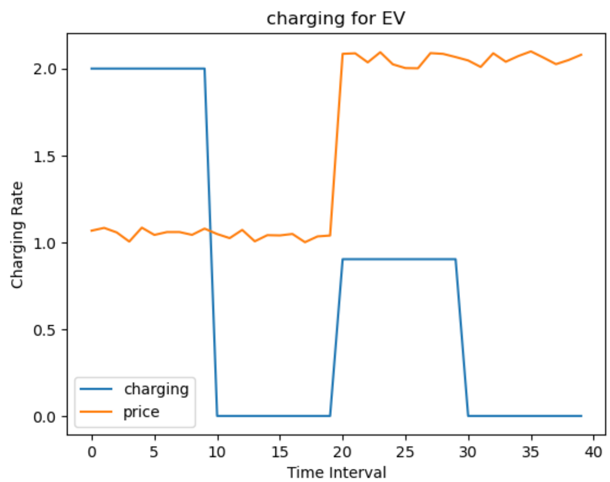


Figure 8

EV 1
Charging Need: 29.02 Kwh
Charing Times

- *Time Slot "0 -10": 1.99 Kwh*
- *Time Slot "20 -30": 0.90 Kwh*

Unavailable time

- *Time slot "10-20" to "20-30"*

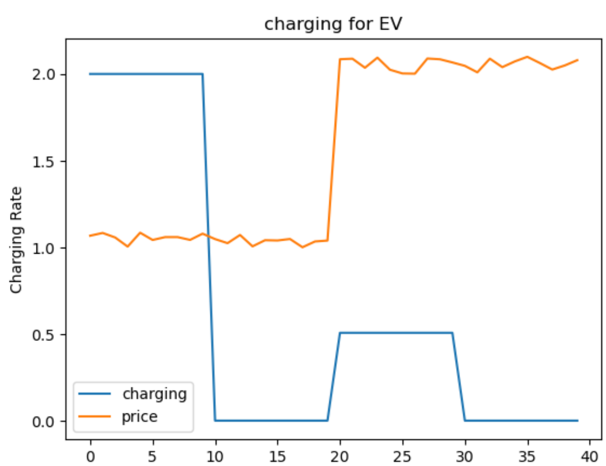


Figure 9

EV 2
Charging Need: 25.06 Kwh
Charing Times

- Time Slot "0 -10": 1.99 Kwh
- Time Slot "20 -30": 0.50 Kwh

Unavailable time

- Time slot "10-20" to "20-30"

4.7 Stage 7

- Assume demand from a vehicle is *random* and *unknown* to the charging authority ahead of the time. If the vehicle can not meet the requested demand, then we incur an "unavailability cost."

In the final stage of the project, we consider a more complex formula scenario where the demand for our vehicles in the fleet are random and unknown apriori. In such cases, we face a trade-off between charging the vehicle during time intervals where the price is high, or not charging it and *risking* the possibility of the vehicle not having enough battery if a *demand* arises.

More concretely the scenario we have in mind is as follows. Suppose that an EV has been used during the day and was brought back to the headquarters at 2pm with only 10% battery remaining. At that time, we can either start charging the vehicle immediately and potentially pay a high price for charging, or can keep the vehicle without charging until the price goes low likely later in the evening. In the former case, we will be paying a high cost for charging but increasing the chances that of this vehicle being *ready* to be used again if there is a demand from an employee at, say, 4pm. In the latter, we will be saving from energy costs but risk the demand from an employee to use a vehicle not being met. We quantify the cost of unavailability of a vehicle to meet a demand requested by U_c and accordingly change the "costs" associated with charging a vehicle *v* as follows:

$$C_v = \sum_{t=1}^{T} c(t) L_v(t) + U_c * 1[\sum_{j=1}^{t} L_v(t) < D_v(t)]$$

Where we have

U_c: Unavailability Cost
C_v: Total cost associated with vehicle v over a duration of T time slots.

