# Spatial Arbitrage through Bidirectional Electric Vehicle Charging

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***Abstract*—Energy arbitrage is typically a temporal process - buying energy when prices are low, and selling when prices are high. However, the spatial variation in electricity prices could generate additional revenue streams if energy were transported to locations with deficits in cheap energy, providing valuable grid services such as congestion relief. In this paper, we develop deterministic and single-stage stochastic optimization frameworks which maximize revenue by optimizing the charging, discharging, and travel of an electric vehicle under spatial and temporal price uncertainty. The model is also capable of incorporating uncertain traffic data. The results show the potential of bidirectional electric vehicle charging as a mobile grid asset; however, only substantial revenue is realized when prices between areas vary significantly and can be forecast with high probability.**

***Index Terms*—Arbitrage, locational marginal pricing, vehicle-to-grid**

## I. Introduction

Traditional energy arbitrage has been performed with large-scale market participants strategically buying and selling energy at key times (e.g., buying during "off-peak" times and selling during "on-peak" times). This is typically performed with large stationary energy storage owned by large firms [1]. However, the landscape of energy arbitrage is changing due to advancements in distributed energy resource capabilities and new market mechanisms. In particular, recent years have introduced the concept of mobile energy storage [2]. Here, we focus on two factors with the potential to impact the landscape of energy arbitrage from the perspective of individual electric vehicle (EV) assets.

First, vehicle-to-grid (V2G) and the more specific vehicle-to-building (V2B) technologies are proliferating rapidly and allowing electric vehicles to play a more prominent role in the energy system [3]. As a couple of examples of how far bidirectional charging has come in recent years, in 2020, Fermata Energy received UL 9741 certification, which covers standards for discharging an EV to an electric power system. In 2021, Ford announced that the top selling vehicle in the U.S. would soon have an electric option capable of discharging back to the power supply. Second, in 2020, the Federal Energy Regulatory Commission (FERC) approved a historical rule, Order 2222, allowing distributed energy resources to participate in wholesale markets [4].

Previous work has shown that V2G can be cost-effective in some scenarios [5]. Furthermore, some benefit to V2G charging can be obtained at the transmission network scale [6],

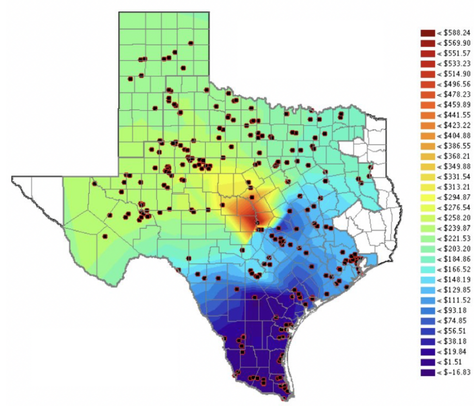


Fig. 1. LMPs across ERCOT showing negative/very low prices in southern Texas and prices exceeding $500/MWh near Austin. ERCOT can have real time prices up to and exceeding $9,000/MWh. Source: [16]

distribution network scale [7], and in microgrids [8]. Various works have proposed optimization strategies which will maximize profit of the electric vehicle in various market settings. For example, trading in day-ahead and intra-day electricity markets [9], providing frequency regulation [10], local energy trading [11], and minimizing grid fluctuations [12]. Some also consider the ability of the EV to participate in multiple grid services [13]. However, these all consider the location of the EV fixed, while in reality, electricity prices can vary significantly over short distances, introducing more potential benefits. For example, Fig. 1 shows a snapshot of the Electric Reliability Council of Texas (ERCOT) nodal LMP map, demonstrating the high spatial variance in LMP (negative LMPs within 50 miles of LMPs that are hundreds of dollars). This indicates that additional owner benefits could be realized by incorporating spatial characteristics.

Towards capitalizing on spatial price differences, some papers have proposed vehicle charging optimization methods which include joint optimization of vehicle routing [14], [15]. These methods consider the traffic and uncertainty around charging locations, but not the possibility of performing arbitrage (e.g. only uni-directional charging is considered). Additionally, the complexity of these methods is very high, due to the large number of potential routes.

