Spatial Arbitrage Through Bidirectional Electric Vehicle Charging with Delivery Fleets

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Abstract

The adoption of electric vehicles (EVs), including electric taxis and buses, as a mode of transportation, is rapidly increasing in cities. In addition to providing economic and environmental benefits, these fleets can potentially participate in the energy arbitrage market by leveraging their mobile energy storage capabilities. This presents an opportunity for EV owners to contribute to a more sustainable and efficient energy system while also reducing their operational costs. The present study introduces deterministic and single-stage stochastic optimization frameworks that aim to maximize revenue by optimizing the charging, discharging, and travel of a fleet of electric vehicles in the context of both spatial and temporal energy prices. The simulations are performed on a fleet of electric delivery trucks, which have to make deliveries to certain locations on specific dates. The findings indicate the promising potential of bidirectional electric vehicle charging as a mobile grid asset. However, it is important to note that significant revenue is only realized in scenarios where there is substantial variation in prices between different areas, and when these price variations can be accurately forecasted with a high level of confidence.

Keywords: Arbitrage, locational marginal pricing, electric vehicles, smart charging, vehicle-to-grid.

Nomenclature

Parameters

Δt	Size of a timestep (hours)
η_c	Charging efficiency
η_d	Discharging efficiency
$E_n^{\max}$	Maximum battery energy of n^{th} vehicle
$E_{n,0}$	Initial energy in the battery of n^{th} vehicle
N	Total number of vehicles
P_n^{drive}	Discharge rate of n^{th} vehicle when driving
$P_c^{\max}$	Maximum charge rate
$P_d^{\max}$	Maximum discharge rate
T	Total number of time steps
t	Discrete time slot index
$T_{A,B}$	Number of time steps takes to travel from A to B (or reverse)
$T_{A,C}$	Number of time steps takes to travel from A to C (or reverse)
$T_{B,C}$	Number of time steps takes to travel from B to C (or reverse)

Sets

$\mathcal{N}$	The set of EVs
$\mathcal{T}$	The set of time index

Variables

$\alpha_{n,t}, \beta_{n,t}, \gamma_{n,t}$	(Binary) symbolizing the presence of n^{th} vehicle is at locations A, B, and C
a_n, b_n, c_n	(Binary) symbolizing the n^{th} vehicle being at location A, B, and C at any time instance.
$c_{n,t}^A$	Grid-side charging power of n^{th} vehicle at location A
$c_{n,t}^B$	Grid-side charging power of n^{th} vehicle at location B
$c_{n,t}^C$	Grid-side charging power of n^{th} vehicle at location C
$d_{n,t}^A$	Grid-side discharging power of n^{th} vehicle at location A
$d_{n,t}^B$	Grid-side discharging power of n^{th} vehicle at location B
$d_{n,t}^C$	Grid-side discharging power of n^{th} vehicle at location C
x, y, z	EV's charged (positive) or discharged (negative) power at locations A, B, and C

1. Introduction

With the advent of distributed energy resource capabilities and new market mechanisms, the energy arbitrage (e.g., buying during "off-peak" times and selling during "on-peak" times) landscape is rapidly changing from large-scale stationary energy storage owned by large firms to mobile energy storage owned by individuals with electric vehicles (EVs) [1]. EVs have the potential to impact energy arbitrage in two significant ways: first, the mobility of EVs allows for them to act as distributed energy resources (DERs), providing additional flexibility to the grid [2]; second, the rise of vehicle-to-grid

(V2G) technology allows EVs to not only consume energy but also supply excess energy back to the grid [3]. This shift towards mobile energy storage provides new opportunities for individual EV owners to participate in energy arbitrage and contribute to a more sustainable energy future, due to several major advantages over traditional gas-powered vehicles such as being environmentally friendly, cheaper to maintain, and generally safer [4, 5, 6, 7].

The adoption of vehicle-to-grid (V2G) technologies has been rapidly increasing, facilitated by the proliferation of EVs in the energy system [8]. This trend aligns with the projected growth of EVs, with an estimated 30–42 million EVs expected to be on the roads by 2030 in the U.S. [9]. To support this transition, significant advancements in bidirectional charging have been achieved. Major automotive manufacturers like Ford are introducing electric options for their top-selling vehicles, highlighting the expanding capabilities of bidirectional charging. In a significant regulatory development, the Federal Energy Regulatory Commission (FERC) approved Order 2222 in 2020, allowing distributed energy resources, including EVs, to participate in wholesale markets [10]. These advancements not only facilitate the integration of EVs into the energy system but also open up new opportunities for their contribution to the overall energy landscape.

The scheduling of EVs for profit maximization is challenging due to uncertainties in EV mobility behavior and market price volatility. This complexity arises in the decision-making process under uncertainty when optimizing EV scheduling [11, 12]. Previous studies have demonstrated the cost-effectiveness of V2G technologies in certain situations, while the feasibility of the V2G-enabled fleet business model depends on evaluating the financial risks associated with accelerated battery degradation [13]. Moreover, the advantages of V2G extend to various scales, including the transmission network, distribution network, and microgrids. By adopting an optimal bidirectional V2G mode for EVs, both the operational stability and economic performance of the system can be enhanced [14, 15].

As previously mentioned, EVs offer promising opportunities to support the electrical grid through smart charging strategies. While unidirectional charging (where EVs draw power from the grid but do not return it) provides essential services like load shifting, frequency regulation, and participation in demand response programs, its capabilities are inherently limited by the inability to discharge energy back to the grid. These unidirectional services allow for optimized charging schedules, cost savings, and enhanced grid stability, particularly during off-peak hours when energy demand is lower. However, bidirectional charging, or V2G technology, extends these benefits by enabling EVs not only to charge but also to discharge energy back to the grid when needed. This added flexibility allows bidirectional EVs to participate in additional grid services such as peak shaving, voltage support, and energy arbitrage, where they can be charged during periods of low electricity prices and discharged when demand or prices are higher. More importantly, bidirectional charging provides flexibility at any state-of-charge, meaning that EVs can continue to support grid needs whether they are charging or discharging. They can be utilized as mobile energy assets that can interact dynamically with the grid. In contrast, unidirectional systems lose flexibility once the EV battery is fully charged, as they can no longer offer grid support until the vehicle has been driven and its charge is partially depleted. By contrasting the dynamic capabilities of bidirectional systems with the more limited scope of unidirectional charging, we aim to highlight the enhanced value and versatility that bidirectional solutions bring to the evolving energy landscape.