- Includes charging costs *and* potentially unavailability costs

$c(t)$: Unit price of electricity at time t
$L_v(t)$: Decision variable indicating how much we charge vehicle v at time slot t
$D_v(t)$: Energy needed from vehicle v at time slot t (this is zero if the EV is not requested)
T: Charging Intervals
1[]: Indicator Function

The results for this complex scenario are shown in Figure 10 below where we can see that our solution adapts well to the demand distribution shown in Figure 11.

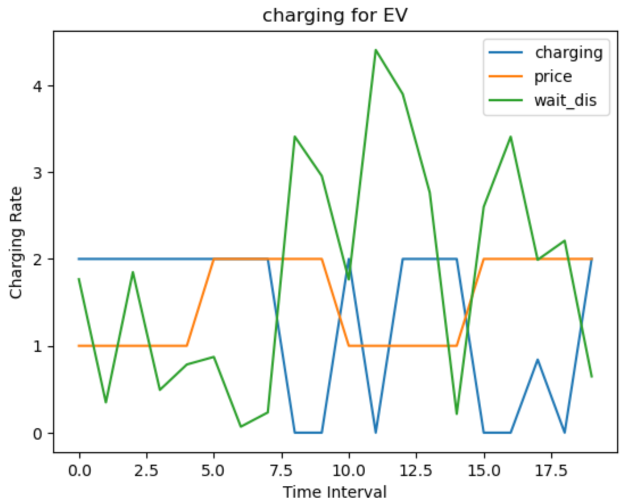


Figure 10: Charge Needs= 26.84

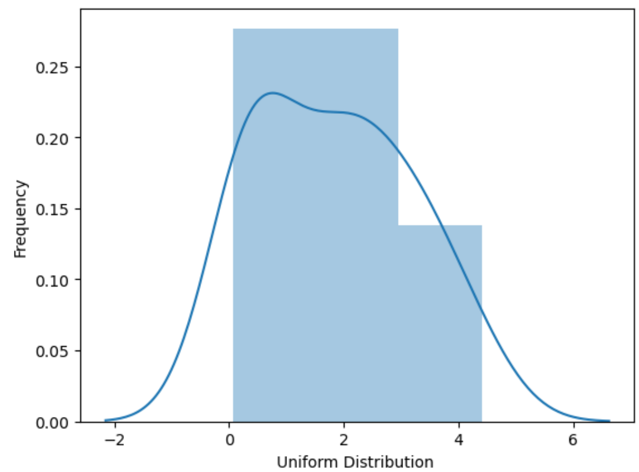


Figure 11

5 Conclusion and Recommendations for Future Work

In this project, we developed a preliminary version of a software tool that would optimally manage the charging operations of an electric vehicle (EV) fleet in conjunction with an adjacent building's energy management system. The current version of the tool can optimize the charging times of each vehicle in the fleet based on known energy prices and known demands on the vehicles. In addition, when the demand is unknown but its probability distribution is known, our tool can optimize the charging decisions in the sense of minimizing the total expected cost (which also include the cost of potentially not meeting the demand on a vehicle).

There are several directions that one can take for future work. First, the tool developed here can be analyzed more thoroughly under different scenarios to assess its performance under different fleet sizes. The tool can also be utilized to develop EV fleet deployment plans for specific use cases. For example, we expect it to be useful in understanding the trade-offs between the fleet's size and overall operating costs. With more vehicles in the fleet, the charging of the vehicles can mostly be done during times when the electricity prices are low. Our tool can help assess whether the additional cost of increasing the fleet size would be justified by these savings in charging them.

An important direction for future work would be to complete the development of our tool according to the initially envisioned plan by integrating it with a large-scale building energy management system. With this integration, it will be possible for the building to receive power from the EVs when doing so helps minimize the costs, e.g., when demand for vehicles is low but the energy usage in the building is high during a time when electricity prices are high.