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A MULTI-OBJECTIVE OPTIMIZATION MODEL FOR VEHICLE-TO-GRID SYSTEMS

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Abstract

This study develops a multi-objective optimization model that considers the preferences of stakeholders in a vehicle-to-grid system. The optimization problem is formulated using a mixed integer linear programming (MILP) model with objectives to meet the requirements of the aggregator and electric vehicle owners. The first objective aims to minimize the customer's charging cost while also maximizing the earnings of the customer from discharging to the grid during periods of peak demand while the second objective ensures that the aggregator's profit is maximized. Simulations using time series over a 48-hour period show the results of the two objectives solved together as a multi-objective problem. Pareto front is used to show the relationship between the two conflicting objectives and for selecting a solution depending on the decision maker's preferences.

Keywords
Vehicle-to-grid, optimal scheduling, electric vehicles, multi-objective optimization.

1. Introduction
The adoption of electric vehicles (EV) has been on the rise for reasons such as their environmental friendliness and lower fuel costs compared to conventional fuel vehicles. Although these factors are attractive and have led to the increasing popularity of EVs as shown by market studies [1], an issue arises because of the effect the large-scale integration of EVs might have on the power grid. Power grid generation and transmission is constrained due to limit in production capacity of generators, transmission lines and transformers. The increase in demand to the power grid by electric vehicles charging can lead to system overload and voltage fluctuations if not properly managed. Fortunately, one of the benefits of electric vehicles is that their batteries can be used as movable energy storage systems in a smart grid and can provide ancillary services such as frequency and voltage regulation. This is known as the vehicle-to-grid (V2G). In a V2G system, electric vehicles can support the grid either by unidirectional charging or bidirectional charging. In the case of frequency regulation and unidirectional charging, the vehicle adjusts it's charging power to provide frequency regulation depending on if the system is in a regulation up or regulation down mode. For bidirectional system, the vehicle can provide power to the grid during periods of peak demand by discharging its battery. A variant to V2G is the vehicle-to-home technology where energy stored in car batteries could be used to power the home during periods of peak demand and can also be utilized as backup power supply in the case of an emergency [2].

The unpredictable availability of electric vehicles in a V2G system requires coordination if the potential of car batteries supporting the grid is to be maximized. The main purpose of this study is to optimize the scheduling of electric vehicle charging and discharging to satisfy the aggregator and EV owners participating in the system. The aggregator in this study serves as the interface between the power grid and the EVs and oversees V2G activities including charging and discharging of vehicles. The main objective of the aggregator is to maximize its profit. The aggregator will also ensure that the EVs are charged to the customer's desired state of charge (SOC) to avoid being penalized for failing to meet the customer's satisfaction. The objective of the EV owner is to minimize the cost of charging its battery to the desired SOC.

The rest of this paper is organized as follows. Section 2 presents previous work related to this study, section 3 describes the methodology to solve the multi-objective problem, section 4 shows the results of simulations using case studies and finally the conclusion and future scope of the present work is presented in Section 5.

2. Related Work

This section reviews previous studies related to the research in this paper, particularly studies that examine how EV owners' preferences affect their charging decision. In [3], the authors carried out a mixed-objective optimization that considers the customer charging cost and valley filling to address grid-operator and customer requirements. This study paid attention to the concerns and satisfaction of customers by considering factors such as battery degradation and customer satisfaction. The first objective function was minimizing the total charging cost for the customer and the second objective to improve the load factor by shifting peak load to times of light load. Weights were applied to the two functions and normalization was also applied to level them and the mixed objective function was solved for different scenarios by varying the weights of each objective function. The authors in [4] studied the optimal scheduling of electricity in an intelligent parking lot considering some characteristics of the consumers such as the EV's battery life, initial SOC, charging period and the desired charging/discharging price limits. The charging/discharging price limits were used to determine when the car battery charges or discharges. This decision is static and does not change with an increase in the SOC of the vehicle or other factors such as range anxiety. In the real world, these preferences or tolerance vary from one individual to the other. A stated preference experiment conducted by [5] was used to determine the charging choices of drivers. The authors conducted a survey with respondents being members of the Electric Auto Association (EAA). The study considered factors such as dwell time, price, range charged, charger power, distance to next charging opportunity, cost at the charging station, electric range remaining in battery and how they influenced charging choice.