In attempts to combine the objective of arbitrage from bidirectional EV charging with the ability of the EV as a mobile energy storage device, this paper aims to analyze the potential for energy arbitrage from a single resource (possibly through an aggregator) to be a *spatial* (also called geographical) arbitrage concept rather than just a temporal one. Spatial arbitrage is performed in a variety of other markets, for example, in the automotive industry when cars are purchased at a cheap price in one geographical location, transported to another, and sold at higher prices [17]. With locational marginal prices (LMPs) varying in both time and space, and the introduction of mobile energy storage, new opportunities for arbitrage are worth considering. Such mobile energy storage has also been considered at the transmission level with large quantities of batteries performing spatio-temporal arbitrage [2]. In [2], these benefits with utility-scale mobile energy storage utilizing spatiotemporal LMP differences has been analyzed; however, this analysis was performed under a deterministic problem formulation and limited by a 10-mile driving radius.

This paper will develop a single-stage stochastic optimization framework from the perspective of the EV owner which aims to schedule charging, discharging, and departure times of an EV travelling between two predetermined geographical locations. The problem is formulated as a stochastic mixed-integer linear program, which can be solved efficiently with standard existing optimization solvers. Uncertainty in both electricity price and travel time will be included in the formulation. A case study will be performed in the ERCOT real time market for an EV traveling back and forth from San Marcos, TX, to Austin, TX, throughout the period of a month.

## II. Problem Formulation

Multiple assumptions are made in this preliminary study. First, the EV is constrained to only travel between two points (however, there is no requirement that the EV *has* to travel; the option for solely temporal arbitrage is a subset of the optimization problem). The travel origin and destination points are predetermined and are not variables in the optimization problem. Second, the EV is restricted to one trip between origin and destination per day, and the location the EV ends the day at must be the starting location of the EV for the next day in the simulation. Charging is also assumed to be 100% efficient. This last assumption can simply be removed with the inclusion of separate variables for charging and discharging the EV; however, for simplicity here, we assume a single charging/discharging variable. Note however, that the framework can be extended to incorporate autonomous vehicles that have additional energy storage onboard. The inclusion of more complex battery management, degradation effects, and charging strategies is an important consideration for the economics and technical impacts of V2G [18] and can be considered as a direction of future work.

Thus, the single-stage, mixed integer linear stochastic program for scheduling the departure of a single EV from location $A$ to location $B$ and the EV's charging/discharging behavior under price and travel uncertainty can be written as the following:

$$\min \quad \sum_{t=1}^{T} \mathbb{E}[\mathbf{x},\mathbf{y},\boldsymbol{\xi}_t^A,\boldsymbol{\xi}_t^B] = \frac{1}{K}\sum_{t=1}^{T}\sum_{k=1}^{K} \xi_{k,t}^A x_t + \xi_{k,t}^B y_t \tag{1a}$$

s.t :

$$\sum_{t=1}^{T}(x_t+y_t)\Delta_t = E_{req}\beta_T \tag{1b}$$

$$\sum_{t=1}^{T}(1-\alpha_t-\beta_t) \geq \frac{1}{K}\sum_{k=1}^{K} T_k^{trav}\cdot\beta_T \tag{1c}$$

$$\alpha_1 = 1. \tag{1d}$$

$$\alpha_t \leq \alpha_{t-1}, \qquad t=2,\dots,T \tag{1e}$$

$$\beta_t \geq \beta_{t-1}, \qquad t=2,\dots,T \tag{1f}$$

$$\alpha_t+\beta_t \leq 1, \qquad t=1,\dots,T \tag{1g}$$

$$-\alpha_t P_{d_{max}} \leq \ x_t \ \leq \alpha_t P_{c_{max}}, \qquad t=1,\dots,T \tag{1h}$$

$$-\beta_t P_{d_{max}} \leq \ y_t \ \leq \beta_t P_{c_{max}}, \qquad t=1,\dots,T \tag{1i}$$

