LA-UR-13-23164
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Intended for: Energy Policy

Issued: 2013-05-01

# Managing Operations of Plug-In Hybrid Electric Vehicle (PHEV) Exchange Stations for use with a Smart Grid

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**Abstract**

We consider a deterministic integer programming model for determining the optimal operations of multiple plug-in hybrid electric vehicle (PHEV) battery exchange stations over time. The operations include the number of batteries to charge, discharge, and exchange at each point in time over a set time horizon. We allow discharging of batteries back to the power grid, through vehicle-to-grid technology. We incorporate the exchange station's dependence on the power network, transportation network, and other exchange stations. The charging and discharging at these exchange stations leads to a greater amount of variability which creates a less predictable and flat power generation curve. We introduce and test three policies to smooth the power generation curve by balancing its load. Further, tests are conducted evaluating these policies while factoring wind energy into the power generation curve. These computational tests use realistic data and analysis of the results suggest general operating procedures for exchange stations and evaluate the effectiveness of these power flattening policies.

*Keywords:* Plug-In Hybrid Electric Vehicle Charging; Deterministic Optimization Model; Variability Reduction

## 1. Introduction

*Problem and Motivation.* In the United States, President Obama has stated that he hopes to have 1 million plug-in hybrid electric vehicles (PHEVs) on the road by 2015 [1] and it is projected that 425,000 PHEVs will be sold in 2015 alone [2]. Romm and Frank [3] suggest a market change will occur in 2020, when PHEVs become the dominate alternative fuel vehicle on the road, which Lebeau et al. [4] project that 7% of the market in 2020 will be PHEVs. In many areas, the existing power grid does not have sufficient extra capacity at peak times to accommodate the projected infiltration of electricity demand from PHEV charging [5], [6]. If each PHEV owner with traditional work hours charges their vehicle upon returning home from work (a peak time already), stress on the power grid will increase. To more easily manage the added stress and to avoid putting extra financial and charging management responsibility on PHEV owners, we propose the adoption of PHEV battery exchange stations. The goal of this work is to create and evaluate policies for exchange station operation.

There are many benefits for using exchange stations for managing PHEV charging. These benefits include better management of peak electricity use, decreased PHEV cost, and vehicle-to-grid (V2G)

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[1]This author was supported by a Sandia National Laboratories and Rensselaer Polytechnic Institute Excellence in Engineering Research Fellowship.

technologies that allow the PHEV battery or vehicle to be plugged into the power grid, to charge or discharge (i.e. see vehicle-to-grid [7], and vehicle-to-building [8]). At an exchange station, a PHEV owner can exchange their battery for a full battery for a fee. The exchange interaction is short, similar to driving through a car wash. Exchange stations allow PHEV owners to avoid the down time associated with charging. In principle, the idea of going to an exchange station is essentially equivalent to the current behavior of car owners who go to a gas station to fill their gas tank. Exchange stations use the power network to charge empty batteries and, in principle, stations could discharge the electric power in full batteries back to the grid using V2G technology [7]. The batteries could be charged during off peak times and discharged during peak times. This would also help to smooth inconsistent power generation from renewable energy sources, such as wind energy [9], [10], while allowing the exchange station to increase profits. V2G in combination with sophisticated control devices and algorithms can help achieve a smarter power grid [11].

One option for PHEV battery exchange station operations is station ownership of batteries and "renting" batteries to users. A PHEV battery allows 40 miles of drive time and costs $14,000 USD, with expectations that the cost will decrease to $10,000 USD by 2030 [12]. Even with the slight decrease over time, the cost of the battery significantly increases the cost of the vehicle which could deter some buyers. Placing the responsibility of owning batteries on the exchange station greatly reduces the initial ticket price for PHEV consumers. We expect that a smaller PHEV cost will increase PHEV ownership. In our model, the user pays the cost for the battery energy and the "infrastructure" for maintaining the batteries (e.g. the batteries themselves, charging facilities). This is not unlike today's gasoline stations, where the user pays for gasoline and maintaining the gasoline "infrastructure" (e.g. pumps, underground storage tanks).

The numbers of batteries that an exchange station manager can charge, discharge, and exchange is influenced by many factors. An exchange station connects to the power grid to charge and discharge batteries. The operations of the power grid constrain how much power they can acquire or return to the grid. Furthermore, both the inventory of batteries and number of physical plug-ins to the power grid at the exchange station limits the number of charging or discharging batteries at any point in time. On the other hand, the exchange station is connected to a transportation network that allows for PHEVs battery exchange. Because the number of requests at each point in time limits the number of full batteries the exchange station can exchange, exchange station managers must make decisions on how many fully charged batteries they should have available at any point in time. Inventory decisions are dictated by how many batteries are charged, discharged, and exchanged in earlier time periods.

*Methodology.* To evaluate exchange station policy options, we use a deterministic integer programming model that considers multiple exchange stations over time. The objective of the model is to maximize profit over all exchange stations, subject to logistical and customer-service constraints. Each exchange station is defined by a neighborhood of exchange stations based on geographic location. We assume that if one exchange station cannot meet PHEV battery exchange demand at a particular point in time, another location within its distinct neighborhood can satisfy this exchange demand. The integer programming model determines the optimal operations at each exchange station over a set time horizon. Exchange station operations include charging depleted PHEV batteries, exchanging full batteries for depleted batteries, and discharging full batteries back to the power grid.

We used the model to perform theoretical and computational analysis to determine general operating procedures. We then analyzed the impact of these procedures on power grid operations. Computational tests used realistic power prices, power loads, wind generation, and battery exchange requests. From this analysis, we determined that exchange stations introduce more fluctuations into the power grid by increasing variation in load and needed generation curves. We created and tested three power load balancing policies to reduce the impact of this variability on power grid operations. The first policy utilizes the exchange stations to flatten the curve by explicitly constraining the charging and discharging behaviors. The second policy does not explicitly constrain these behaviors; instead it encourages them through dynamic power pricing. The third policy considers a combination of the previous two.

*Literature Review.* Although this work examines the use of exchange stations to manage PHEV charging, several recent surveys have been conducted on topics related to individual owners who charge PHEV batteries from the power grid. Models that alter electric prices to motivate PHEV users to charge during cheaper lower power demand times have been presented [13], [14]. Both controlled and uncontrolled user charging has been examined [15], [16], where more benefits are realized with controlled charging. Sioshansi [17] discusses different types of charging strategies for individual users and concludes that real time pricing is ineffective when examining the changes needed in generation and emissions. Studies have been conducted to determine the best communication protocols for communicating with sophisticated PHEV plug-in devices that aid the user [18], [19]. Other models analyze different charging locations, such as homes or business parking lots, in combination with time for PHEV charging [20], [21], [18].

All of these models place more responsibility on the PHEV owner. A daily schedule has to be developed to decide when to charge the battery, and also when to discharge if V2G technology is adopted. Users will need information about options for charging and discharging of their battery. In addition, an inconvenience is placed on the user when waiting for the vehicle to charge and finding the most convenient location to charge. The Better Place company is setting up 'switch' stations (exchange stations) internationally in countries such as Israel, Denmark, and Australia, which verifies that PHEV exchange stations are feasible [25]. This company uses a robotic system to exchange the depleted battery in less time than a typical gas station stop [26].

Other literature has analyzed PHEV exchange stations in a different context. The problem of where to optimally locate exchange stations is considered [27], [28], [29] and how stations can be sited to support both the transportation system (PHEVs) and the power grid (V2G) [30]. Mak et al. look at deployment planning for exchange station infrastructure (sites, connections) based on incomplete information (e.g. adoption rate of PHEVs) [31]. Worley and Klabjan look at exchange stations but do not consider V2G or the impact on the power grid [32]. Avci et al. [33] examine switch stations in comparison to charging stations and conclude that switch stations encourage the adoption of PHEVs. The actions at exchange stations are examined, specifically focusing on the needed exchange station capacity [34] and also the swapping actions [35], without incorporating the necessary charging to allow the swapping.

Further, some recommend the adoption of charging stations instead of exchange stations for PHEV owners. Huang looks to optimize the operations of a charging station where users plug in vehicles [22]. Other papers make the case for charging stations by looking at the charging time by vehicle and charging power [23], [24].

Some work has looked at how to balance the power load curve. For example Liu et al. [36] look at load balancing based on geographic location when factoring in green renewables, but do not considered PHEV batteries. Galus et al. [37] look at using PHEVs to balance wind generation, but do not consider this in the context of exchange stations. The integration of PHEVs with wind energy is examined [38], [39], [40] but these studies do not consider models with the other necessary actions required at exchange stations. Gao et al. [41] do consider wind with exchange stations, however their objective specifically looks at balancing wind with power. We instead look at how to place small restrictions or incentives to encourage balancing actions while maintaining the profit maximization objective.

*Primary Contributions.* The primary contributions of this research include the development of a decision model for managing detailed operations at exchange stations over time. We introduce policies to reduce variability in the power generation curves caused by variability from regular operations, operations at the exchange stations, and wind energy. We demonstrate that our model and policies can be used as management tools through computational tests using realistic data. These tests validate that managers can easily input their specific data and determine the optimal management decisions in real time using this model.