Several studies have put forth optimization strategies aimed at maximizing the profit of EVs across different market scenarios. These strategies encompass a range of applications, such as providing frequency regulation [16], operating costs and CO_2 emissions [17, 18], trading in day-ahead and intra-day electricity markets [19], local energy trading [20], and minimizing grid fluctuations [21]. Additionally, some studies have explored the potential for EVs to participate in multiple grid services [22]. In line with the ongoing efforts to optimize energy management systems (EMS) for EVs, [23, 24] introduced a climate-adaptive EMS, designed specifically for multimode connected plug-in hybrid electric vehicles (PHEVs) and heavy-duty vehicles under varying climate conditions integrating ambient temperature and traffic data into the state space. However, it is important to note that these approaches typically assume a fixed location for the EV, disregarding the fact that electricity prices can exhibit significant variations over short distances. Considering this aspect could unlock further potential benefits in optimizing EV operations. Therefore, unlike other V2G optimization studies that use fixed EV locations [25, 26, 27], our model uniquely captures the value of mobility in spatial arbitrage.

In areas with locational marginal prices (LMPs), time-varying price signals can help identify areas in need of congestion relief and better represent the cost to deliver power to specific locations at specific times. New opportunities for mobile energy storage arise in these situations, capturing both spatial and temporal benefits, which we aim to explore in this paper.

Previous studies have investigated the use of mobile energy storage at the transmission level, focusing on spatio-temporal arbitrage using utility-scale batteries [3]. However, these studies were restricted to a driving radius of 10 miles. Therefore, it is essential to further analyze the potential benefits of spatio-temporal LMP differences in a more comprehensive and realistic manner. To leverage spatial price differences, several studies have introduced optimization methods for vehicle charging that incorporate joint optimization of vehicle routing [28, 29]. These approaches take into account factors such as traffic conditions and charging location uncertainties. However, they do not consider the potential for arbitrage, limiting their focus to unidirectional charging. Furthermore, the complexity of these methods is significantly high due to the extensive number of possible routes. To address these limitations, further enhancements are required to incorporate bidirectional charging and mitigate the computational complexity associated with optimizing vehicle routing.

This work represents an expanded and enhanced version of our preliminary conference paper [30]. The present paper aims to explore the potential of spatial (also called geographical) arbitrage in the context of bidirectional EV charging given more practical vehicle constraints such as delivery schedules. Unlike stationary models found in the literature [31, 32, 33], where EVs perform energy arbitrage without moving, our study introduces a novel approach by incorporating spatial dimensions—considering not only the timing of charging and discharging activities but also the locations where these activities occur. This integration of spatial and temporal factors is particularly relevant for delivery fleets, which must navigate logistical constraints while taking advantage of LMP differentials. By combining the objective of arbitrage with the EV's role as a mobile energy storage device, our study focuses on analyzing the potential for fleets of electric delivery trucks to align delivery objectives with a secondary revenue stream resulting from intelligent charging and discharging.

Here we investigate the potential of large delivery fleets to provide spatial arbitrage. Delivery vehicles have inherent flexibility in travel requirements that private vehicles do not – given an operator makes real-time decisions about when are where to send vehicles. The flexibility we refer to in the context of delivery vehicles pertains to their operational scheduling, which can be optimized to maximize efficiency and profitability. Unlike private vehicles, which are used based on the owner's personal convenience and preference, delivery trucks operate within a commercial framework where their routes and schedules can be strategically planned. In other words, trip constraints can be transferred between vehicles, whereas, for private vehicles, each is bound to a specific trip schedule. This controlled usage allows for a higher degree of flexibility in optimizing their operational patterns compared to private vehicles. Additionally, the increasing adoption of EVs within delivery fleets enhances their potential for energy arbitrage due to their larger battery capacities and higher utilization rates. This strategic approach allows fleets to not only meet delivery demands but also contribute to profitability through well-timed charging and discharging activities. Moreover, the ability to manage these fleets on a large scale underlines the significant economic and environmental benefits that can be realized compared to smaller private EVs.

To this end, we develop a framework that integrates the charging, discharging, delivery, and departure time scheduling of multiple vehicles into a single-stage optimization model. In other words, the novel approach integrates the dual objectives of delivery scheduling and energy arbitrage within a single optimization framework, uniquely positioning EV fleets as both operational and energy trading assets. To efficiently solve this problem, we formulate it as a mixed-integer linear program, which can be effectively solved using existing optimization solvers. Our study is distinguished by its comprehensive modeling of practical constraints and its demonstration of substantial profitability gains through spatial arbitrage, offering significant contributions to both the theoretical and practical understanding of electric fleet management. We conduct a case study in the ERCOT real-time market to evaluate the performance of our proposed framework for electric delivery trucks traveling between San Marcos, San Antonio, and Austin, Texas. The case study allows us to have an initial understanding of the effectiveness and efficiency of the scheduling and optimization strategies in a market setting. Initial results demonstrate that delivery schedules can be adhered to while grid services are provided that benefit both EV owners and the power grid.

2. Model

This preliminary study is based on several assumptions. Firstly, there is no requirement for EVs to travel separately from their delivery routes; the only requirement is that the EVs make the required delivery by the required time. Additionally, the option for temporal arbitrage is just one subset of the optimization problem. To simplify matters, a separate charging and discharging variable for each vehicle is assumed (e.g. the car can only be charging *or* discharging at any given time). The details of the charging infrastructure, such as the number, type, and locations of chargers, are not explicitly modeled. Instead, maximum charge and discharge rates are specified. The model assumes perfect foresight of real-time electricity prices across all locations and periods. It should be noted that this framework has the potential to be extended to include autonomous vehicles that have additional onboard energy storage.

2.1. Electric Vehicle Fleets

Consider a set $\mathcal{N} = \{1, \ldots, N\}$ of EVs that are going to be charged in different locations $[A, B, C]$ during a specific time. To establish a framework for the operation cycle, we partition the horizon time into a set $\mathcal{T} = \{1, \ldots, T\}$ consisting of T discrete time slots. Each of these time slots corresponds to a charging/discharging control interval, typically lasting 15 minutes. The control interval between any two consecutive slots is represented by Δt. The assumption made in this case does not impact the general applicability of the proposed algorithm, and it can be adjusted to suit the specific needs of the study case; for example, in markets with different real-time pricing intervals.

The power demand of each EV $n \in \mathcal{N}$ in time slot $t \in \mathcal{T}$ at locations A, B, C has limits $-P_d^{\max} < 0$ and $P_c^{\max} > 0$, respectively. These limits can reflect the charging and discharging limits of a particular charging station. We thus have the constraints

$$-P_d^{\max} \leq x_{n,t} \leq P_c^{\max} \tag{1a}$$
$$-P_d^{\max} \leq y_{n,t} \leq P_c^{\max} \tag{1b}$$
$$-P_d^{\max} \leq z_{n,t} \leq P_c^{\max} \tag{1c}$$

Note that variables $x_{n,t}, y_{n,t}, z_{n,t}$ represent the n^{th} EV's charged (positive) or discharged (negative) power at location A, B, and C at time slot $t \in \mathcal{T}$, respectively. It is worth noting that the charging rate can be influenced by various factors, including the type of charger, battery size, the EV model, and even the current state of charge of the battery. Moreover, to better reflect real-world constraints, minimum charging and discharging rates will be introduced in future iterations of the model, ensuring that all charging activities adhere to technical limitations. It's also worth mentioning that this adjustment can be implemented easily within the existing framework.