$$0 \leq E_0 + \sum_{\tau=0}^{t}(x_\tau+y_\tau)\Delta_t - \frac{KE_{req}}{\sum_k T_k^{trav}}(1-\alpha_\tau-\beta_\tau) \leq E_{max}, \qquad t=1,\dots,T \tag{1j}$$

$$\alpha_t,\beta_t \in \{0,1\}, \quad t=1,\dots,T \tag{1k}$$

where the decision variables are within vectors $\mathbf{x}$, $\mathbf{y}$, $\boldsymbol{\alpha}$, and $\boldsymbol{\beta}$, each of length $T$. Variable $x_t$ represents the EV's charged (positive) or discharged (negative) power at location $A$. Variable $y_t$ represents the EV's charged (positive) or discharged (negative) power at location $B$. Vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are comprised of binary elements and indicate whether or not the EV is at location $A$ at a time $t$ or location $B$ at time $t$, respectively.

Uncertain parameters are the electricity price at each time $t=1,\dots,T$ at location $A$ and $B$, $\boldsymbol{\xi}_t^A$ and $\boldsymbol{\xi}_t^B$, respectively, and the travel time between points $A$ and $B$, $\mathbf{T}^{trav}$. These uncertain parameters are assumed to have a finite number of considered realizations $K$ and equal probability masses, although this can be modified if one knows that certain scenarios are more likely to be similar to the present situation, for example. Constant input parameters are the timestep $\Delta_t$, maximum charging ($P_{cmax}$) and discharge ($P_{dmax}$) rates, initial state of charge $E_0$, maximum state of charge $E_{max}$, and the energy that is required to get from $A$ to $B$ $E_{req}$.

The objective (1a) aims to minimize the expected cost to charge and discharge the EV throughout the timeperiod $T$ (here, 24 hours with 15-minute timesteps); which maximizes the expected profit from performing arbitrage (spatial and temporal). Constraint (1b) aims to ensure that the total energy discharge throughout the day equals the total energy charged throughout the day. Constraint (1c) ensures that $\beta_t$ remains zero until $T_{trav}$ steps after the vehicle has departed location $A$. The vehicle is assumed to start at location $A$ in the first timestep, which necessitates constraint (1d); once the vehicle has left $A$, it is not able to return to $A$ within that same day (constraint (1e)); once the vehicle has arrived at $B$, it must stay at $B$ until the end of the day (constraint (1f)), and the vehicle

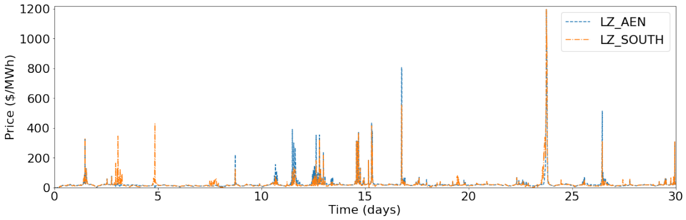


Fig. 2. Historical real time market settlement point prices for March 2020 in the AEN and South Load Zones.

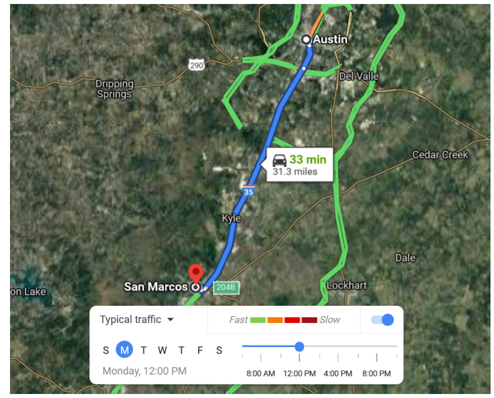


Fig. 3. The two considered cities and roughly 30 mile travel distance. Traffic data was obtained from Google Maps' typical traffic estimates for each day and time.