## 2. Problem Statement and Model

This section formally defines the PHEV exchange station management problem and a deterministic integer programming model. For the problem, specific exchange station characteristics are defined with their dependence on the power grid and on a transportation network. See Table 1 for a list of the notation and descriptions for all parameters and decision variables.

| Parameters | Description |
|---|---|
| $T$ | Time horizon |
| $n$ | Number of exchange locations |
| $\Phi$ | Set of all clusters |
| $p_e$ | Price to exchange a battery |
| $\alpha$ | Discount rate if a exchange request is satisfied at a secondary location |
| $r_{jt}$ | Number of exchange requests at location $j$ at time $t$ |
| $p_{ct}$ | Power price (earnings) to charge (discharge) one battery at time $t$ |
| $\sigma_j$ | The normalized energy received(for charging) or given(for discharging) when charging one battery at location $j$ |
| $b_j$ | Number of batteries at location $j$ |
| $k_j$ | Number of plug-ins available for charging/discharging at location $j$ |
| $\beta_p$ | Customer service level for primary customers |
| $\beta_s$ | Customer service level for secondary customers |
| $c_{tout}$ | Capacity of the power grid eligible for charging batteries (grid to exchange locations) at time $t$ |
| $c_{tin}$ | Capacity of the power grid eligible for discharging batteries (exchange locations to grid) at time $t$ |

| Decision Variables | Description |
|---|---|
| $x_{pjt}$ | Number of primary batteries exchanged at location $j$ at time $t$ |
| $x_{sjt}$ | Number of secondary batteries exchanged at location $j$ at time $t$ |
| $x^+_{cjt}$ | Number of batteries charging at location $j$ at time $t$ |
| $x^-_{cjt}$ | Number of batteries discharging at location $j$ at time $t$ |
| $x_{fjt}$ | Number of full batteries at location $j$ at time $t$ |

Table 1: Notation and Descriptions for the Parameters and Decision Variables.

Consider a set of $n$ exchange stations. Each exchange station $j$ has an inventory of batteries $b_j$ that is constant over time. The notation $k_j$ denotes the plug-in capability at exchange station $j$ which can be used to charge or discharge a battery. The plug-ins at each location can vary depending on the level of charging (either 1, 2, or 3, see [42]). This charging level determines how much energy is received (when charging one battery) and given (when discharging one battery). A traditional residential property is considered level 1 charging and could take up to 8 hours to fully charge a PHEV battery, where level 3 charging is more sophisticated and can charge a battery in less than 30 minutes. Parameter $\sigma_j$ quantifies the specific charging infrastructure capability at location $j$ by defining the normalized $kWH$ received or given in one time period.

We assume that the power grid is well designed, and modeled it as a single entity. We remove the detailed power flow model to focus on scheduling battery charging and discharging. We leave for future work the problem of incorporating a detailed model of the power grid. At time $t$, the power grid has capacity $c_{tout}$ for supplying all stations for charging and has capacity $c_{tin}$ for obtaining power from all stations from discharging. To model the connection between the power grid and a station, we use two sets of calculations of the variables: one for power flow to the stations over time and another for flow from the stations over time. We define parameter, $p_{ct}$, to be the price per $kWH$ for charging batteries at time $t$, and the profit for exchange stations from discharging one $kWH$.

PHEV users drive their vehicles on a transportation network and use the transportation network to travel to exchange stations. The only information about the transportation network required for our model is the number of PHEV users who arrive at a particular exchange station $j$, at each point in time $t$. We let $r_{jt}$ represent the number of battery exchange requests (demand) for exchange station $j$ at time $t$. The parameter $p_e$ defines the cost to exchange one battery (fee the customer pays to exchange their depleted battery for a full one). We assume there is a constant price for exchanging a battery over our time horizon, $T$ (one day), in order to be consistent with existing regulations on gas station pricing. We consider each hour within one day to be a time period, however, as defined, it is broad enough to allow other input time periods and horizons.

Because multiple locations are considered, we model the scenario such that a specific exchange station cannot meet all of its demand. We cluster each of the $n$ exchange stations based on geographic proximity. Let $\Phi$ denote the set of all clusters, where each exchange station $j$ is in exactly one cluster $\phi \in \Phi$.

If a PHEV needs to exchange its battery at time $t$, we assume it has a primary exchange station $j \in \phi$. If exchange station $j$ cannot fulfill the demand of this PHEV battery request at $t$, then we assume the PHEV is able to exchange its battery at a neighboring secondary location $k \in \phi$ also at $t$, because they are geographically close. We discount the money earned at the secondary station due to the inconvenience. The parameter $\alpha$, in the range $[0, 1]$ is multiplied by $p_e$ to calculate the discounted money earned at the secondary station.

The decision variables $x_{pjt}$ and $x_{sjt}$ represent the number of primary and secondary batteries exchanged at station $j$ at time $t$. The sum of these two variables represents the total number of batteries exchanged at station $j$ at time $t$. The primary purpose of the exchange stations is to fulfill demand, therefore, we include constraints dictating that each exchange station must maintain a set customer-service level, $\beta_p$ for the primary met requests, and $\beta_s$, for the secondary requests, for the entire time horizon, $T$, of the problem.

At each exchange station, we model two states, full and depleted, and three actions for the batteries. The three actions modeled are charge, discharge, and exchange. If a battery is full, the actions include discharge, exchange, or do nothing. If a battery is depleted, the actions include charge or do nothing.

We use the variable $x_{fjt}$ to define the number of full batteries at exchange station $j$ at time $t$. The number of depleted batteries is calculated as $b_j - x_{fjt}$, because the battery level of an exchange station is constant over time. The variable $x^+_{cjt}$ defines the charging and variable $x^-_{cjt}$ defines the discharging actions at exchange station $j$ at time $t$. We note at a particular exchange station, there exists an optimal solution where charging and discharging does not occur at the same time, as a solution with charging and discharging occurring at the same time at a specific location can be equivalently represented as a solution with solely charging or solely discharging[2]. This is a direct result of the

[2]Take the example of an exchange station location with 10 plug-ins. If the optimal solution is to charge 7 and

power prices $p_{ct}$ being the same for charging and discharging.

When operating the exchange station, if we decide to charge a battery at time $t$ then at time $t+1$ this battery is full. If we choose to discharge or exchange a full battery at time $t$, then at time $t+1$ this battery or the exchanged battery is depleted. This is based on the assumption that it takes one time period to fully charge or discharge a battery, where we consider one time period to be one hour. This approximate one-hour charging requirement is comparable to level 2 or level 3 charging [42].

We develop an deterministic integer programming model that looks at scheduling multiple PHEV exchange station operations. We assume there exists a central manager that maximizes profit over all locations and the finite time horizon of the problem. All of the locations depend on each other because they are all connected to the same power grid, which limits the collective amount of charging and discharging. Further, the met demand at one location, or the inability for one location to meet demand, influences the demand for other locations within the same cluster. As a result, charging and discharging actions of one location affect the other locations. The objective function maximizes the total profit across all exchange stations by including profit earned from discharging and exchanging batteries and expenses from charging and failing to meet demand.

The deterministic clustered multiple location model is as follows:

$$\max \sum_{t=1}^{T}\sum_{j=1}^{n} p_e(x_{pjt}+\alpha x_{sjt}) - p_e(r_{jt}-(x_{pjt}+x_{sjt})) - p_{ct}\sigma_j(x^+_{cjt}-x^-_{cjt})$$

subject to:

$$x^+_{cjt} \le b_j - x_{fjt} \qquad \text{for } j=1,\dots,n, \text{ for } t=1,\dots,T \qquad (1)$$

$$(x_{pjt}+x_{sjt}) + x^-_{cjt} \le x_{fjt} \qquad \text{for } j=1,\dots,n, \text{ for } t=1,\dots,T \qquad (2)$$

$$x_{fjt+1} = x_{fjt} - (x_{pjt}+x_{sjt}) + x^+_{cjt} - x^-_{cjt} \qquad \text{for } j=1,\dots,n, \text{ for } t=1,\dots,T-1 \qquad (3)$$

$$x^+_{cjt}, x^-_{cjt} \le k_j \qquad \text{for } j=1,\dots,n, \text{ for } t=1,\dots,T \qquad (4)$$

$$x_{pjt} \le r_{jt} \qquad \text{for } j=1,\dots,n, \text{ for } t=1,\dots,T \qquad (5)$$

$$\sum_{j\in\phi} x_{sjt} \le \sum_{j\in\phi}(r_{jt}-x_{pjt}) \qquad \forall\phi\in\Phi, \text{ for } t=1,\dots,T \qquad (6)$$

$$x_{pjt} \ge \beta_p r_{jt} \qquad \text{for } j=1,\dots,n, \text{ for } t=1,\dots,T \qquad (7)$$

$$\sum_{j\in\phi} x_{sjt} \ge \beta_s\left(\sum_{j\in\phi}(r_{jt}-x_{pjt})\right) \qquad \forall\phi\in\Phi, \text{ for } t=1,\dots,T \qquad (8)$$

$$\sum_{j=1}^{n} x^+_{cjt} \le c_{t_{out}} \qquad \text{for } t=1,\dots,T \qquad (9)$$

$$\sum_{j=1}^{n} x^-_{cjt} \le c_{t_{in}} \qquad \text{for } t=1,\dots,T \qquad (10)$$

$$0 \le x_{fjt} \le b_j \qquad \text{for } j=1,\dots,n, \text{ for } t=1,\dots,T \qquad (11)$$

$$x_{fj0} = b_j \qquad \text{for } j=1,\dots,n \qquad (12)$$

$$x_{fjt}, x_{pjt}, x_{sjt}, x^+_{cjt}, x^-_{cjt} \in \{\mathbb{Z}^+ \cup 0\} \qquad \text{for } j=1,\dots,n, \text{ for } t=1,\dots,T \qquad (13)$$