Let $10\% \leq E_n^{\text{init}} \leq 90\%$ and $E_n^{\max} \geq 0$ denote the initial state of charge (SOC) and the maximum capacity of the battery of each EV $n \in \mathcal{N}$, respectively. Let $0 < \eta_n^c \leq 1$ and $0 < \eta_n^d \leq 1$ define as the energy transfer efficiencies for charging and discharging of EVs $n \in \mathcal{N}$, respectively. We introduce slack variables $c_{n,t}^{\{.\}}$ and $d_{n,t}^{\{.\}}$ to indicate the charging and discharging power of each EV $n \in \mathcal{N}$ in time slot $t \in \mathcal{T}$ for a specific location (A, B, or C), respectively, as given by

$$x_{n,t} = c_{n,t}^A - d_{n,t}^A \tag{2a}$$
$$y_{n,t} = c_{n,t}^B - d_{n,t}^B \tag{2b}$$
$$z_{n,t} = c_{n,t}^C - d_{n,t}^C \tag{2c}$$
$$0 \leq c_{n,t}^A \leq P_c^{\max} \alpha_{n,t} \tag{2d}$$
$$0 \leq d_{n,t}^A \leq P_d^{\max} \alpha_{n,t} \tag{2e}$$
$$0 \leq c_{n,t}^B \leq P_c^{\max} \beta_{n,t} \tag{2f}$$
$$0 \leq d_{n,t}^B \leq P_d^{\max} \beta_{n,t} \tag{2g}$$
$$0 \leq c_{n,t}^C \leq P_c^{\max} \gamma_{n,t} \tag{2h}$$
$$0 \leq d_{n,t}^C \leq P_d^{\max} \gamma_{n,t} \tag{2i}$$

where vectors $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma} \in \{0, 1\}$ are comprised of binary elements and indicate whether or not the EV $n \in \mathcal{N}$ is at locations A, B or C at a time $t \in \mathcal{T}$, respectively. Constraints (2d)-(2i) describe the charging and discharging limits at locations A, B or C, respectively, given by the available bi-directional charger at those locations.
Denoting the state of charge level of each EV $n \in \mathcal{N}$ in time slot $t \in \mathcal{T}$ by $E_n(t)$, the EV's dynamics can be updated by

$$\begin{aligned} &E_n(t) = E_n(t-1) + \Big(\eta_n^c (c_{n,t}^A + c_{n,t}^B + c_{n,t}^C) - \\ &\frac{d_{n,t}^A + d_{n,t}^B + d_{n,t}^C}{\eta_n^d} - P_n^{drive}(1 - \alpha_{n,t} - \beta_{n,t} - \gamma_{n,t})\Big)\Delta t \end{aligned} \tag{3}$$

where $E_n(0) = E_n^{\text{init}}$ and P_n^{drive} represent the power consumption rate of EV while driving at each time step of Δt. The SOC of each EV $n \in \mathcal{N}$ in the time slot $t \in \mathcal{T}$ is bounded by the lower and upper SOC limit, denoted by

$E^{\min}$ and $E^{\max}$, respectively. We have

$$E_n^{\min} \leq E_n(t) \leq E_n^{\max} \tag{4}$$

Constraints (1)-(4) guarantee that the battery of each EV is within their physical range when providing delivery or doing arbitrage. Additionally, to safeguard against the complete depletion of the electric vehicles' batteries at the close of each day, our model includes a constraint guaranteeing a sufficient state of charge, thereby ensuring the uninterrupted execution of the delivery tasks, denoted as $E_n(T) = E_n^{\text{final}}$.

2.2. Spatial-temporal Model

We identify two possible states of the considered EVs: i) parking EVs at the charging stations for park-and-charge, and ii) driving on the road and going to the delivery points. As mentioned earlier, the present state of an EV $n \in \mathcal{N}$ in the time slot $t \in \mathcal{T}$ at locations A, B, and C are described by binary variables $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, respectively. Moreover, we use $T_{A,B}$, $T_{A,C}$ and $T_{B,C}$ to define the travel/driving time from regions $A \leftrightarrow B$, $A \leftrightarrow C$, and $B \leftrightarrow C$, respectively. Therefore, the spatial-temporal constraints of the EVs can be expressed as follows:

$$\alpha_{n,t} + \beta_{n,t} + \gamma_{n,t} \leq 1 \tag{5a}$$

$$\alpha_{n,t} + \beta_{n,t+\tau} \leq 1 \qquad \text{if} \quad \alpha_{n,t} = 1 \qquad \tau \in [1, T_{A,B}] \tag{5b}$$

$$\beta_{n,t} + \alpha_{n,t+\tau} \leq 1 \qquad \text{if} \quad \beta_{n,t} = 1 \qquad \tau \in [1, T_{A,B}] \tag{5c}$$

$$\alpha_{n,t} + \gamma_{n,t+\tau} \leq 1 \qquad \text{if} \quad \alpha_{n,t} = 1 \qquad \tau \in [1, T_{A,C}] \tag{5d}$$

$$\gamma_{n,t} + \alpha_{n,t+\tau} \leq 1 \qquad \text{if} \quad \gamma_{n,t} = 1 \qquad \tau \in [1, T_{A,C}] \tag{5e}$$

$$\beta_{n,t} + \gamma_{n,t+\tau} \leq 1 \qquad \text{if} \quad \beta_{n,t} = 1 \qquad \tau \in [1, T_{B,C}] \tag{5f}$$

$$\gamma_{n,t} + \beta_{n,t+\tau} \leq 1 \qquad \text{if} \quad \gamma_{n,t} = 1 \qquad \tau \in [1, T_{B,C}] \tag{5g}$$

$$a_n \geq \alpha_{n,t}, \qquad a_n \leq \sum_{t \in \mathcal{T}} \alpha_{n,t} \tag{5h}$$

$$b_n \geq \beta_{n,t}, \qquad b_n \leq \sum_{t \in \mathcal{T}} \beta_{n,t} \tag{5i}$$

$$c_n \geq \gamma_{n,t}, \qquad c_n \leq \sum_{t \in \mathcal{T}} \gamma_{n,t} \tag{5j}$$

$$\sum_{n \in \mathcal{N}} a_n \geq N_A \tag{5k}$$

$$\sum_{n\in\mathcal{N}} b_n \geq N_B \tag{5l}$$

$$\sum_{n\in\mathcal{N}} c_n \geq N_C \tag{5m}$$

$$\alpha_{n,0} = 1 \qquad n \in \mathcal{J}_A \tag{5n}$$

$$\beta_{n,0} = 0 \qquad n \in \mathcal{J}_B \tag{5o}$$

$$\gamma_{n,0} = 0 \qquad n \in \mathcal{J}_C \tag{5p}$$

Each vehicle can't be present at points A, B, and C at the same time. Therefore, constraint (5a) ensures that the vehicle $n \in \mathcal{N}$ is not at points A, B, and C in the time slot $t \in \mathcal{T}$ simultaneously. While the EV is driving between two locations, all the binary variables should remain zero until the EV reaches the destination. constraints (5b) - (5g) aims to ensure that binary variables of the associated locations remain zero until the time steps after the vehicle $n \in \mathcal{N}$ has departed the first location. For the delivery option, it assumed that at least a specific number of vehicles should visit each location (constraints (5k)-(5m)). A subset of vehicles is assumed to start at locations A, B, and C in the first timestep, respectively, which necessitate constraints (5n)-(5p).