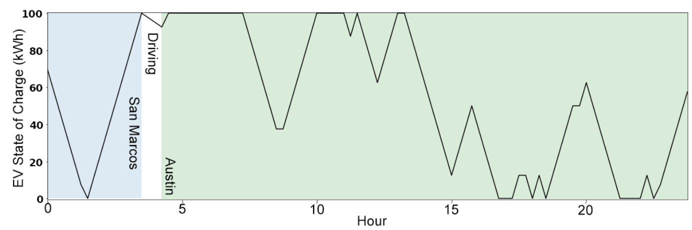


Fig. 4. State of charge of the EV across one scenario. The EV partially discharges at San Marcos before charging up for its journey to Austin, where it both buys and sells energy.

cannot simultaneously be at points $A$ and $B$ (constraint (1g)). Constraints (1h) and (1i) describe the charging and discharging limits at locations $A$ and $B$, respectively, given by the available bi-directional charger at those locations. Lastly, constraint (1j) ensures that the EV state of charge does not go outside of the given minimum and maximum bounds.

## III. Simulation Results

We consider the months of January, March, and July 2020 in our simulations. 15-minute historical zonal pricing data from the South and Austin Energy (AEN) load zones are used for the electricity prices in San Marcos and Austin, respectively, as shown in Fig. 2 for March. As a single EV is a small energy resource, we assumed that the EV must buy and sell energy at zonal prices (which average prices across all nodes in that zone) rather than nodal prices, which have much higher levels of variability but are typically used by larger and more centralized resources.

Since we were unable to find publicly available historical traffic data for this region, we utilized fifteen minute "typical traffic" data for each weekday from Google maps, which is based on historical traffic patterns. See Fig. 3 for the distance between San Marcos and Austin and an example of Google Maps' typical traffic feature. Across the entire month, when the EV chooses to perform spatial arbitrage, the EV then starts the next day at that location. Lastly, the EV modeled was a Tesla Model S with 100 kWh battery capacity, access to DC Fast Charging stations (50 kW), with the assumption that these stations can perform bidirectional charging at the same rate. The initial state of charge of the EV is set to be 70 kWh, and the rate of discharge while driving was assumed to be 1 kWh per every 4 miles travelled.

Lastly, the framework was implemented in Python using CVXPY [19] and the Gurobi solver [20]. The simulations were performed locally on a 2017 MacBook Pro with 16 GB of RAM and a 2.3 GHz Intel Core i5. Each optimization took less than a minute to run.

### A. Perfect information / Deterministic case

First, we analyze the best case scenario for the EV — when prices and travel times from San Marcos and Austin are known exactly. The "perfect information" formulation of (1) for determining the decisions within a single day of driving is given by

$$\begin{aligned} \min \quad & \sum_{t=1}^{T} c_t^A x^t + c_t^B y^t \\ \text{s.t}: \quad & \sum_{t=1}^{T} (1 - \alpha_t - \beta_t) \geq T^{trav} \cdot \beta_T \\ & (1b), (1d) - (1j) \end{aligned}$$

where $T^{trav}$ is a natural number representing the nearest number of 15-minute timesteps from $A$ to $B$ and $c_t^A$ and $c_t^B$ are the exact hub prices at time $t$ and locations $A$ and $B$, respectively.

Figure 4 shows the state of charge and location of the EV throughout one of these considered days (a day where the EV makes approximately $40). Interestingly, in addition to spatial arbitrage, the EV also performs temporal arbitrage once it is parked in Austin. After discussing the stochastic case in the next subsection, the results for both cases will be tabulated and discussed.

### B. Stochastic case

Using the formulation given in (1), where the number of considered scenarios $K$ is equal to the number of the days in that month minus one (all other days of the month are considered except for the day for which decisions are being

TABLE I
PROFIT FROM SPATIAL ARBITRAGE FOR THREE MONTHS

| Month | Assumption | Monthly Revenue | Best Daily Profit | Worst Daily Profit | Travel Days |
|---|---|---|---|---|---|
| **Jan** | Perfect Information | \$128.81 | \$31.78 | \$0.86 | 14 |
| **Jan** | Stochastic | \$6.79 | \$12.78 | -\$13.33 | 15 |
| **March** | Perfect Information | \$345.33 | \$78.27 | \$1.11 | 14 |
| **March** | Stochastic | \$6.45 | \$7.04 | -\$7.78 | 30 |
| **July** | Perfect Information | \$168.43 | \$40.38 | \$0.68 | 12 |
| **July** | Stochastic | \$16.52 | \$6.20 | \$3.23 | 15 |

planned for), we now analyze the performance of the EV scheduling algorithm when the prices and traffic patterns are not known a priori.