The objective function maximizes the expected profit over all locations and time, which considers the exchange prices and actions, charging and discharging prices and actions, and location charging

discharge 3 batteries at time $t$, this can equivalently be represented as a solution with 4 batteries charging at time $t$.

capability. Constraints (1) limit the number of batteries charged to those that are depleted at time $t$ and exchange station $j$. Constraints (2) disallow discharging or exchanging more batteries than are full at each time $t$ and exchange station $j$. Constraints (3) compute the number of full batteries at time $t+1$ based on the number of full batteries and actions taken at time $t$ within the same exchange station. Constraints (4) disallow charging and discharging more batteries than plug-ins available at each exchange station $j$. Constraints (5) disallow exchanging more batteries than the number of requests. Constraints (6) limit the amount of secondary met demand for each cluster to no more than the unmet demand for that time period. Constraints (7) and (8) force the amount of primary and secondary met demand to be greater than the dictated customer-service levels, respectively. Constraints (9) and (10) restrict the number of batteries charged or discharged based on the capacity of the power grid both into and out of the exchange stations. Constraints (11) restrict the number of full batteries to be no more than the total inventory level $b_j$ at exchange station $j$. Constraints (12) state that each exchange station $j$ starts with a complete set of full batteries. Constraints (13) state that the number of batteries that are full, exchanged, charged, or discharged must be 0 or a positive integer.

## 3. Theoretical and Computational Results

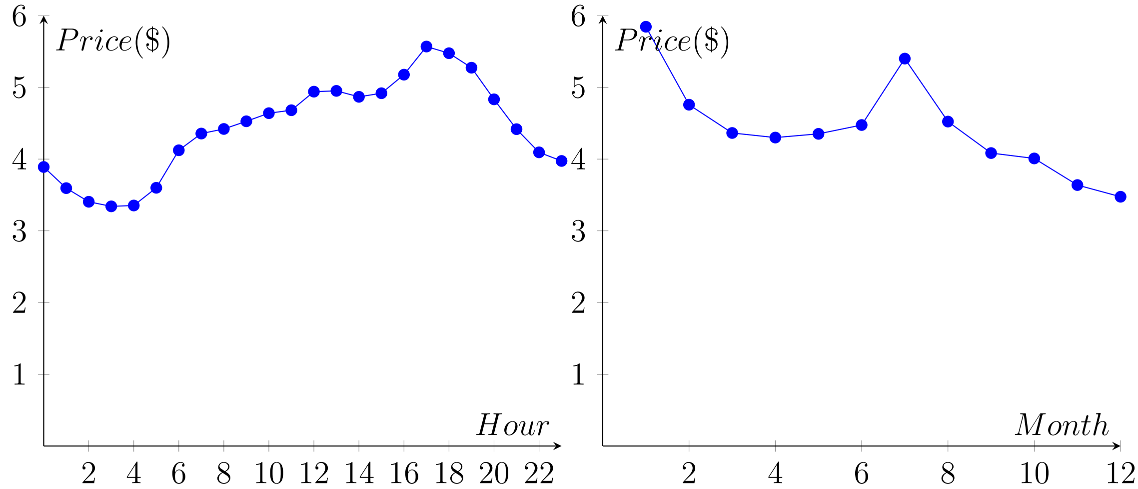
In this section, we first present a theoretical analysis on the level of batteries needed to meet 100% of PHEV exchange requests or demand. We then perform computational tests, using different input parameters for the battery level, plug-in level, customer-service level, and number of locations to gain insight into general operating procedures for the PHEV exchange stations. This analysis is extended to look at the impact of the exchange stations on the power grid with and without wind energy.

**Theorem 3.1.** *For an exchange station $j$ to meet 100% of PHEV exchange demand, the starting inventory level, $b_j$, must be greater than or equal to the sum of the two greatest consecutive time period battery exchange request values.*

*Proof.* Proof by contradiction. Let $r_{jt}$ and $r_{jt+1}$ represent the greatest request values for time periods $t$ and $t+1$. Further, let us assume that $r_{jt}+r_{jt+1}$ is greater than the sum of requests for any other two consecutive time periods. Specifically $r_{jt}+r_{jt+1} \geq r_{j\bar{t}}+r_{j\bar{t}+1}$ where $\bar{t}$ and $\bar{t}+1$ can represent any two consecutive time periods such that $\bar{t} \neq t$. Assume that $b_j < r_{jt}+r_{jt+1}$ and that 100% of the PHEV requests can be met. Let $x_{fjt}$ represent the number of full batteries at time $t$ where $0 \leq x_{fjt} \leq b_j$. This means there are $b_j - x_{fjt}$ depleted batteries at time period $t$, because there is a constant level of batteries over time. From our assumption, that all PHEV exchange demand can be met we know $x_{fjt} \geq r_{jt}$. At time $t$, $r_{jt}$ full batteries are exchanged for $r_{jt}$ depleted batteries. The number of full batteries at time $t+1$ depends on the number of depleted batteries that were charging at time $t$. An upper bound for the number of full batteries at time $t+1$ is $x_{fjt} - r_{jt} + b_j - x_{fjt} = b_j - r_{jt}$. Based on our assumption $b_j - r_{jt} < r_{jt+1}$ we cannot meet all PHEV requests at time $t+1$. This contradicts that 100% of PHEV requests are met. □

### *3.1. Computational Results: Exchange Station Parameter and Solution Analysis*

We now show results from computational tests performed on the model to gain insight into general operating procedures for the exchange stations. The integer programming solver CPLEX 12.4 was used to solve all test instances of the problem to optimality. Realistic data was used to represent the exchange stations and power grid, which validates the ability of this tool to be used by any exchange station manager, with their respective data.




(a) Hour

(b) Month

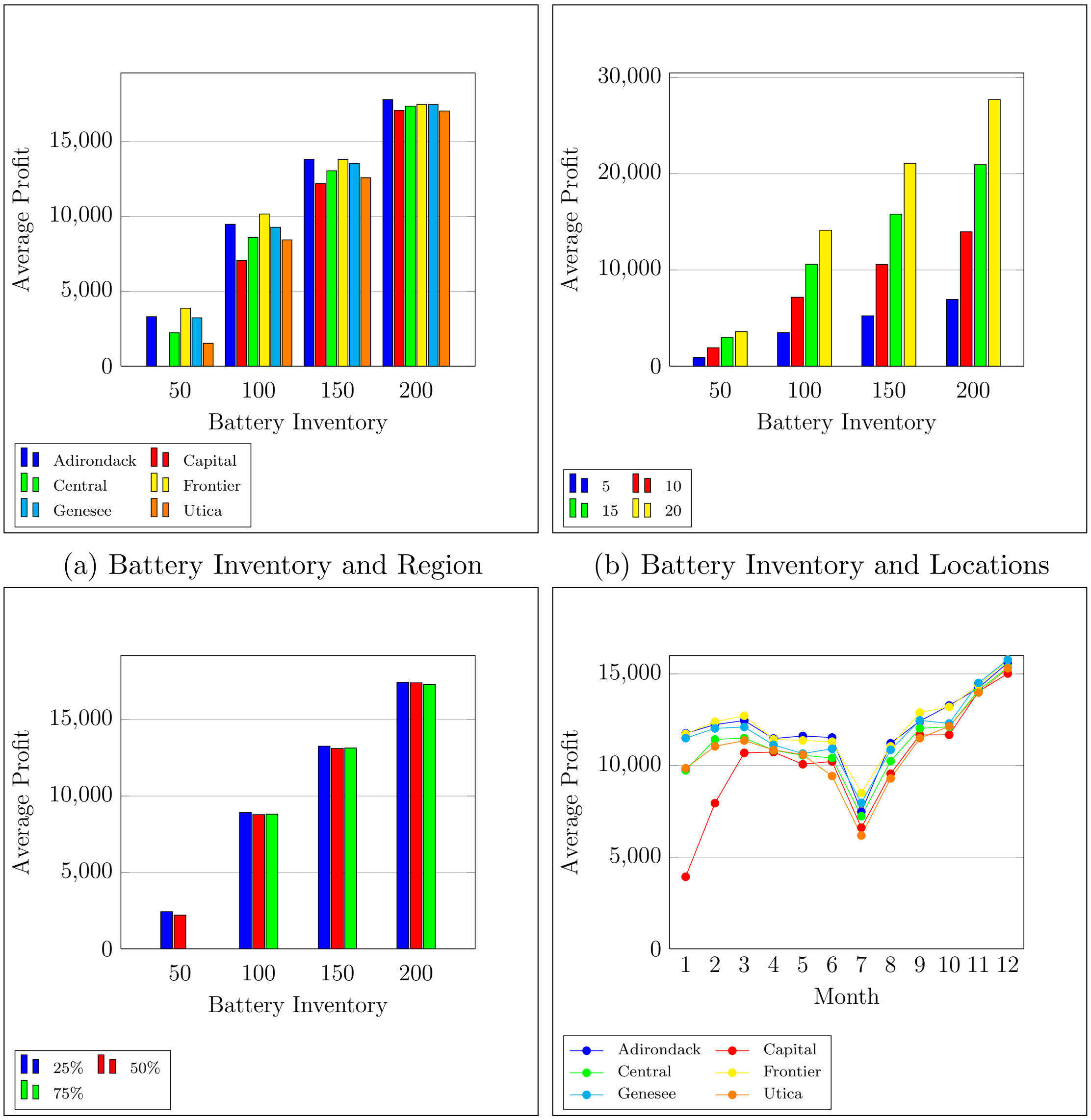
Figure 1: Average Charge Price by Hour and Month

The number of PHEV battery exchange requests mimics current gas station behavior. Starting from daily and hourly gas station refueling percentages from Chevron [43], we derive a set number of requests per hour and day for an area with 10,000 vehicles and a 30% infiltration of PHEVs ($3,000$ PHEVs). This assumes a PHEV-rich community where exchange stations are already established. We then sampled uniformly at random from these data to determine the specific number of requests, $r_{jt}$, at location $j$ at time $t$.