This study considers the heterogeneity of EV owner's charging decisions based on their travel patterns, dwell time at the charging station, and state of charge of their batteries on arrival at the charging station. Charging decision will be determined not only by the price of electricity at the charging period or the objective of the aggregator but also the willingness of the EV owner to meet its minimum required charge.

3. Methodology

3.1 Problem formulation

For this study, MATLAB and GAMS are used for the simulation and optimization of the scheduling problem. A total of 48 intervals of 1 hour each is used for the simulation of 2 days. The second day was added to ensure that the departure time of vehicles that arrived late the first day and couldn't complete charging at the end of the day could still be determined the next day.

Data on drivers' travel pattern was obtained from the 2017 National Household Travel Survey (NHTS) [6]. The aggregator in this study is assumed to be a smart parking lot that serves EV owners that are at work, going for leisure activity, shopping etc. The arrival time distribution of vehicles is modeled after NHTS arrival time data for customers engaging in the activities listed above. The dwell time which is the time the vehicle spends at the parking lot was randomly generated between 1 and 12 hours and the departure time was estimated as the sum of the arrival time and the dwell time.

The time of use (TOU) electricity price pattern was obtained from ComEd [7], a power balancing authority operation under PJM, a regional transmission organization. This was adjusted to match the US average price of energy for commercial use which is \$0.1071 per kWh [8]. The cost of charging at public stations vary significantly depending on the location of the parking lot. For this study, the total cost of customers using the parking lot was assumed to be the sum of the price of electricity and \$0.40/hr. assumed to be the amount the parking lot charges customers for use of its facility. The types of vehicles used in the study were generated based on the sales distribution of plug-in electric vehicles in the market obtained from [9] and [10].

3.2 Mathematical formulation

The first objective function shown in Equation 1 below is formulated to minimize the amount EV owners spend on charging their cars. This is achieved by charging the EV batteries in periods when the price for charging is less expensive. The earnings that the customers make from discharging their vehicle batteries in a bidirectional charging system are also accounted for in the objective function. The customers aim to minimize cost by discharging during periods when the electricity price is high and charging their vehicle when the electricity price is low.

$$\min \sum_{t=1}^{T}\sum_{i=1}^{I} C_{cost}^{t} * C_{chg}^{i,t} - \sum_{t=1}^{T}\sum_{i=1}^{I} D_{cost}^{t} * C_{dch}^{i,t} \quad (1)$$

The first part of Equation 1 is the total cost of charging, where C_{cost}^{t} is the cost of charging at time t and $C_{chg}^{i,t}$ is the charging power of the i[th] vehicle during period t. The charging power is assumed to be a level 2 charger which varies between 0 and 6.6kW. The second part is the total amount the EV owner gains from discharging his/her vehicle where D_{cost}^{t} is the cost of discharging at time t, and $C_{dch}^{i,t}$ is the discharging power which also varies between 0 and 6.6kW. The second objective function, which is to maximize the aggregator's profit is given in Equation 2 below:

$$\max \sum_{t=1}^{T} P_{total}^{t} * \left(C_{cost}^{t} - C_{buy}^{t}\right) - \sum_{i=1}^{I}(Tsoc^{i} - Fsoc^{i,t}) * PC^{t} \quad (2)$$

The first part of Equation 2 is the total profit that the aggregator makes from providing power to EV owners where P_{total}^{t} is the total power provided every period t, C_{cost}^{t} is the cost of charging at time period t and C_{buy}^{t} is the cost power the aggregator purchased from the regional transmission organization (RTO). To ensure that the cars are charged to meet the EV owner's targeted level, a penalty cost is introduced. According to [11] the penalty cost is defined as the cost of not meeting the customer's desired SOC. In this study, the penalty cost was assumed to be the peak cost of electricity. Failure of customers to meet this is charged as a loss to the aggregator. The second part of the equation is the amount of unfulfilled charge at the end of charging. $Tsoc^{i}$ is the target or customer's desired SOC and $Fsoc^{i,t}$ is the customer's final SOC at departure, PC^{t} is the penalty cost factor. The objective functions are subject to the following constraints:

1.) Charging or discharging only takes place when the vehicle is available in the parking lot.

$$C_{chg}^{i,t} + C_{dch}^{i,t} = 0 \ \forall \ , \mid arr_{time}^{i} \leq t \leq dep_{time}^{i} \quad (3)$$

Where arr_{time}^{i} and dep_{time}^{i} are the arrival and departure time of EV i respectively.

