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Day Ahead Optimization of an Electric Vehicle Fleet Providing Ancillary Services in the Los Angeles Air Force Base Vehicle-to-Grid Demonstration

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Abstract

The Los Angeles Air Force Base Electric Vehicle Demonstration is a currently ongoing vehicle-to-grid demonstration project with the objective of minimizing the cost of operation of a fleet of approximately 30 electric vehicles (EVs) through participation in the California Independent System Operator (CAISO) frequency regulation market. To accomplish this, a hierarchical control system has been developed to optimize, plan, and control the charging, market bidding, and response to grid system operator control of the EVs. This paper presents an overview of the day-ahead optimization model component of the hierarchy. The model is a mixed integer linear program that optimizes daily EV charging and regulation capacity bids strategies in order to minimize operation costs and maximize ancillary service revenue. A deterministic approach is used due to several practical concerns of the demonstration project, including model complexity and the availability and uncertainty of input data in day-ahead decision making, and the limited size of the fleet. The model includes additional user-defined parameters to tune model behavior to better match real-world conditions and minimize the risks of uncertainty.

The paper conducts scenario analysis to explore the impact of these parameters on high level model behavior and resulting bid strategy. The parameters explored include hourly regulation prices, local load conditions leading to retail demand charges, forced symmetry constraints for regulation bids, SOC penalty values to reserve higher states-of-charge in vehicles, and expected regulation resource utilization while providing reserves. These analyses show significant sensitivity in the frequency regulation bidding strategy to the regulation utilization, as well as large differences in the regulation prices between regulation up (discharging capacity) and regulation down (charging capacity). Results also suggest enforcing symmetry in regulation appears to have significant impacts in regulation revenue when there is large relative disparities between prices in the up and down direction. Finally, imposing a small cost on low SOC values significantly impacts the fleet-wide average SOC, making the system more resilient to uncertainty in the mobility demands gathered at the time of making day ahead decisions.

Keywords: electric vehicles; vehicle to grid; demonstration; ancillary services; frequency regulation; optimization

List of Symbols

$\mathcal{B}_i$	Energy capacity of EV i
$b_i^{av}(k)$	Binary availability for EV i
$b_i^{ch}(k)$	Binary variable indicating charging or discharging
$\mathcal{C}_e$	Total cost of energy
$\mathcal{C}_d$	Total demand charges (power)
$\mathcal{C}_{SOC}$	SOC Penalty cost total
$c_e(k)$	Price of electricity at interval k
$c_D(h), c_U(h)$	Hourly regulation prices down, up
c_{I_j}	Demand charge for each demand period
c_{SOC}	SOC penalty value [\$/%-hr]
Δt	duration of interval, in t k , in this case 5 minutes
Δt_h	duration of bid interval h , in this case 1 hour
$\Delta t_{\mathcal{K}}$	duration of demand interval $\mathcal{K}$, in this case 15 minutes
$E_{flt}(\mathcal{K})$	Energy consumed by fleet in interval $\mathcal{K}$
$E_{base}(\mathcal{K})$	Energy consumed by base in interval $\mathcal{K}$
$E_i(k)$	Energy stored in EV i at interval k
$E_{max,mo}(I_j)$	Maximum observed energy consumption in each demand period
$f_D(h), f_U(h)$	AGC utilization factors down, up
η_i^{ch}	Charging efficiency for EV i
η_i^{dis}	Discharging efficiency for EV i
h	Hourly time interval
I_j	Time interval of demand charge j
J	Optimization objective
$\mathcal{K}$	Time interval for demand charges
k	Time interval
$P_i(k)$	Charging power for EV i and interval k
$P_i^{reg}(k)$	AGC charging power for EV i and interval k
$P_{flt}(k)$	Net charging of full fleet
P_i^{min}	Maximum discharge rate for EV i
P_i^{max}	Maximum charge rate for EV i
$R_D(h), R_U(h)$	Hourly regulation bids down, up
$R_D(k), R_U(k)$	Regulation capacity down, up available at interval k
R_D^{min}, R_U^{min}	Minimum allowable regulation bid down, up
$\mathcal{R}_{reg}$	Total regulation revenue
SOC_i^{min}	Minimum state-of-charge of EV i
SOC_i^{max}	Maximum state-of-charge of EV i
T	Time horizon of optimization