3. Methods

In this section, an optimization program is introduced for the energy management of a fleet of EVs or electric delivery trucks traveling between three locations. The program is single-stage and employs mixed integer linear optimization techniques. It also considers the charging and discharging behavior of EVs as well as the departure of every single EV. We aim to minimize the total charging cost of EVs owned by an aggregator.

3.1. Stochastic Problem Formulation

We have formulated the optimization problem under the assumption that the arrival time, departure time, and charging demand of electric vehicles at each location are unknown. We aim to find the optimal charging solution for each EV n to minimize the expected total EV charging and discharging cost in an operational horizon T (here, 24 hours with 15-minute time steps). In other words, this objective seeks to maximize the profits derived from spatial and temporal arbitrage, while taking into account the associated expenses of the

EV charging and discharging processes. Then we can formulate the charging optimization problem for the aggregator owing fleet of EVs as follows.

$$\underset{\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}}{\text{Minimize}} \quad \sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}}(\xi_t^A x_{n,t} + \xi_t^B y_{n,t} + \xi_t^C z_{n,t}) \tag{6}$$

subject to:

Constraints (1)-(5)

where the decision variables are within vectors $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{\alpha}, \boldsymbol{\beta}$, and $\boldsymbol{\gamma}$. The electricity price at each time $t \in \mathcal{T}$ at location A, B, and C, are denoted by $\boldsymbol{\xi}_t^A$, $\boldsymbol{\xi}_t^B$ $\boldsymbol{\xi}_t^C$, respectively.

4. Case Study

In our study, we utilized two weeks from January and August 2022 for simulations. We sourced 15-minute interval real-time zonal pricing data from the Electric Reliability Council of Texas (ERCOT) load zones [34] to determine electricity prices for San Antonio, San Marcos, and Austin, as depicted in Fig. 1 for the associated periods. This visual representation delineates the fluctuating electricity prices across three prominent zones: San Antonio (solid line), San Marcos (dash-dotted line), and Austin (dashed line). Notably, sharp price spikes are evident at specific intervals, most pronounced in the time steps between 100 and 300. While the majority of the data showcases relatively stable price ranges, these intermittent spikes underscore the inherent volatility and complexity of real-time electricity pricing in the Texas grid. These intermittent peaks will be relevant when later analyzing the arbitrage strategy employed.

Given that a fleet of EVs doesn't represent a significant energy resource, we posited that the electric delivery trucks would transact energy based on zonal prices, and the vehicles are price-takers (e.g., they are unable to directly influence market electricity prices through their charging/discharging actions). These prices represent an average across all nodes in a particular zone. In contrast, nodal prices, which are generally more variable and are typically employed by larger, centralized resources, were not considered for this analysis. Note, however, that these prices could easily be incorporated into the framework in place of the zonal assumption.

Due to the unavailability of public historical traffic data for the targeted regions, we relied on fifteen-minute "typical traffic" data for week-

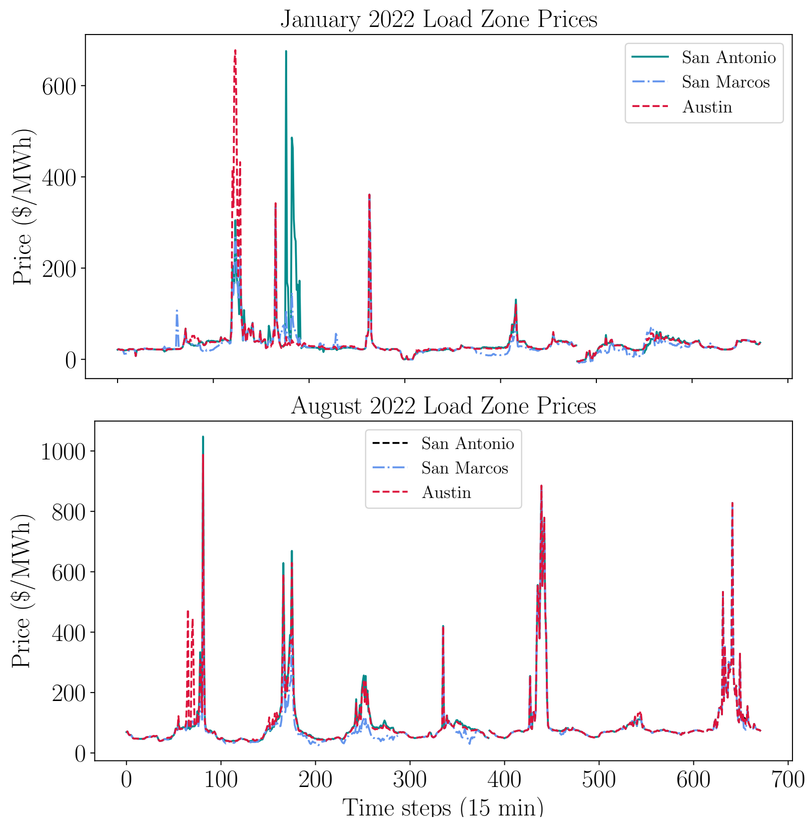


Figure 1: Historical real-time market settlement point prices for January and August 2022 in the three geographical locations.

days, sourced from Google Maps. This data is derived from historical traffic patterns to estimate travel times between the cities. Fig. 2 illustrates the relative locations of San Antonio, San Marcos, and Austin: roughly 31 miles separate Austin and San Marcos, and 50 miles separate San Marcos to San Antonio. This provides a reasonable proxy but may not fully capture real-world congestion and travel time variability.