2.) Charging and discharging cannot take place at the same time.

$$I_{chg}^{i,t} + I_{dch}^{i,t} \leq 1 \ \forall \ i, t \quad (4)$$

Where $I_{chg}^{i,t}$ and $I_{dch}^{i,t}$ are binary variables indicating charging and discharging respectively.

3.) The maximum level of the SOC is set to 90% of the battery capacity to protect the battery from degradation due to overcharging.

$$soc^{i,t} \leq 0.9 * Bat_{cap}^{i} \qquad \forall \ i, t \quad (5)$$

Where Bat_{cap}^{i} is the battery capacity for the specific vehicle.

4.) The vehicle cannot discharge if the SOC is below the minimum required SOC.

$$I_{dch}^{i,t} = 0 \ \forall \ i, t \mid Msoc^{i} \geq soc^{i,t} \quad (6)$$

Where $Msoc^{i}$ is the minimum desired SOC.

5.) The SOC can increase, decrease or remain the same after the change of every period

$$soc^{i,t} = soc^{i,(t-1)} + (C_{chg}^{i,t} * \eta_{chg}) + (C_{dch}^{i,t} * \eta_{dch}) \quad (7)$$

Where η_{chg} and η_{dch} are the charging and discharging efficiencies respectively.

6.) The total power charged during each period is given by

$$P_{total}^{t} = \sum_{i=1}^{I} C_{chg}^{i,t} \tag{8}$$

4. Results

A Pareto optimal front was determined by solving both objective 1 and objective 2 together [12]. The result of the Pareto front shows the conflicting nature of the different objectives. As shown below in Figure 1, an increase in aggregator's profit leads to an increase in the customer's charging cost.

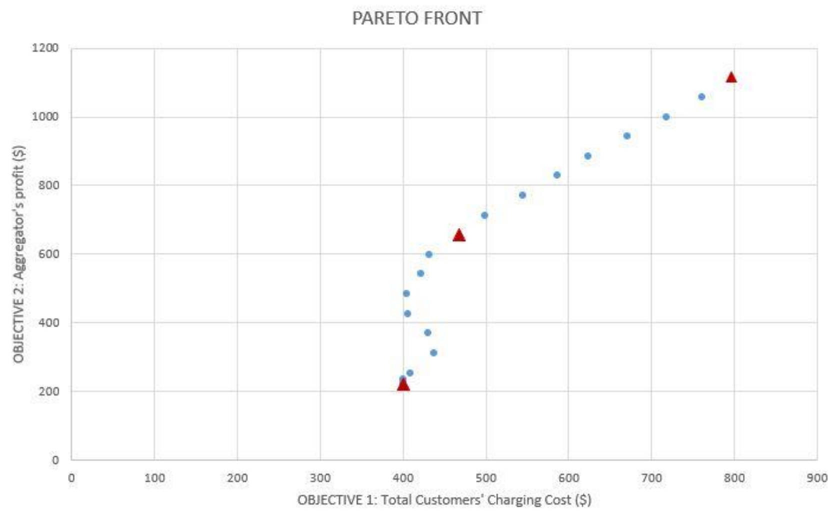

Figure 1: Pareto Front

Results for 3 cases are shown involving 100 simulated vehicles.

- Case 1: The lowest point in the generated Pareto front.
- Case 2: A selected point between the highest and lowest points on the Pareto front.
- Case 3: The highest point on the Pareto front.

Figure 2 shows the results for the final, minimum and target state of charge for 25 random vehicles at the Pareto point in case 1. As shown in the figure, even though all the vehicles met their required minimum SOC, most did not meet the target SOC. This is because minimization of the customers' charging cost and maximization of earnings rather than charging to the target state of charge is of greater priority at this point on the Pareto front. In Figure 3, it is shown that discharging takes place at periods where the cost of energy is relatively high.