1 Introduction

1.1 Motivation

Electric vehicles (EVs) have been touted as a panacea for our carbon-hungry, energy importing transportation sector. Their ability to shift the energy production burden away from distributed, inefficient internal combustion engines to the electricity sector supports national priorities in energy security and public health, and opens up opportunities for decarbonization of personal mobility [1, 2]. Further, their commercial renaissance corresponds with significant introduction of intermittent, renewable energy resources into the electricity grid. As renewable generation becomes more prominent, some electricity system decision-makers are looking to increase storage capacity [3], and EVs appear to be a promising, low-cost energy storage resource for the grid. However, the interaction of individual EVs

with electricity grid and market operators can be far too onerous from such a small resource to warrant electric vehicle participation directly. This creates a niche for an entity that aggregates a population of electric vehicles to present them to the market operator in a size that is useful for grid operations.

The EV aggregator will play a number of important roles in vehicle-to-grid (V2G) services offered into markets. They will need to understand the availability of the EVs that they represent, take positions and assume the financial risks associated with providing the services in a market, manage their resources in a way to meet any capacity and energy obligations made (e.g. ensure that there is adequate energy stored prior to a service provision period), and finally to determine which vehicles will provide the requested grid service in real-time. All of these must be accomplished while ensuring that the mobility needs of vehicle owners are met, and the cost of EV ownership is reduced. For consumers and fleet operators, the deployment of EVs also creates opportunities for operational cost reduction (e.g. from demand side management) and revenue from new and existing markets, by employing novel planning and control strategies to leverage idle EV capacity.

In the present paper, we focus on a real-world demonstration of one such aggregation at the Los Angeles Air Force Base Electric Vehicle Demonstration (LAAFB EVD). The LAAFB EVD integrates a mixed fleet of roughly 30 electric vehicles capable of bi-directional charging into the wholesale frequency regulation market run by the California Independent System Operator (CAISO) to minimize the net cost of operating the fleet [4]. The demonstration is the first of its kind to take an operational vehicle fleet, replace it with electric vehicles, and participate as a full market resource (subject to all rules and financial obligations) in a frequency regulation market in the US. The hierarchical control system that enables many EV aggregator functions in the LAAFB EVD project is composed of a fleet scheduling tool to gather input data, day-ahead and hour-ahead charging and market participation optimization models based on LBNL’s Distributed Energy Resources - Customer Adoption Model (DERCAM) [5,6], and a real-time myopic optimal controller for charging instructions described in [7]. Of particular interest to this discussion is the formulation and design choices made in the development of the day-ahead market participation optimization model.

1.2 Market Opportunities and Context

The costs of owning and operating an electric vehicle can be reduced through offering vehicle-to-grid services¹. Service opportunities in current markets are found either in the management of retail electricity purchases, or in wholesale electricity market participation. Retail bill management falls into two major categories: (1) taking advantage of time-varying electricity tariffs by charging/discharging to minimize retail electricity costs; and (2) managing peak electricity demand charges, set by the highest consuming 15-minute interval in a month, which can account for nearly 50% of retail electricity bills for commercial account customers. While savings on retail electricity can be a significant opportunity for vehicle-to-grid capable EVs, wholesale market revenue opportunities are more varied.

Grid services in wholesale markets include offering planning capacity, energy, and operational reserves. Planning capacity is an offer to participate in the wholesale energy market during a period of performance in the planning horizon (months to years). In contrast, wholesale energy and operational reserves are offered day-ahead or hour-ahead. Energy offers are simply for buying or selling a quantity of electricity, and the market matches buyers and sellers to determine the price and quantity of electricity each is awarded. Energy markets offer the opportunity for EV owners to charge when the cost of electricity is lowest and even arbitrage energy purchases between high and low priced periods. Operational reserves are used to maintain balance between supply and demand in the event of unexpected changes in either. Operational reserve based ancillary services, such as synchronous reserve and frequency regulation reserve, are of particular interest to EVs with bi-directional capability, as

¹Vehicle-to-grid services potentially introduce additional costs. Key among these is battery degradation costs. A full accounting of all additional costs is not considered in this analysis.

they typically require low energy commitments with reasonable payment for being held in reserve [8].