For the present simulations, we modeled electric delivery trucks equipped with a battery capacity ranging from 630 to 770 kWh [35]. This capacity was randomly assigned to each truck. Each battery also has a random roundtrip efficiency between $90 - 100\%$ [36]. These trucks have access to DC Fast Charging stations with a capacity of 150 kW. We operated under the assumption that these charging stations could facilitate bidirectional charging at the same rate, although the framework can incorporate different

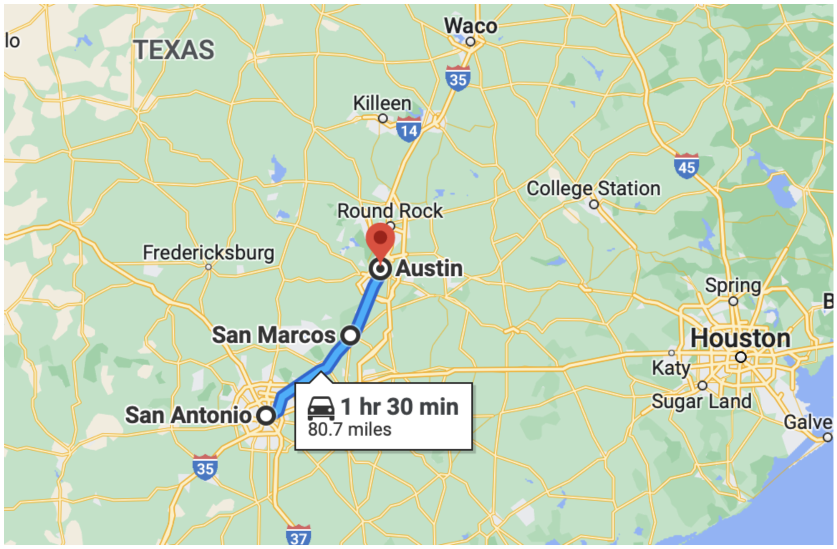


Figure 2: Relative location of the three considered cities within Texas. Typical traffic for each hour and day of the week was obtained from Google Maps.

charge/discharge limits. Throughout the week, if an EV opted for spatial arbitrage, it would begin the subsequent day from its starting location. In our base scenario, we considered a fleet of 10 delivery trucks, with each truck making a minimum of six deliveries daily. The initial state of charge for these EVs was randomized between 420 to 490 kWh. Furthermore, the consumption rate while driving was estimated to be between 63 to 77 kWh per hour if an average of 60 miles/hour is assumed. Lastly, our framework was developed in Python and employed the Gurobi solver [37] for optimization. All simulations were executed locally on a personal Apple laptop equipped with the M1 chip using 16 GB RAM.

4.1. Considered Scenarios

To understand the benefits of performing spatial arbitrage, we considered three different scenarios:

- *Spatial Arbitrage:* The delivery fleet must adhere to a given delivery schedule, can both charge and discharge, and the electricity price changes throughout time and space. This scenario models a realistic operational environment where the fleet can optimize both its route and charging strategies to maximize profit by taking advantage of spatial and temporal variations in electricity prices.

- *Counterfactual:* The delivery fleet must adhere to a given delivery schedule, and can both charge and discharge, but the delivery schedule does not take into account prices which vary by location; only by time. This scenario focuses on the potential for temporal arbitrage alone, providing a comparison to understand the significance of spatial movement in increasing profitability.
- *Stationary Arbitrage:* The delivery fleet is assumed to be stationary but can charge and discharge at the warehouse location (San Antonio). This scenario focuses on the potential for temporal arbitrage alone, providing a comparison to understand the significance of spatial movement in increasing profitability

The purpose of the *Counterfactual* case is to remove the incentive of the EVs to travel or take unnecessary trips due to prices that vary across locations, yielding a result that adheres to the delivery constraints while still having the option to perform temporal arbitrage. The profits reported for this case are then calculated using the actual time-varying prices.

Table 1 elucidates the economic and operational outcomes derived from a week-long simulation optimizing the use of a fleet of ten electric delivery trucks engaged in arbitrage across three scenarios. The scenarios are crafted to assess the impact of strategic movement and charging decisions on the cost-effectiveness, distance traveled, and energy consumption within the fleet operations. In January, the *Spatial Arbitrage* scenario shows the highest profitability, with the fleet earning $\$3,996.63$. This represents a 42.7% increase in profits compared to the *Counterfactual* scenario, where the trucks earn $\$2,786.90$ despite adhering to the same number of deliveries. This comparison demonstrates the added value of spatial arbitrage when distinct electricity pricing is available across locations. The *Stationary Arbitrage* scenario, where trucks do not travel, still manages a profit of $\$2,961.74$, which is 5.9% higher than the *Counterfactual* scenario but 25.9% less than the *Spatial Arbitrage* scenario, emphasizing the potential gains from engaging in spatial arbitrage even when the trucks are also tasked with deliveries.

Moving to August, the profitability for the *Spatial Arbitrage* scenario increases dramatically to $\$7,851.94$, which is a 96.8% surge from January's profits. This dramatic rise suggests a higher efficiency in operational strategy or potentially greater disparities in electricity prices during this month, leading to more lucrative arbitrage opportunities. In comparison, the *Counterfactual* scenario's profit in August is $\$5,316.51$, a significant 90.8% increase from January's earnings, indicating that even without spatial arbitrage, the seasonal variations in electricity prices or delivery schedules can significantly affect profitability. When we compare the two scenarios, the *Spatial Arbitrage* profits in August outperform the *Counterfactual* by 47.7%, which is a slightly higher margin than seen in January (42.7%). This increase suggests that spatial arbitrage becomes even more advantageous when the differential in electricity pricing between locations widens.

In the *Stationary Arbitrage* scenario, where trucks remain stationary and do not partake in delivery tasks, there is a purely financial focus on energy arbitrage. This case shows a consistent approach, with zero distance traveled and a slight decrease in profits from January to August by 5.8%, with a profit of $\$1,009.91$ in August. This decrease could be due to a lower potential for temporal arbitrage or an overall decrease in energy prices during this month, reflecting the varying dynamics of the energy market across different times of the year. In summary, the observed cost savings, distance driven, and energy consumption metrics across the different scenarios highlight the effectiveness of spatial arbitrage in optimizing fleet operations. The significant reduction in costs during the Spatial Arbitrage scenario is primarily driven by the fleet's ability to capitalize on locational marginal price (LMP) differentials, strategically charging during low-price periods and discharging during high-price periods. The increased distance driven in this scenario reflects the fleet's strategic movements to exploit these price differentials, with the additional energy consumption being offset by higher profits.

Table 1: The cost, distance driven, and total battery throughput over the week-long simulation. We compare the spatial arbitrage case with the delivery counterfactual, the case where bi-directional charging is performed only at the warehouse.

Scenario	January			August		
	Cost ($)	Distance (mi)	Energy Consumption (kWh)	Cost ($)	Distance (mi)	Energy Consumption (kWh)
Spatial Arbitrage	−3996.63	10813.40	87262.10	−7851.94	9000.30	81349.74
Counterfactual	−2786.90	6570.90	76798.62	−5316.51	6726.09	78098.00
Stationary Arbitrage	−2961.74	0.00	75611.50	−1009.91	0.00	69151.15

Figure 3 presents the cumulative net charging activities of a fleet of EVs engaged in spatial arbitrage, delineated by location, for one week in January and one week in August. The vertical axis represents the cumulative power (in MW), while the horizontal axis denotes the hours over the week. Note that positive cumulative power relates to battery charging activities, while negative cumulative power indicates discharging back to the grid, enabling the vehicles to act as mobile energy storage units. The color coding distinguishes the locations: pink for Austin (AU), purple for San Marcos (SM), and green for San Antonio (SA). In both months, the fleet's charging (positive values) and discharging (negative values) behaviors demonstrate a clear response to the price signals indicated in Fig. 1, which portrays the historical real-time market settlement point prices for the same weeks in January and August. The variation in charging and discharging across different locations demonstrates the strategic spatial arbitrage, where energy is moved to where it is most economically advantageous, thereby maximizing profits and contributing to grid stability.