As seen in Table I, over all of the considered months and cases, arbitrage results in an overall positive monthly profit. However, the impact of the uncertainty is clear — the profit obtained in the cases where there is no uncertainty is significantly higher than in the stochastic cases. In fact, some of the cases in the stochastic scenario result in days where the EV loses money, whereas in the perfect information cases, the EV always makes a profit (even if some days there is not much money to be made from arbitrage). This likely indicates our framework is overly simplistic and should perhaps consider a two-stage scenario-based approach, a receding horizon control approach with price and traffic forecasting, or another more sophisticated option.

### C. Spatial vs. temporal arbitrage

Table I also lists the number of days in which the algorithm determined that the EV should travel between the two considered cities, which is found to be generally around half of the days in the month. As the framework allows for the EV to perform in-place temporal arbitrage as well as spatial arbitrage, it is interesting to analyze the benefit of the spatial component. Towards this, we define the stochastic temporal-only arbitrage problem as

$$\min \quad \sum_{t=1}^{T} \mathbb{E}[\mathbf{x}, \boldsymbol{\xi}_t^A] = \frac{1}{K} \sum_{t=1}^{T} \sum_{k=1}^{K} \xi_{k,t}^A x_t \tag{3a}$$

s.t :

$$\sum_{t=1}^{T} x_t \Delta_t = 0 \tag{3b}$$

$$-P_{d_{max}} \leq \; x_t \; \leq P_{c_{max}}, \quad t = 1, \ldots, T \tag{3c}$$

$$0 \leq E_0 + \sum_{\tau=0}^{t} x_\tau \Delta_t \leq E_{max}, \quad t = 1, \ldots, T \tag{3d}$$

where the new objective (3a) is now only a function of the price at location $A$ and the charging/discharging power at location $A$. Constraint (3b) still ensures that the net power charged/discharged throughout the day is zero, resulting in the EV returning to the same state of charge as it started with at the beginning of the day. Lastly, constraint (3d) is now modified to enforce the state of charge bounds without the discharging induced from driving.

It is worth noting that driving the EV to perform arbitrage has costs not explicitly accounted for in the present formulation, such as battery degradation [18]. Additionally, driving the EV, of course, decreases the state of charge of the battery. Thus, the price differential between two areas must be beneficial enough to actually warrant moving the EV throughout the day (an aggregator managing a fleet of EVs could perhaps harness additional geographical diversity). Here, while we do not provide a detailed formulation about the long-term costs to the vehicle from driving, we perform a brief analysis on the difference between an arbitrage formulation where the EV remains stationary and the cases above where the EV is allowed to move to one other location, once per day.

TABLE II
PROFIT FROM STATIONARY ARBITRAGE IN MARCH 2020

| Stationary Location | Assumption | Monthly Revenue |
|---|---|---|
| San Marcos | Perfect Information | \$293.44 |
| San Marcos | Stochastic | \$3.05 |
| Austin | Perfect Information | \$293.84 |
| Austin | Stochastic | \$1.32 |

In Table II, the month of March is considered for the comparison of the perfect information and stochastic stationary arbitrage schemes. While every case results in a positive monthly revenue, every case also performs worse than the spatial arbitrage case. In particular, even the perfect information case receives 15% less revenue. This is intuitive, since the spatial arbitrage case contains the stationary case as a subset — the EV always has the option of staying in its origin city and not traveling to its destination city.