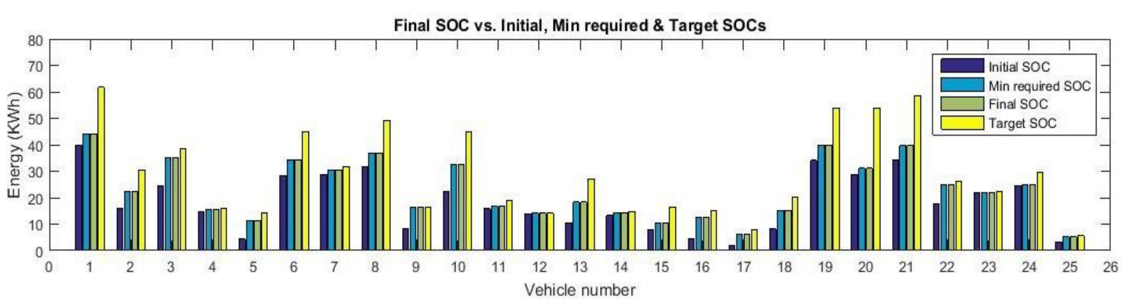

Figure 2: SOC levels for 25 random vehicles in case 1

Figure 4 shows simulation results at the Pareto point in case 2. As illustrated by the figure, more EVs compared to case 1 reached their target SOC. This is because there is an increased consideration for the aggregator's objective which is to maximize profit at this Pareto point compared to case 1.

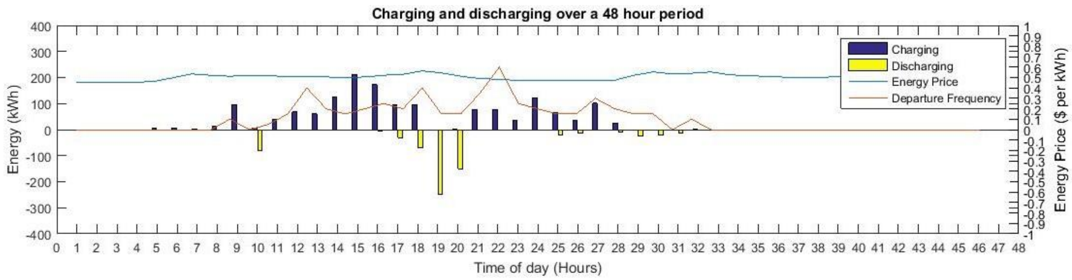

Figure 3: Charging and discharging pattern in case 1

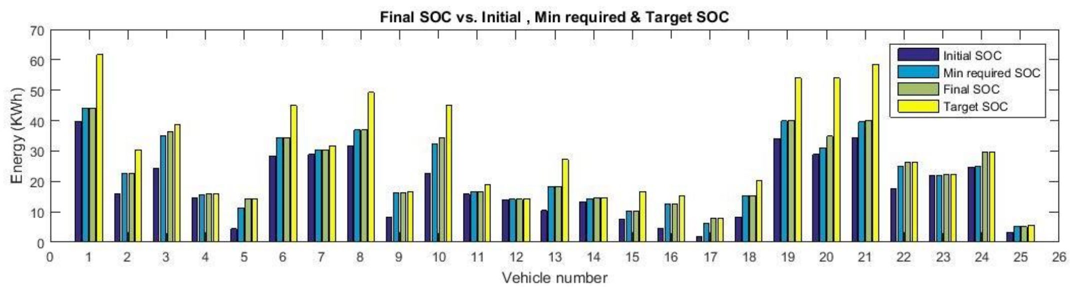

Figure 4: SOC levels for 25 random vehicles in case 2

Furthermore, Figure 5 below shows that more charging and discharging takes place in case 2 compared to case 1. The increase in charging is due to the fact that at this point on the Pareto front, there is increased consideration of the aggregator's objective of maximizing its profit compared to case 1. Another goal of the aggregator is to ensure that cars meet their target SOC before departure. This results in another observable pattern seen in Figure 5. A lot of charging tends to take place prior to departure of the vehicles.