August displays an intensified pattern of arbitrage activities, reflecting the higher price volatility illustrated in Fig. 1. The escalated pricing dynamics in August, particularly noticeable with Austin's steep and frequent price peaks, correlate with the larger profits achieved in the *Spatial Arbitrage* scenario for this month, as outlined in the earlier provided Table 1. The consistent pattern across both months confirms that the fleet of EVs is utilized not only for energy storage but also as a mobile energy resource that shifts energy geographically according to arbitrage opportunities. This is in line with the optimization problem's objective to maximize profits through strategic spatial and temporal energy trading while adhering to physical constraints such as a vehicle's presence in a single location at any given time. Such integration could contribute to stabilizing grid prices and providing a buffer against extreme price fluctuations. It is worth mentioning that the computational time required for optimization is directly impacted by the model's complexity and the number of binary variables. In the current spatial arbitrage case study, simulating one day typically takes less than 5 minutes, while a week-long simulation takes approximately 31 minutes.

Figure 4 illustrates the distribution of a fleet of electric vehicles across San Antonio, San Marcos, and Austin, juxtaposed with the corresponding real-time electricity market prices for each location. It captures the fleet's strategic positioning throughout a week in August, reflecting the balancing act between fulfilling delivery requirements and capitalizing on arbitrage opportunities by leveraging temporal and spatial price differentials in the energy market. In San Antonio, the fluctuation in the number of vehicles corresponds with shifts in energy pricing, suggesting that vehicle distribu-

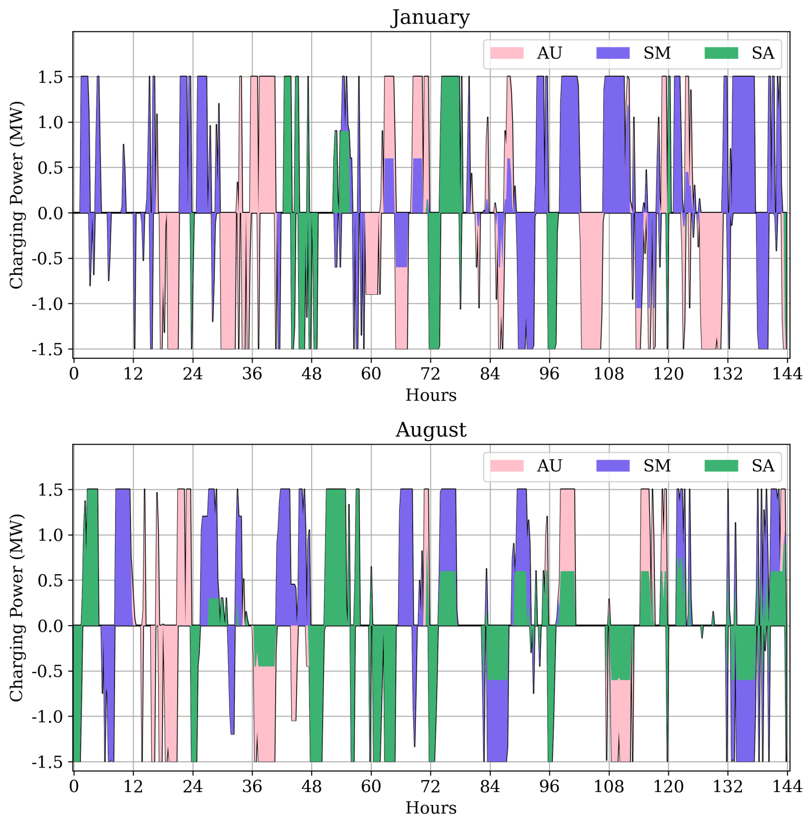


Figure 3: Cumulative fleet charging and discharging broken down by the three locations (AU = Austin, SM = San Marcos, SA = San Antonio), for a week in January and a week in August.

tion is, at least in part, a reaction to economic incentives. During peak price periods, the presence of fewer vehicles may reflect a strategic dispatch to other locations, likely in pursuit of lower charging costs or higher revenue from discharging. Conversely, a rise in the number of vehicles during off-peak price periods suggests a collective strategy to capitalize on cheaper charging opportunities.

The San Marcos graph indicates a similar, though not as pronounced, pattern of vehicle distribution in response to price changes. This is likely a result of the geographic and economic positioning of San Marcos between San Antonio and Austin, making it a strategic midpoint for charging and discharging activities, as well as fulfilling the minimum delivery requirement. In

Austin, the pronounced spikes in energy prices align with substantial drops in the number of vehicles, which supports the notion that vehicles are actively being repositioned in anticipation of or in response to these price surges. This behavior underscores the sophisticated optimization model at play, where the delivery schedule is maintained (as evidenced by at least six vehicles consistently being dispatched for deliveries) while still maximizing arbitrage profits. The results in Table 1 highlighted the profitability of such operations, with August showing a more substantial profit margin than January. This figure underpins those results, illustrating how the fleet's dynamic redistribution aligns with economic incentives to optimize profits while adhering to delivery obligations. This fleet's ability not only reinforces the financial viability of such operations but also highlights the potential of EV fleets as flexible energy resources that can support grid stability.

Figure 5 provides a comparative analysis of the number of trips made by a fleet of EVs under two scenarios: a counterfactual delivery schedule and a spatial arbitrage strategy during one-week periods in January and August. The diagram illustrates the directional flow and volume of trips between three locations—Austin (A), San Marcos (SM), and San Antonio (SA)—with the thickness of the arrows indicating the relative number of trips. Through a detailed examination, it is apparent that in January, the spatial arbitrage model incurs a higher number of trips compared to the counterfactual, yet the profits do not proportionally reflect this increase due to weaker price correlations. For instance, while the trip count increases by 50% from the counterfactual to the arbitrage scenario, profits may not exhibit a commensurate rise. Conversely, August shows a more strategic engagement with fewer trips but significantly greater profitability, suggesting that arbitrage efficiency is highly dependent on market conditions and price volatility.