### D. The impact of price variability

Even in the cases where perfect information is given to the EV, the monthly profits vary wildly — \$128.81 in January, \$345.33 in March, and \$169.43 in July. Visually analyzing the LMPs from March (Fig. 2), January (Fig. 5), and July (Fig. 6), it is challenging to immediately determine what would cause such differences. March does seem to have a greater number of large price spikes, however, January has spikes which reach a higher magnitude overall. These spikes are generally over a short timeframe, which makes them hard to take advantage of without perfect information.

Considering the benefit from spatial arbitrage comes from differences in prices across the two zones, we next looked at the difference in these prices, shown in Fig. 7. The two months with the largest profit from spatial arbitrage are also the two months with the largest difference in prices between the two areas across time. Whereas, the month of January has the lowest number of days in which the EV decides to travel (from Table I), the lowest level of price variation between areas, and results in around a third of the profit of March, the month with the most variation.

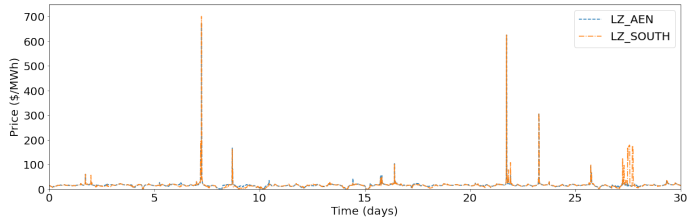


Fig. 5. Historical real time market settlement point prices for January 2020 in the AEN and South Load Zones.

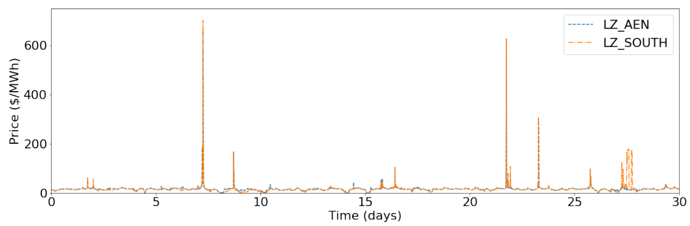


Fig. 6. Historical real time market settlement point prices for July 2020 in the AEN and South Load Zones.

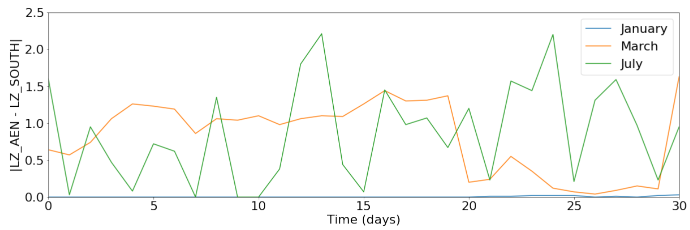


Fig. 7. Absolute difference in real time prices between the AEN and South Load Zones for the three considered months.

## IV. Conclusion and Future Work

We provided a preliminary framework for electric vehicles performing both temporal and spatial arbitrage. The single-stage stochastic formulation included uncertainty in both electricity price and travel times between two predetermined locations. We found that, due to the averaging of zonal prices versus the higher variation of nodal prices, the ability of the EV to make a substantial profit is highly dependent on the the EV to knowing when price spikes will occur. The results are indicative of this — the scenario where the EV has perfect knowledge of future prices and traffic patterns results in significant cost function reductions. Nevertheless, even in the stochastic case, the scheme still produces positive revenue on nearly all considered days, although sometimes the revenue is minimal.

Future work could include developing a computationally efficient framework which allows the EV to travel to multiple destinations, and multiple destinations within a single day. Optimization across a fleet of EVs (e.g. through an aggregator) could also be considered to introduce heightened diversity into the considered financial portfolio. Incorporating the cost of battery degradation is also an important financial consideration. The 30 mile distance from the two considered locations in the case study had a relatively small variation in traffic delays, but the inclusion of a wider radius of destinations would likely introduce a higher level of stochasticity. One of the most important directions of future work is incorporating more intelligent price forecasting and predictive optimization rather than day-ahead scheduling, which, as shown in this paper, can severely impact the efficacy of arbitrage. Lastly, two-stage, rather than single-stage stochastic optimization, would also likely improve the performance of the algorithm.

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