National Grid in New York provides historical hourly electric supply charges at a regional level for the Adirondack, Capital, Central, Frontier, Genesee, and Utica geographical regions [44]. We used these regions for our computational tests, referring to them as geographic regions. We used prices per $kWH$ from the year 2011 for the $p_{ct}$ values for cost of charging and discharging batteries. Figure 1a shows the average of these prices across all regions and days on an hourly basis. Figure 1b provides the average charge price by month. Both of these charts factor in a $\Pi$ value of 9.4, which is consistent with level 2 or 3 charging [42]. In the tests, we included the actual prices for the specific region, month, and day, as parameters for the model. An exchange price, $p_e = 5$ was used for these tests, which coincides with the average power prices shown in Figure 1a. If a battery exchange request cannot be met at its primary location, we discount the profit the exchange stations assume by 10% by using $\alpha = 0.9$.

For each set of tests, we define a battery inventory level, $b_j$ equal to 50, 100, 150, or 200 batteries, with respective plug-in levels, $k_j$ equal to 25, 50, 75, and 100. With these values, we assume that the battery inventory level is always twice that of the plug-in capabilities at the exchange station. We consider 5, 10, 15, and 20 locations. These locations are clustered into neighborhoods of 5 locations each, thereby assuming that 5 exchange stations are geographically close together. We analyze customer-services levels, $\beta_p$ and $\beta_s$, equal to $25\%, 50\%$, and $75\%$, for both primary and secondary demand. Currently, the power grid capacities, $c_{t_{out}}$ and $c_{t_{in}}$, were set high enough to allow each exchange station to charge and discharge as much as desired, based on their battery and plug-in levels.

For each region and month, we use 5 random days and determine and analyze the optimal exchange station operations. This resulted in a total of 17,280 test instances (6 geographic regions, 12 months, 5 days, 4 battery/plug-in levels, 4 location levels, 3 customer-service levels). The appropriate historical




(a) Battery Inventory and Region

(b) Battery Inventory and Locations

(c) Battery Inventory and CSL

(d) Month and Region

Figure 2: Average Profit (Objective Function Valule) by different parameters.

hourly power price information is based on the randomly selected days for each month.

For each test iteration, we captured the same metrics of output information. We tracked the objective function value, average primary met demand, and solutions for the number of batteries that are charged, discharged, and exchanged at each point in time. Figures 2a, 2b, 2c, and 2d examine the impact of the different input parameters on the objective function value.

It is interesting to see that the objective function value increases with the battery level (Figure 2a). This phenomenon is expected because larger battery levels enable the exchange stations to meet more requests and to discharge batteries sitting in inventory. We do not consider a fixed charge for battery purchase; instead we assume that the infrastructure is already in place and we are making operating decisions. We observe that for small battery inventory levels (e.g., 50), the difference in objective function value varies across region dramatically. A diminishing return can be noticed if we look at the objective function value divided by the number of batteries. This phenomenon occurs because most of the money earned is from exchanging batteries.

Figure 2b displays the average objective function value as a function of battery level and number of locations. These values are averaged over all six geographic regions. There exists a clear trend towards higher profits as more locations are considered, which is to be expected, based on the design of the model. A greater number of locations means a greater number of requests and a higher total number of batteries available for discharging back to the grid.

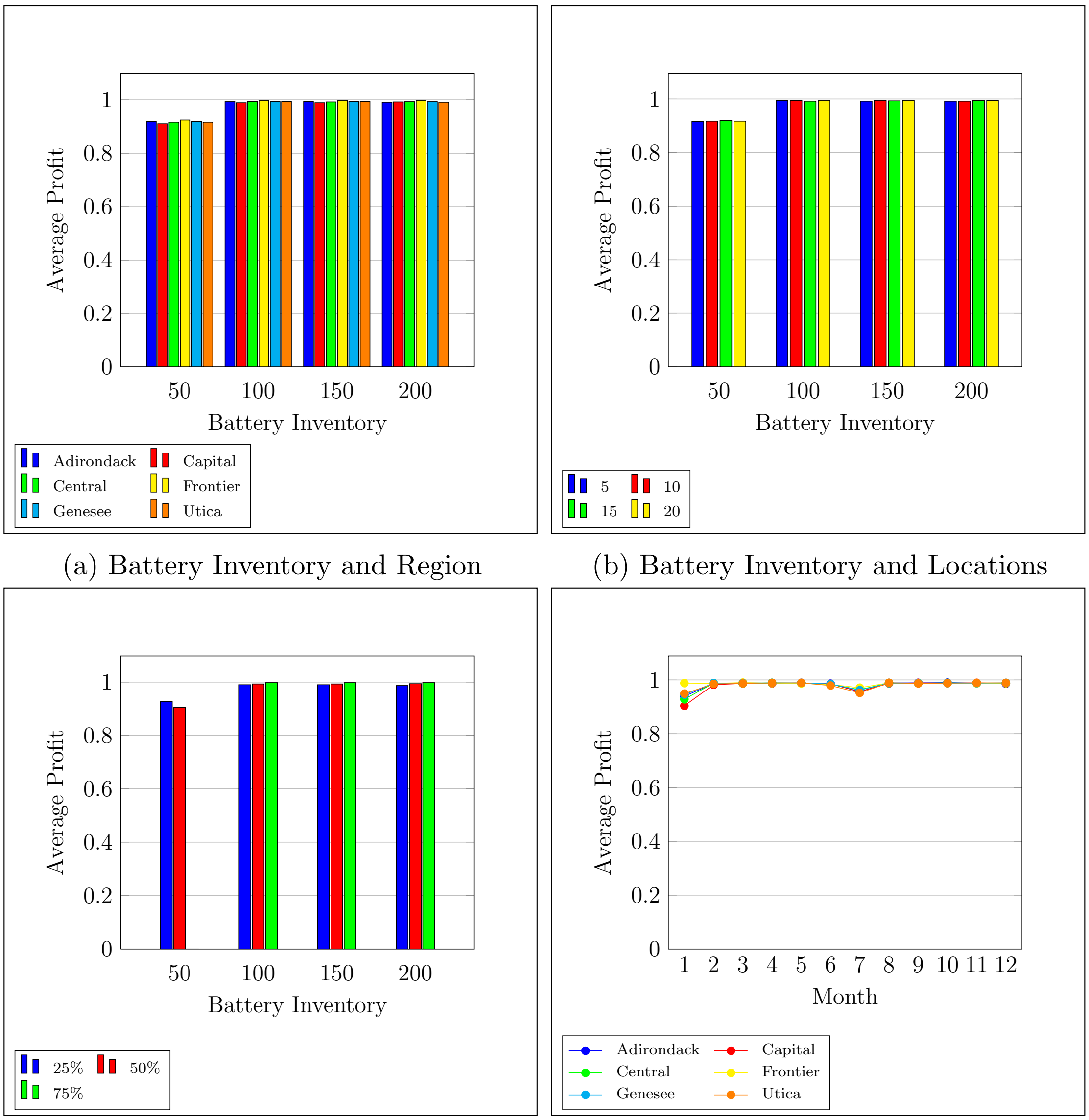
Figure 2c displays the average objective function value for different battery inventory levels and customer-service levels. This shows that when enough batteries are available (greater than 50) at each exchange station, the objective function value does not greatly differ across the different customer-service levels. This leads to the observation that similar demand levels are met regardless of the forced customer-service levels. This observation is verified in Figure 3c. This finding is very promising because the primary focus of the exchange stations is to meet exchange requests from PHEV drivers.

Figure 2d displays the average objective function value by region and month. The price to charge or discharge a battery is the only parameter that changes by month. From this chart, we can clearly see that these prices influence the profitability by region, specifically for January and July. Looking back at Figure 1b, we notice that the two months with the highest average charge price are January and July. Therefore, exchange station operators can adjust their exchange prices based on changes in power charge prices, which will lead to increased profitability. One outlier is the Capital region for January, with a very small average objective function value. This is in part due to very high power charge prices (on average \$7.60 for Capital while other regions average \$5.49).

Figures 3a, 3b, 3c, and 3d present the results of analysis on the average primary met demand metric. Figure 3a displays the average primary met demand for different battery levels and regions. We see that if there are sufficient battery inventory levels, the exchange stations can satisfy almost 100% of demand. Even for the case with smaller battery levels (50 batteries), slightly more than 90% of demand is met. We observe that there is no significant difference between the amount of met demand for 100, 150, and 200 battery inventory levels. This signifies that meeting demand is a high priority, even for limited battery inventory levels. Further, the average primary met demand is fairly consistent across the different regions in the state.