Energy consumption from additional trips is overshadowed by the energy involved in arbitrage operations. In other words, the adoption of spatial arbitrage is accompanied by an increase in energy usage, predominantly driven by heightened battery cycling for charging and discharging. Nevertheless, this increase in energy consumption, which could be hypothetically pegged at 30%, is compensated by a more pronounced surge in profits, perhaps exceeding 50%, highlighting the method's effectiveness despite its energy demands. Despite the lower absolute profit levels in January, spatial arbitrage still represents a considerable improvement over the counterfactual approach. If the profits in the counterfactual scenario are considered a baseline, spatial

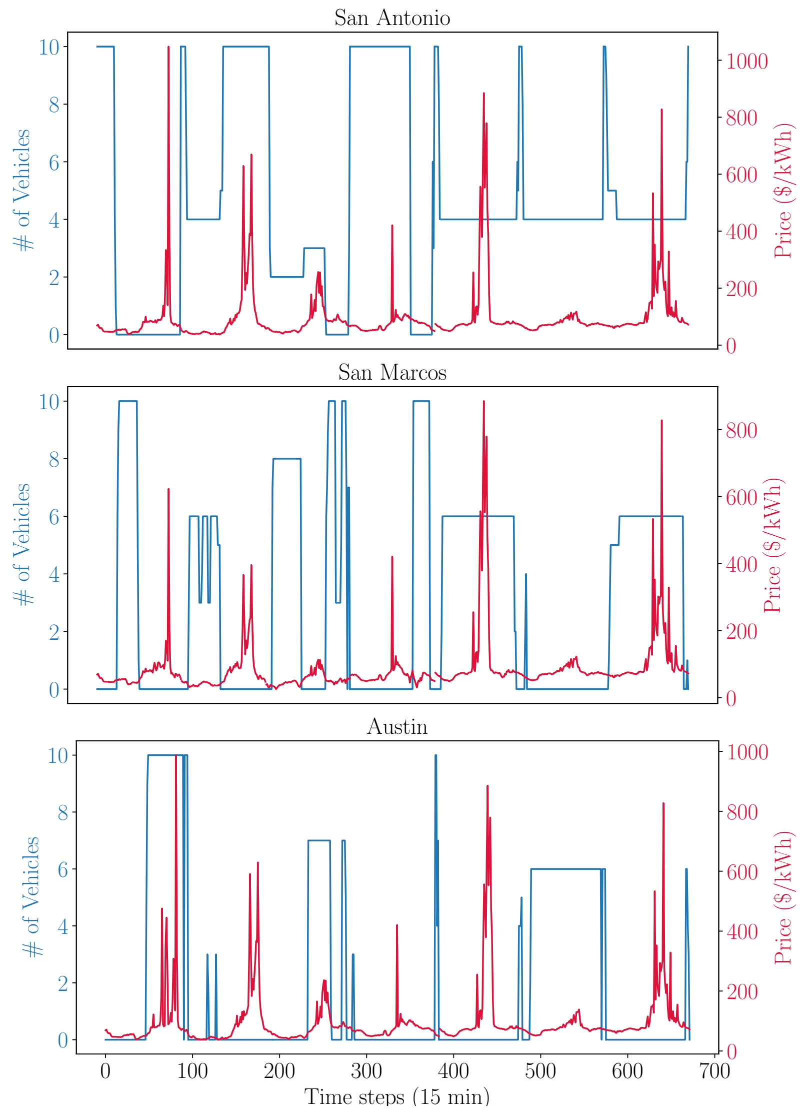


Figure 4: Distribution and pricing dynamics of the EV fleet performing spatial arbitrage in August

arbitrage could represent an increase to 150% of this baseline in January and up to 200% in August.

The analysis also reveals that the additional energy consumed for the trips mandated by spatial arbitrage is substantially less than the overall energy consumption recorded. This underscores that while the baseline energy expenditure for the minimum required trips is comparatively modest, the actual consumption under arbitrage is higher, reflecting the trade-offs for increased profit margins. The variance in the number of trips between January and August can be attributed to the better alignment of electricity prices between locations in the latter month, which enables a more effective arbitrage strategy with reduced trip requirements to maintain or enhance profitability. Additionally, it is crucial to recognize that the mileage accrued under spatial arbitrage is likely to be greater than that under the counterfactual. This must be weighed against the consequent implications for vehicle maintenance, wear-and-tear, and the longevity of the battery.

Despite January's intensive operational demands, spatial arbitrage displays a definitive advantage in terms of profitability and operational efficiency, especially pronounced in August. This analysis furnishes valuable insights into the feasibility and potential of spatial arbitrage as a strategic operational approach for EV fleets. By exploiting the temporal and spatial fluctuations in energy prices, fleet operators have the potential to significantly elevate profit margins. However, this must be prudently balanced against energy consumption concerns, battery health, and the overarching aim of sustainable operations.

The cumulative state of charge (SOC) of EVs operating under a spatial arbitrage scenario for January and August is displayed in Fig. 6. It illustrates the charging and discharging cycles of the EVs corresponding to the energy arbitrage opportunities that arise due to price fluctuations.

In August, the SOC pattern shows more pronounced fluctuations compared to January, suggesting a more active engagement in arbitrage as the vehicles frequently adjust their SOC in response to changing energy prices. This indicates a strategy that aggressively capitalizes on higher price differentials during this month. The graph also shows that while the overall SOC trends follow a similar pattern across the two months, the amplitude and frequency of the fluctuations differ. This difference can be tied to the seasonality in electricity price volatility and demand for energy, which affects how often and how significantly EVs need to be charged or discharged within the spatial arbitrage model.

The requirement that SOC levels return to a baseline (E_n^{final}) at the end of each day (every 96-time steps) introduces a cyclic pattern in the graph and ensures that vehicles maintain enough charge to perform necessary deliveries without the risk of battery depletion. This constraint not only safeguards the operational reliability of the EVs but also reflects a balanced approach to

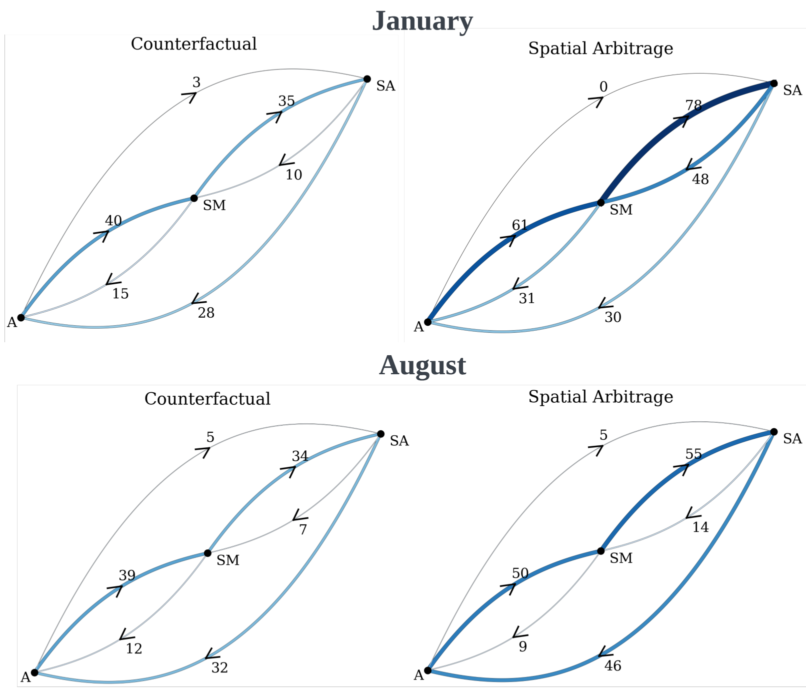


Figure 5: A visualization of the number of trips carried out in the spatial arbitrage scenario versus the counterfactual delivery schedule, for both January and August. Note that the arrow widths are proportional to the number of trips.