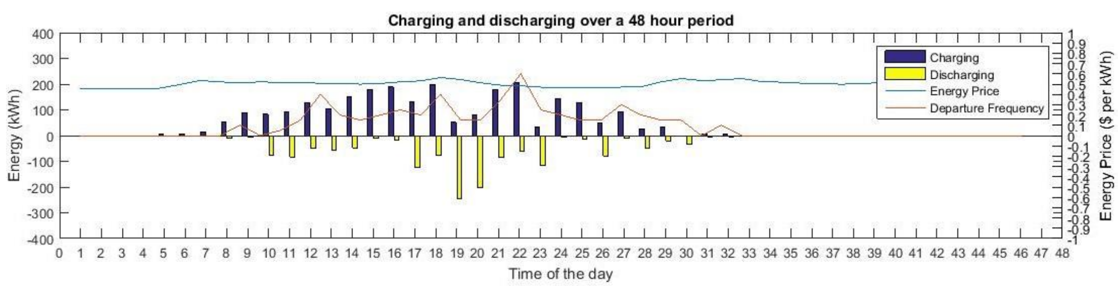

Figure 5: Charging and discharging pattern in case 2

The third case occurs at the highest point on the Pareto front. At this point, the goal of objective 2 or the aggregator's objective is given the greatest priority. As shown in Figure 6 below, the target SOC was achieved for most of the EVs.

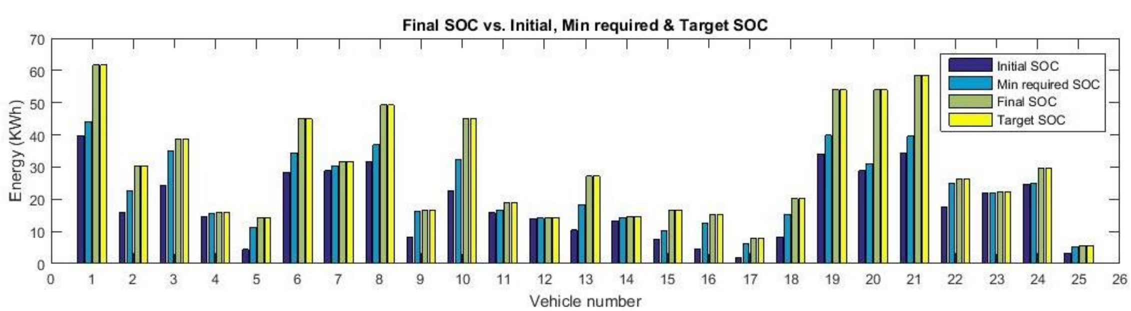

Figure 6: SOC levels for 25 random vehicles in case 3

Figure 7 shows similar charging levels to case 2. The increased charging enables the aggregator to maximize its profit. The discharging rate in case 3 is reduced compared to case 2. This is because customers' earnings which is a goal of Objective 1 is of lesser priority at this point on the Pareto front.

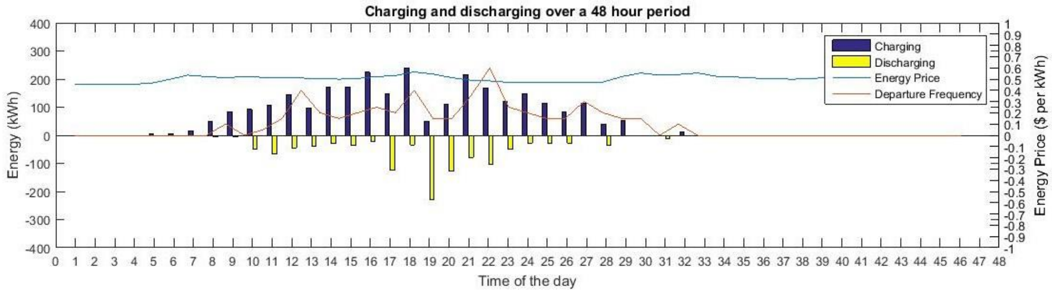

Figure 7: Charging and discharging pattern in case 3

5. Conclusion

This study presents a multi-objective model for scheduling the charging and discharging of electric vehicles in a vehicle-to-grid system. A mixed integer linear model consisting of two separate objective functions was formulated and Pareto optimal solutions for the different objectives were obtained. Simulation was performed using 3 test cases and the results show how charging and discharging behavior vary from one objective to the other. This is useful for decision-making depending on the priority of the power system manager. In the future, the scope of this work can be extended by determining an optimal solution from the Pareto front using fuzzy set theory. In addition, a more detailed objective regarding the power grid such as power emission control and power transmission loss will be considered in future work.

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