Figure 3b shows the average primary met demand as a function of the battery inventory level and number of locations. The trend in this chart is very similar to that seen in Figure 3a. For each distinct battery level, we do not see much difference in the met demand when considering different numbers of exchange station locations.

Figure 3c shows the average primary met demand for different battery and customer-service levels. For a battery inventory level of 50, it is infeasible to meet 75% of the requests at all time periods.



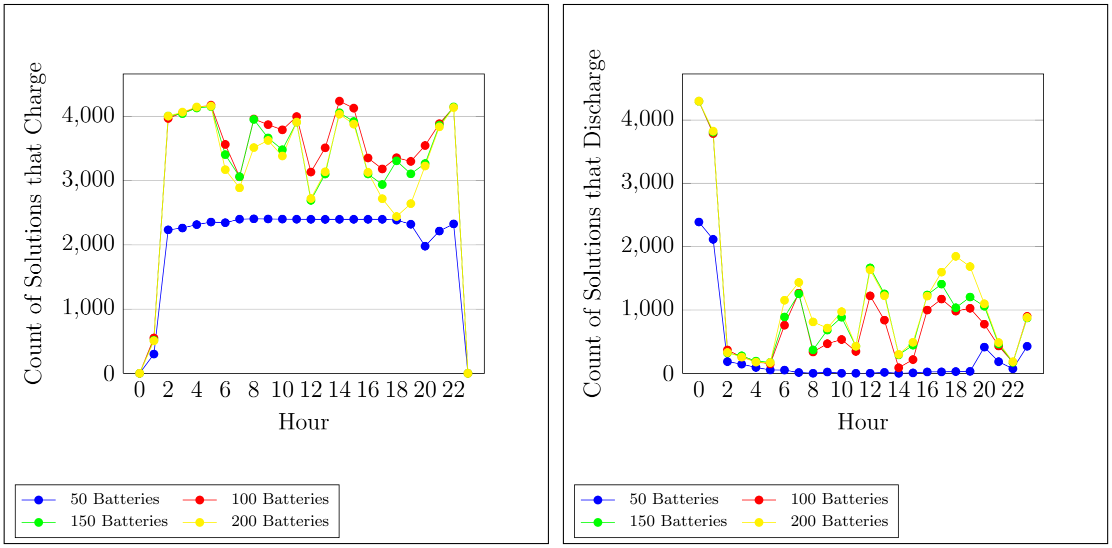

(a) Battery Inventory and Region

(b) Battery Inventory and Locations

(c) Battery Inventory and CSL

(d) Month and Region

Figure 3: Average Primary Met Demand by different parameters.




(a) Charge

(b) Discharge

Figure 4: The count of tests instances that charge or discharge any number of PHEV batteries by time and battery inventory level.

For the tests that were feasible, we notice that well above the dictated customer-service levels of 25%, 50%, and 75%, were met on average.

Figure 3d shows the average primary met demand by month and geographical region. We again notice that consistently above 90% of primary met demand is met on average. However, there is slightly more variation by month. Primary demand met for different regions varies more noticeably in January and July. This is a result of higher charge prices (see Figure 1b) compared to the exchange price, which encourages discharging at the exchange stations instead of exchanging. Exchange station operators can adjust the exchange price accordingly, which will lead to higher profits, but also a greater percentage of met demand.

### *3.2. Computational Results: Policy Observations*

In this section, we focus on analyzing the results to gain general insight into operating policies at each exchange station. Figures 4a and 4b give, for each battery inventory level, the total count over all test instances (geographic region, month, day, customer-service level, and number of locations) that are charging or discharging any number of batteries by hour. The total number of test instances by hour is 4,320 (17,280 total instances divided by 4 battery levels). The four lines within the graph represent instances with 50, 100, 150, or 200 PHEV batteries in inventory at each exchange station.

For the smallest battery inventory level (50 batteries) charging across time is very consistent due to limited discharging during the day. The lack of discharging is a result of prioritizing PHEV exchange requests, rather than discharging batteries, which is motivated by profit earned. For higher battery levels, we see a much less consistent charging and discharging strategy across time of the day. When examining each solution, we notice that each exchange station keeps enough inventory to meet exchange requests and then uses the remaining inventory of batteries to alternate between charging and discharging based on the power price. For example, if an exchange station has batteries in inventory that are currently unneeded to meet demand, at time $t$ if the power price $p_{ct} > p_{ct+1}$, then the exchange station will discharge the extra batteries and recharge them at $t+1$, resulting in profit earned.

The exchange and charge prices impact exchange station operations provided they are profit driven. If the exchange price is greater than the charge price and the exchange station has sufficient battery inventory levels to meet the customer-service levels at this time period and in the future, they will choose to meet 100% of PHEV exchange requests. This reinforces the need for each exchange station to have the appropriate battery inventory level based on their demand. Even if the exchange price is less than the charge price, for these tests, 100% of battery exchange requests were met for just over 85% of the time. This means that the charging price was not sufficiently high enough over the exchange price to stimulate complete discharging instead of meeting demand. This arises from penalizing unmet demand in the objective function.

### *3.3. Computational Results: Exchange Stations' impact on the Power Grid*

In this subsection, we discuss the implications of the charging and discharging behaviors of the PHEV exchange stations on the power grid. These behaviors add variability to the power generation needed, leading to a less balanced or flat curve. We evaluate three exchange station operating policies and assess their performance under different conditions.

Under these experiments, we consider the power grid with and without wind energy in conjunction with the PHEV exchange stations. For these tests, we focus on one specific set of exchange station data: 20 exchange station locations, each with 200 batteries, 100 plug-ins, and a 25% customer-service level. The exchange price will remain at $5 and the power prices will continue to be extracted from the National Grid data. We use this test instance and examine the impact of different geographic regions, months, and days.

We derive the existing power load data of this model from historical data from 2011 provided by National Grid [45]. Without wind energy, this load is equal to the generation in the grid. Incorporating PHEV exchange stations introduces more fluctuations in the updated load and generation curves, as is seen in Figure 5. In this figure, the blue and green curves are identical and the red curve represents the load and generation curves when factoring in PHEV exchange stations. When the red curve is higher than the blue and green curves, this signifies charging at the exchange stations, and discharging when the curve drops below the blue and green curves. We can see that the red curve has more variability based on the charging and discharging behaviors. This variability in the behavior leads to a less flat or balanced needed generation curve.

Wind energy adds another level of variability into the power network. The National Renewable Energies Laboratory publishes historical wind data by geographical site, day, and hour [46]. We mapped wind data from the year 2006 at different sites in New York state to the appropriate National Grid classified power regions. This allowed us to obtain the total wind energy experienced for each region (Adirondack, Capital, Central, Frontier, Genesee, and Utica) by day and hour. When wind energy is added to the power grid, the generation curve is the load curve minus the wind energy experienced. Figure 6 presents these curves. In this example, we see that the wind energy introduces additional fluctuations.

Many researchers have examined ways to balance the power generation curve with PHEVs. To reduce the negative impact of both wind energy and exchange stations on the power generation curve, we consider three exchange station operation policies. All three of these policies follow the same steps shown in Figure 7, only differing in the details on how each step is implemented. As is shown in Figure 7, we first solve the original version of the PHEV exchange station model presented in Section 2 based on the original unaltered set of data. We collect the optimal solution, specifically the number of batteries charged, discharged, and exchanged at each point in time. The optimal exchange station operation is then converted into energy taken from or given to the power grid. These values by hour

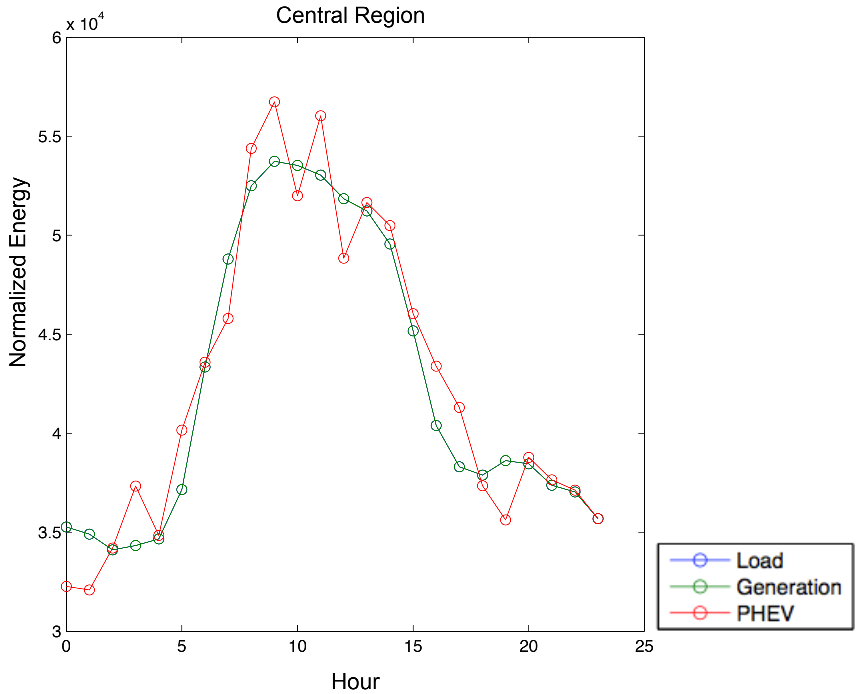



Figure 5: The load, generation, and generation with PHEV exchange station curves by hour. This represents a specific instance for the Central region.