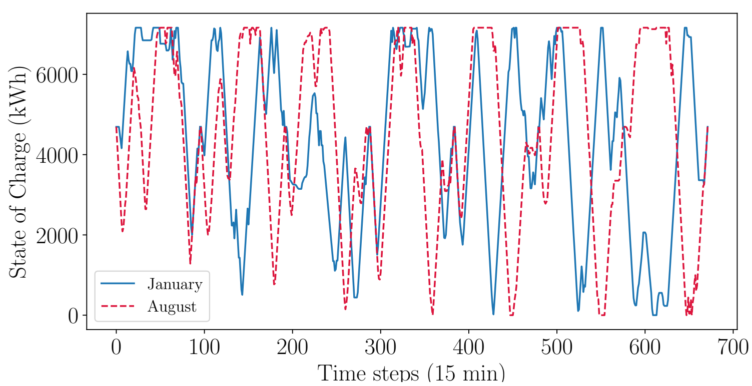


Figure 6: Cumulative state of charge of the EVs across spatial arbitrage scenario.

energy management, aligning profit-making from arbitrage with the logistical demands of delivery schedules.

4.2. Sensitivity Analysis

In order to assess the robustness and generalizability of our optimization model, we conducted a sensitivity analysis focusing on three key parameters: battery efficiency, maximum battery capacity, and the number of deliveries at each location. The results, illustrated in Figures 7, reveal the following:

- **Battery Efficiency:** As shown in Figure 7.a, the model is highly sensitive to changes in battery efficiency. A decrease in efficiency leads to a significant reduction in profitability, highlighting the importance of maintaining high battery efficiency to optimize fleet performance. This factor is critical in long-term planning, as battery degradation over time can impact the fleet's operational effectiveness.

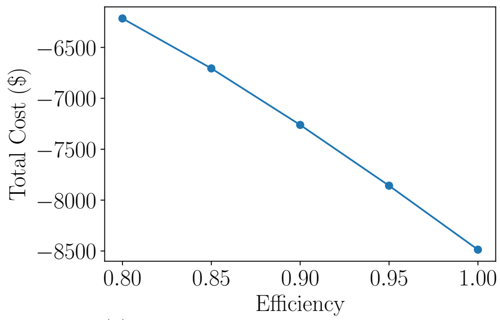
- **Maximum Battery Capacity:** Figure 7.b demonstrates that the model's performance remains relatively stable across a range of battery capacities, indicating that within the tested range, the fleet's ability to perform energy arbitrage is not highly sensitive to variations in capacity. However, exceeding certain thresholds may lead to diminishing returns, emphasizing the need to balance capacity with other operational considerations.

- **Number of Deliveries at Each Location:** The sensitivity of the model to the number of deliveries is shown in Figure 7.c. The results indicate that an increase in the number of deliveries leads to higher operational costs and reduced profitability. While the model can handle moderate increases in delivery demand, significant increases may constrain the fleet's ability to optimize energy arbitrage, reducing the overall effectiveness of the strategy.

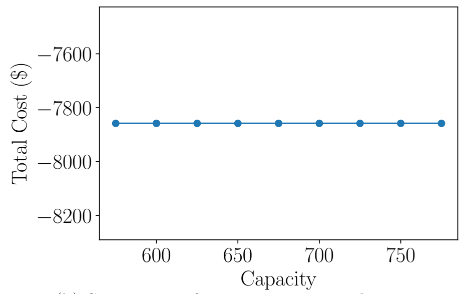
Overall, the sensitivity analysis confirms that while the model is most sensitive to changes in battery efficiency, it remains robust to variations in battery capacity and delivery demand within the tested ranges.

5. Conclusion

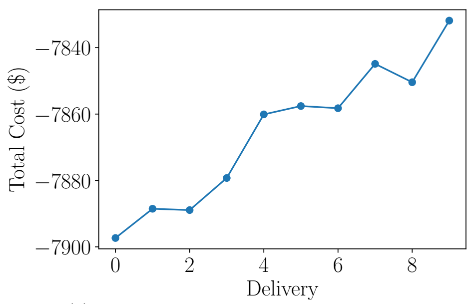
We introduced a streamlined computational framework tailored for a fleet of electric trucks, facilitating both temporal and spatial arbitrage. Demonstrated findings reveal that fleet-wide EV optimization, when managed by an aggregator distinct from delivery duties, enriches the financial portfolio's



(a) Sensitivity of cost to battery efficiency.



(b) Sensitivity of cost to maximum battery capacity.



(c) Sensitivity of cost to the number of deliveries.

Figure 7: Distribution and pricing dynamics of the EV fleet performing spatial arbitrage in August

diversity. The proposed model integrates charging, discharging, routing, and scheduling decisions into a single-stage stochastic program. Through simulations based on real-world pricing data, the results demonstrate the financial viability and operational feasibility of leveraging electric vehicle fleets as mobile energy storage to capitalize on locational marginal price differentials.

The case study analysis highlights several key findings. First, spatial arbitrage consistently outperforms both the counterfactual and stationary arbitrage benchmarks, with profits increasing by as much as 47.7% compared to non-spatial optimization strategies. This substantiates the value derived from strategic positioning and energy trading across locations. Second, although additional trips are required to enable spatial arbitrage, the energy expenditures from these trips are marginal compared to consumption from charging and discharging. Therefore, the energy overhead is outweighed by profit gains. Third, seasonal pricing dynamics significantly impact arbitrage outcomes, with wider spreads and higher volatility enabling greater returns. This underscores the importance of real-time market awareness and forecasting.

While the results showcase promising potential, for subsequent research, it would be invaluable to factor in battery degradation costs, charging infrastructure limitations, and forecasting uncertainties as they play a pivotal role in financial deliberations. Constraints on battery cycling could possibly be included in the optimization to introduce a cost-benefit trade-off analysis. More complex constraints on delivery windows, locations, and large fleet management, in general, would also add to the fidelity of the simulation framework. Overall, the model provides a valuable framework to optimize electric vehicle operations at the nexus of transportation and energy system needs. This integration of mobility and electricity markets via vehicle-to-grid capabilities offers environmental and economic value for numerous stakeholders.

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