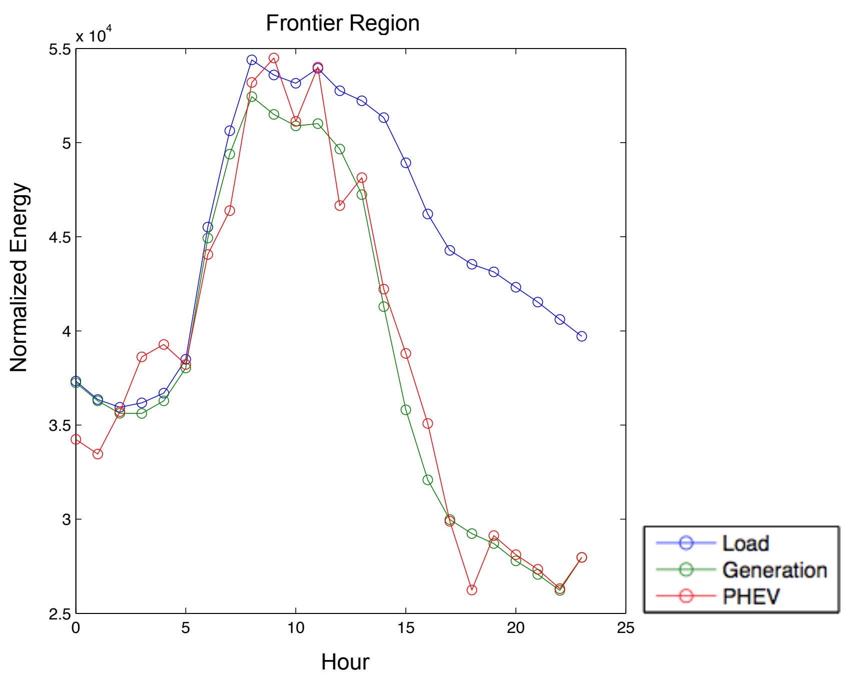



Figure 6: The load, generation, and generation with PHEV exchange station curves by hour. Considering wind energy leads to a generation curve that is at or below the load. This represents a specific instance for the Frontier region.

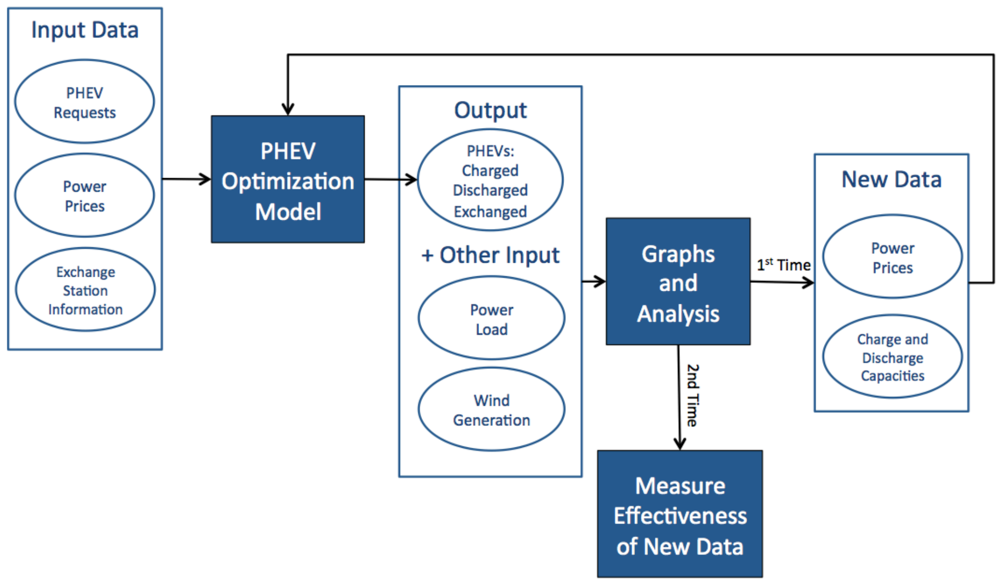



Figure 7: An outline of the implementation of the curve flattening policies. We first solve the PHEV exchange station model. Based on the solution to this model and the corresponding power load and wind data, we alter the capacities and/or power prices and resolve the model based on the new data. We verify the effectiveness of the policy by calculating the curvature of the original and updated power generation curves.

are then combined with existing power and wind load data to arrive at updated power curves. We then analyze these curves and output new power prices and/or charge and discharge capacities based on the policy used. These new data are then input into the PHEV exchange station model and the process is repeated. During this second iteration with new input data, at the graph and analysis step, we do not generate new data but instead measure the effectiveness of the new data by calculating the change in the flatness of the power generation curve with the original and new data. The three policies are then compared to see which policy is most effective at flattening out the total power generation curve (incorporating original load, PHEV load, and if included, wind).

The idea behind all of our curve flattening or load balancing policies is to encourage a change in charging and discharging behavior at the exchange stations in order to reduce the peak to average ratio [47]. The peak to average ratio is one measure of the balance of the load. Our strategies look at reducing the generation (if it is higher than a measure of the average at a point in time) and increasing the generation for the opposite, through charging and discharging behaviors at the exchange station. To encourage this change of behavior we examine altering the power prices, similar to the use of power tariffs (e.g. [49]and [48]), and limiting capacity for charging and discharging. The amount that we change the price and capacity is based on the magnitude that the generation curve is from a measure of the average, which we call the ideal flat generation curve. Our ideal flat generation curve is the horizontal line that is the easiest to obtain. In other words, this is the line that requires the least amount of change or the line $p$ that minimizes $\sum_{t=1}^{24} |\text{current generation} - p|$.

Researchers have examined different ways to determine optimal tariffs to achieve the appropriate demand response from customers (e.g. [50], [51], [52]). We take a simple approach that alters the power prices and/or capacity based on a linear function of the magnitude of the desired change in behavior. The coefficient of the linear function was determined based on a variety of computational experiments and can be easily altered by the end user. Even with these simple policies, we see desirable change in behavior resulting in flatter, more balanced generation curves.

The first policy is denoted PHEV Cap. In PHEV Cap, we utilize Constraints 9 and 10 to limit the collective charging and discharging behaviors of the exchange stations. The details of this policy are presented in Algorithm 1. In the PHEV Cap policy, we look at the first iteration power generation curve with exchange stations (historical power load + exchange stations) and compare this to an ideal flat generation curve. Based on the relation between the two curves, we update the dynamic power capacity values by time for charging (to the exchange station) and discharging (from the exchange station). These capacity values are updated appropriately based on how far or close they are to the ideal power generation curve. Specifically, a time period that exceeds the ideal generation curve by 10 units, will be limited to 5 units above the ideal generation curve, where a time period that exceeds the ideal generation by 5 units will be limited to 2.5 units above the ideal curve during the second iteration.

**Algorithm 1** Policy 1: PHEV Cap

Input: power generation curve, $PG_t$, (load - wind, if wind is considered), for hours within a day $t = 1, \ldots, 24$
Input: power generation curve with PHEV exchange station, $PGPHEV_t$, for hours within a day $t = 1, \ldots, 24$
Find the point $p$ that minimizes $\sum_{t=1}^{24} |PG_t - p|$
Set $p = 1.1 * p$ to allow for some PHEV charging
Define arrays $c_{t_{out}}$ and $c_{t_{in}}$ for $t = 1, \ldots, 24$ to represent the new charging and discharging capacities
**for** t=1, ..., 24 **do**
  **if** $PGPHEV_t > p$ **then**
    Set $c_{t_{out}} = \frac{1}{2}(PGPHEV_t - p)$
    Set $c_{t_{in}} = PGPHEV_j - p$
  **else**
    Set $c_{t_{out}} = p - PGPHEV_t$
    Set $c_{t_{in}} = \frac{1}{2}(p - PGPHEV_t)$
  **end if**
**end for**
Return $c_{t_{out}}$ and $c_{t_{in}}$ for $t = 1, \ldots, 24$

The second policy is denoted PHEV Price. With this policy, we do not explicitly constrain the charging and discharging behaviors at the exchange stations, but instead try to encourage these behaviors by changing the power prices. We again look at an ideal power generation curve in comparison to the existing power generation curve with PHEV exchange stations. If at a specific point in time the curve with PHEVs is higher than the ideal curve, we want to encourage more discharging and less charging. The opposite is true when the curve with PHEVs is below the ideal curve. Algorithm 2 explains the details of this policy. As with the capacity values, the prices are updated based on how far they are from the ideal power generation curve.

The last policy combines these two policies by constraining the charging and discharging capabilities of the exchange stations as dictated in Algorithm 1 and adjusting the power prices according to Algorithm 2. We refer to this policy as PHEV Cap Price.

**Algorithm 2** Policy 2: PHEV Price

Input: power generation curve, $PG_i$, (load - wind, if wind is considered), for hours within a day $i = 1, \ldots, 24$

Input: power generation curve with PHEV exchange station, $PGPHEV_i$, for hours within a day $i = 1, \ldots, 24$

Input: current power prices $c_i$ for hours within a day $i = 1, \ldots, 24$

Find the point $p$ that minimizes $\sum_{i=1}^{24} |PG_i - p|$

Set $p = 1.1 * p$ to allow for some PHEV charging

Find the point on $PGPHEV$ that is the greatest above $p$ and set to $max\_above$

Find the point on $PGPHEV$ that is the greatest below $p$ and set to $max\_below$

Define array *price* of size 24 to represent the new charging and discharging prices

**for** j=1, ..., 24 **do**

  **if** $PGPHEV_j > p$ **then**

    Set $price_j = c_j + \frac{(PGPHEV_j - p)}{max\_above} * 0.75 * c_j$

  **else**

    Set $price_j = c_j - \frac{(p - PGPHEV_j)}{max\_below} * 0.75 * c_j$

  **end if**

**end for**

Return *price*

All three of these policies were tested for each of the 6 regions, 12 months, and 5 random days within each month, for a total of 360 tests iterations. The resulting curves by hour from one test instance are shown in Figure 8, which incorporates wind energy. In this figure, we see the blue original power load curve from input data and the corresponding green original generation curve, which is the load curve minus wind energy. The red generation curve is the green generation curve with the extra load from all of the PHEV exchange stations. The next three curves represent the updated power generation curves incorporating PHEV exchange stations utilizing the three respective curve flattening policies. For this example, we see that both the PHEV Cap and PHEV Cap Price policies perform well in terms of reducing generation curve variability. The PHEV Price policy is less successful. In the PHEV Price curve, we see undesirable oscillating behavior.

This example suggests that the PHEV Cap and PHEV Cap Price policies will be more effective. To confirm this observation, we formalize a metric to quantify the effectiveness of the policies. This metric uses the curvature of a line to measure its degree of flatness, where a curvature of 0 signifies a completely horizontal line. We present two different calculations for the curvature of a line.

Each generation curve consists of 24 discrete points. The first curvature calculation sums the deviation between discrete points, specifically:

$$curvature = \sum_{i=2}^{24} c_i - c_{i-1}. \tag{14}$$

The second curvature calculation first finds the value $p$ that minimizes Equation 15. The curvature of the line $c$ is then set to the value of Equation 15 for this specific $p$ value.

$$\sum_{i=1}^{24} |c_i - p| \tag{15}$$

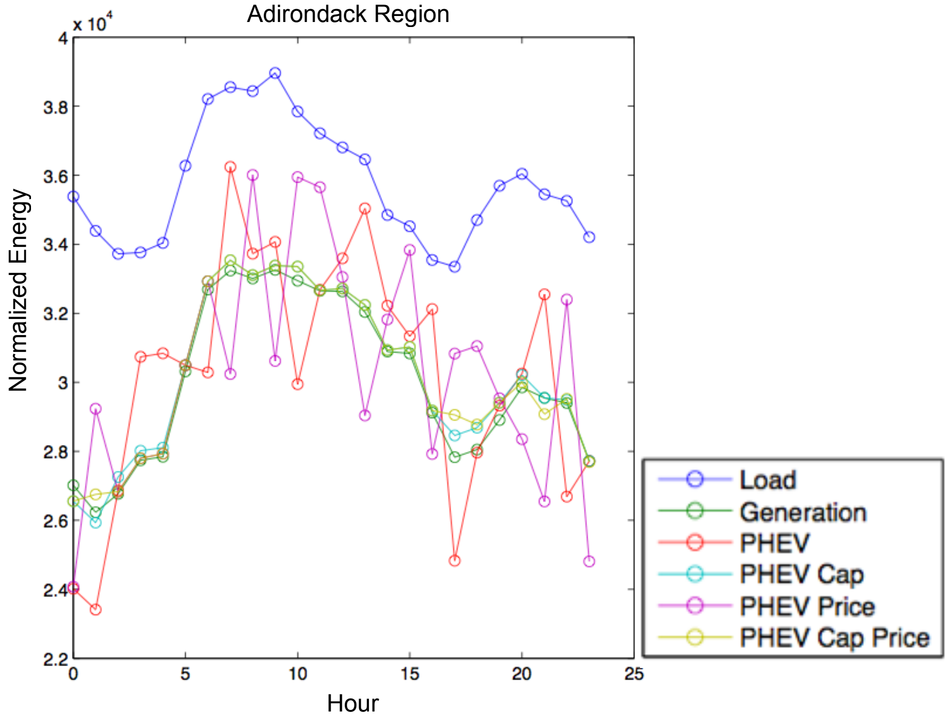


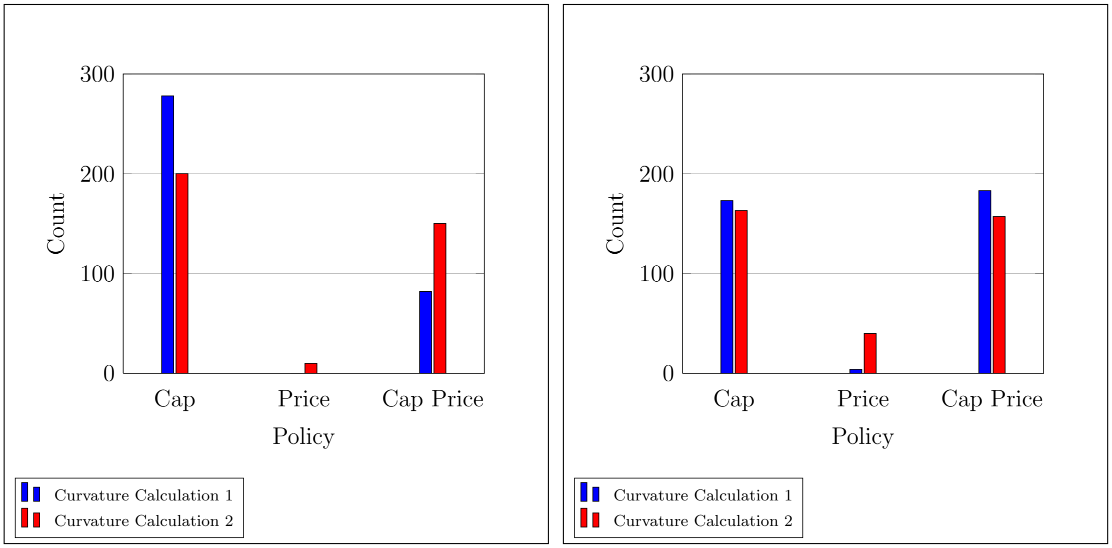

Figure 8: One visualization of the different power generation curves for a specific test instance over 24 hours. The load curve represents current demand. The generation curve is the load curve with the assistance of wind energy. The PHEV curve adds the charging and discharging impact to the generation. The next three curves, PHEV Cap, PHEV Price, and PHEV Cap Price show the new generation curves with wind and PHEV exchange stations based on the different curve flattening policies.

We refer to these functions as curvature calculation 1 and curvature calculation 2, respectively.

These two curvature calculations are then applied to the curves for power load, power generation, power generation with PHEV exchange stations, and the power generation under each of the three flattening policies. The percentage improvement to the curvatures is then calculated by comparing the new power generation curve with PHEV exchange stations utilizing a policy to the original power load curve curvature value, specifically $\frac{curvature_{load} - curvature_{policy}}{curvature_{load}}$, where a positive number signifies improvement in the flatness property of the curve. The impact of each of the policies on the objective function value of the model (profit over all exchange stations) is also captured, by calculating the percentage difference between the objective function value of the unconstrained model to the model implementing one of the three policies.

We seek to determine not just the most effective policy for each of the 360 tests instances but the policy that is most effective overall. Figure 9a counts the number of times, for each of the curvature calculations, that each of the policies showed the greatest improvement in the curvature (i.e., led to the flattest final power generation curve with PHEVs) when wind energy is not considered. Figure 9b displays the count of time for each curvature calculation that shows the greatest improvement when wind energy is considered. From these counts, it is clear that the PHEV Price policy is not effective, leading us to focus on the other two policies.

Figures 10a and 10c display histograms for the count of times (out of 360 instances) a percentage




(a) Without Wind



(b) With Wind

Figure 9: Count of the times that each curve flattening policy led to the greatest improvement in the new power generation curve with PHEVs both with and without wind.

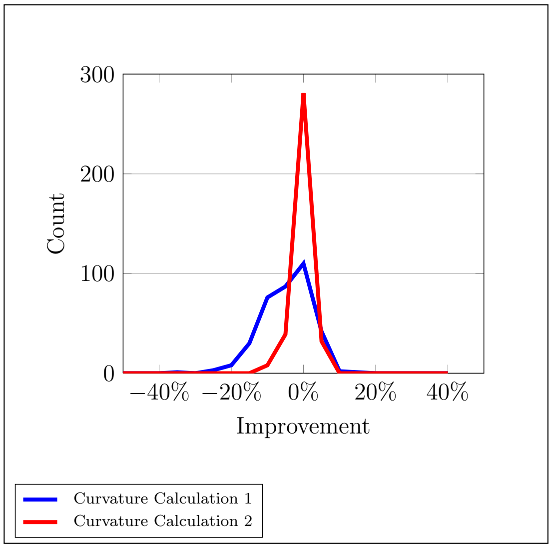
improvement value was realized, without and with wind, respectively for the PHEV Cap policy. From these histograms, we first observe that there is a greater range of improvement when wind energy is incorporated. This means that the capacity policy is not always able to flatten out the curve generated with the wind variabilities. We do observe that the majority of the improvements for both curvature calculations lie close to 0%, which results in a generation curve consistent with the existing load curves.

Figures 10b and 10d display these same histograms based on the percentage improvement over 360 test instances when implementing the PHEV Cap Price policy, without and with wind, respectively. On first inspection, Figures 10a and 10b appear very similar. When examining the details, we note that for curvature calculation 1, the PHEV Cap policy leads to a greater number of non-negative improvement values than the PHEV Cap Price policy. For curvature calculation 2, we see a slightly greater number of non-negative improvement values for the PHEV Cap Price policy.

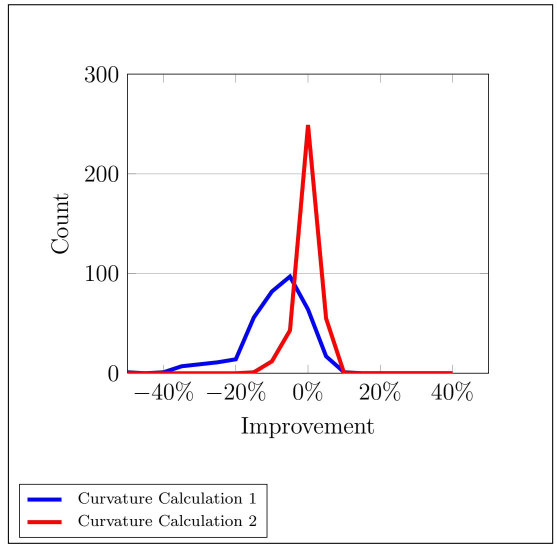
Looking at Figures 10c and 10d, we can compare the PHEV Cap and PHEV Cap Price policies when wind energy is incorporated. Again the graphs appear very similar with only slight differences. These differences include a greater number non-negative improvement values for the PHEV Cap Price policy based on both curvature calculations.

From this analysis, we can conclude that even though there are slight differences, both the PHEV Cap and PHEV Cap Price policies are effective at flattening out the power generation curve. Most often the new power generation curve is returned to a state very similar to the existing power load curve, represented by a close to 0% improvement. Further, we observe that the most effective policy is achieved by adding strict constraints, as opposed to influencing behavior through prices.

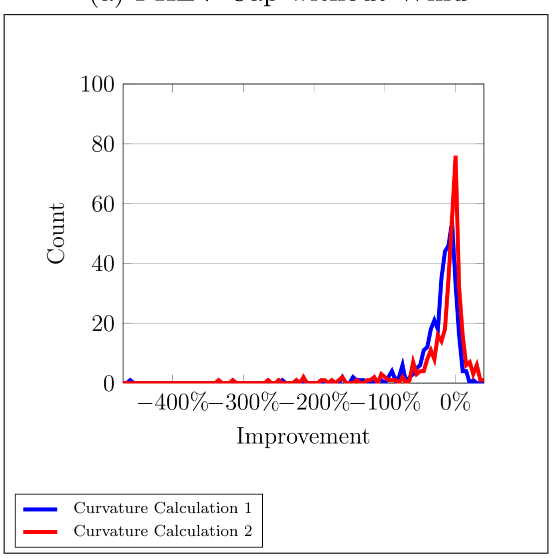
If either of these policies were implemented they would negatively impact the objective function value of the exchange stations, due to increased constraints. The impact is approximately 20% to 25% reduction in realized profits, on average. This could pose a significant burden on the exchange stations. However, we do note that in all 360 test instances the exchange stations always remain profitable even with the flattening policies.



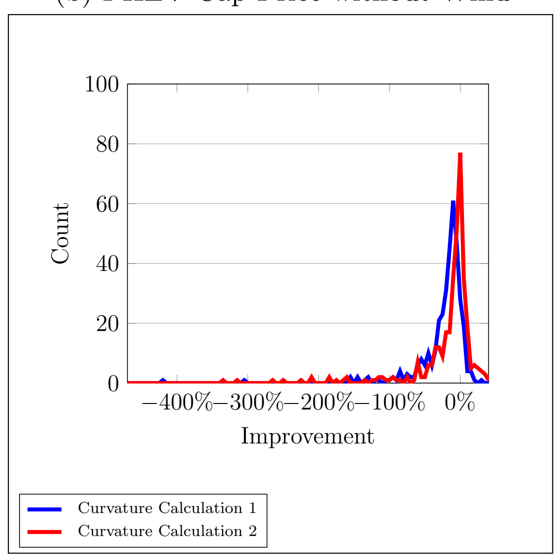

(a) PHEV Cap without Wind




(b) PHEV Cap Price without Wind




(c) PHEV Cap with Wind




(d) PHEV Cap Price with Wind

Figure 10: Count of the times that each curve flattening policy led to the greatest improvement in the new power generation curve with PHEVs both with and without wind.

*Computational Results Summary.* We performed three sets of computational tests. Each test set addressed different questions. We first looked at the objective function values and average primary met demand for different test instances. From these tests, we conclude that profitability (objective function values) is influenced mainly by battery inventory level and number of exchange stations considered. We did observe slight variations in objective function value for different months and regions. One main finding is that different forced customer-service levels did not impact the objective function values. This means if the prices are set appropriately, the exchange stations are motivated to fulfill their primary purpose, meeting PHEV exchange request demand. When looking at the average primary met demand, we noticed that more than 90% of demand is met consistently and most often almost 100% of demand is met.

We then analyzed the optimal solutions obtained by specifically looking at the times when batteries are charged and discharged. From these tests we observed that if a small inventory of batteries is considered at the exchange stations, very little discharging occurs; instead the focus is on charging batteries in order to meet exchange requests. A larger inventory of batteries allows for the benefit of discharging to the grid but increases variability as batteries are charged in order to meet exchange requests, but the remaining inventory oscillates between charging and discharging based on the power prices.

The last set of computational tests looked at how the exchange stations impact the power grid. Due to the fluctuations in charging and discharging, these exchange stations introduce increased variability for the grid, leading to a less flat generation curve. We created and implemented three policies for the exchange stations to lessen the variability. As a result of the tests, we concluded that the most effective policies incorporate a strict constraint on the collective amount of charging and discharging the exchange stations can do at each point in time. Changing the power prices to influence desirable behavior was less effective. These tests were extended further by incorporating wind energy. For most cases considered, we were able to use the exchange stations to offset the variability introduced with wind energy. This means that exchange stations can be used to complement wind energy to arrive at a power generation curve with a similar degree of flatness as the generation curve without these renewable energies (original power load).

When collectively examining all three sets of computational tests, we make main conclusions about the impact of price and battery inventory level. Although, we observed that price was a driver for profitability and meeting customer requests, we were unable to utilize strictly price to encourage a change in exchange station behavior to balance the power generation curve. However, price with battery inventory level leads to some interesting conclusions. With a high enough battery inventory level, exchange stations react to charge/discharge prices to increase their profitability by discharging batteries in inventory at high price times and charging them at low price times. This uncontrolled oscillating behavior is originally undesirable as it leads to a less flat power generation curve. This result would originally lead policy makers to encourage exchange stations to maintain an appropriate battery level on hand to solely meet customer exchange requests and not utilize this resource to flatten the power generation curve. However, we have shown that, even with high battery inventory levels, controls limiting the collective amount of charging and discharging are effective at dampening this undesirable oscillating behavior that leads to (i) a more balance power generation curve, (ii) high percentage of met customer requests, (iii) profitability at the exchange stations, and (iv) the ability to compliment other renewable resources such as wind energy.

## 4. Conclusions

In this paper, we examined the problem of operating many PHEV exchange stations. Using a deterministic integer programming model, we determined the optimal number of batteries to charge, optimal number of batteries to discharge back to the power grid using V2G technology, and optimal number of batteries to exchange over time when seeking to maximize profits.

Using the model, we performed a theoretical and computational analysis to suggest insight for general operating procedures at exchange stations. We determined the necessary number of batteries to hold in inventory to meet 100% of PHEV battery exchange requests. Using historical realistic power and gas station data, we showed the impact of battery inventory levels, customer-service levels, geographical regions, the number of exchange station locations, and month on the objective function value and average primary met demand.

From these results, we determined that if the price to exchange a battery is set appropriately, then the focus of the exchange station is to meet exchange requests. If exchange stations then have an excess inventory of batteries, they can alternate between charging and discharging these batteries based on the fluctuations in power prices. This suggests that exchange stations will act in the best interest of the consumers when provided a financial incentive to do so, rather than under added regulations (constraints).

We also examined the impact of adding exchange stations to the power grid. We showed that these exchange stations, as with other sustainable energies, such as wind, introduce variability in power system operation. We created and tested three different generation curve flattening policies by adjusting the charging capacity, discharging capacity, and power prices charged at the exchange stations. Based on results of computational tests, we determined that one of these policies is not effective, but the other two are able to limit the negative impact of wind energy production and exchange station operation. As a result, exchange stations should adopt either the PHEV Cap or PHEV Cap Price policy.

By collectively examining the computational tests, we have showed the impact of price and battery inventory level. With an appropriately set exchange price and battery inventory level, exchange stations can benefit the community by meeting customer exchange requests, benefit their company by maintaining profitability, and benefit the environment by balancing the power generation curve and complimenting existing renewable energy.

There are a number of important directions to consider in the future. First, the power network and number of PHEV exchange requests by time are inherently stochastic. The model we developed should be extended to include stochastic elements. Further, we simplified the power network by only modeling its connection to the exchange stations. By incorporating the entire power network in the model, we could model the true capacities for the charging and discharging behaviors of the exchange stations based on how they affect the power flows in the power network.

## Disclaimer

The views expressed in this article are those of the authors and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government.

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