In the LAAFB EVD, the EV fleet aggregation is allowed to participate in the wholesale market for ancillary services, but all energy consumed by the vehicles is settled at a Southern California Edison retail rate, per guidance by the California Public Utilities Commission. The LAAFB EVD targeted provision of the most valuable ancillary service in CAISO: frequency regulation reserve [8]. Frequency regulation is a centrally controlled service that continuously attempts to balance supply and demand between the five minute ISO economic dispatch to minimize both deviations in system frequency from nominal and unscheduled electricity interchanges with neighboring balancing authorities. The control system, known as Automatic Generation Control (AGC), sends real power setpoint commands from the system operator to resources providing the reserve every 2-10 seconds. The commands will be within the market-awarded reserve capacity range, in units of megawatts held in reserve for one hour or MW-h. In most markets in the US, reserve capacity offers are symmetrical, meaning that the resource that offers any amount of capacity is offering to either decrease or increase their output up to the offer amount around their energy market award. In CAISO, AGC offers are separate for up (generation) and down (load) capacity and setpoints are delivered on a 4 second interval.

1.3 Relevant Literature

To capture value in the electricity market, an EV aggregator must decide the size of their service offer within the constraints of market timelines. In many ancillary service markets in the United States, this offer must be bid at least one day before providing the service [8]. The challenge is determining an economically optimal schedule of charging and grid service offers in the face of significant day-ahead uncertainty. Uncertain quantities include the energy demands on the battery (both from providing grid services and for mobility), the time in which a vehicle is plugged in to its EV supply equipment (EVSE), and the prices that will be received for providing services. To manage these uncertain decisions, the aggregator can leverage optimization techniques that either explicitly include the stochasticity [9–12] of the resource or attempt to robustly manage the representations of the risk in a deterministic optimization framework [13, 14]. The latter was selected for the LAAFB EVD to limit complexity in an ambitious demonstration project.

The opportunity for electric vehicles to participate in providing grid services has been well examined from a technical potential, optimization and control perspective. Kempton and Tomić performed seminal work describing the opportunity for vehicle grid interactions [15] and much work, such as that performed by Galus et. al, attempts to further refine the role that electric vehicles will have in grid operations [2].

Many attempts to develop optimal grid participation strategies for electric vehicles have been proposed in the literature. In some, unidirectional modulated charging grid interactions are considered in an optimal control framework [16], while others have used electric vehicles as a proxy for a more general distributed resource in a model predictive control type approach to providing grid services [17], and still others approach the problem with generalized bi-directional or unidirectional grid services that EVs can provide [18–20]. All of these employ some simplification to the modeling of either the electric vehicles (such as uni-directional power flow) or the gride services offered (generalizing grid services without a market context), however some do explicitly consider the service of interest in the present paper, frequency regulation [9, 11, 14, 21]. Some models explicitly consider the point of view of the charging services aggregator [11, 13, 18, 21] or market participation, constraints and bidding timelines [13, 22, 23], however these models focus on available price data, often from the PJM market, and are never interested in participation rules of any specific market context, which can vary considerably [8].

Most work in optimization of V2G services has been deterministic, relying on average input values from large aggregations of thousands of vehicles to provide services [21] or perfect

forecasts [13] to determine optimal charging and reserve offers. More recent work has focused on methods to directly handle the uncertain input parameters for vehicle-to-grid optimization through the use of stochastic dynamic programming [9], fuzzy optimization [11], robust [14] and stochastic optimization [10, 12]. However, most of these approaches require significant historical data to create models of the uncertainty in their inputs. This requirement may be unreasonable for small aggregations with limited historical data.

1.4 Focus of this Study

The present paper describes the day ahead optimization model being applied to the LAAFB EVD and examines the optimization’s sensitivity to parameters designed to manage some of the uncertainty inherent in the input data. A deterministic approach to optimization of vehicle charging and frequency regulation provision is taken due to the lack of historical data for the frequency regulation signal and electric vehicle usage, as well as to reduce complexity and required run-time in a live demonstration. Parameters that penalize low battery states of charge (SOC) and estimate energy content of the frequency regulation signal to handle these optimization uncertainties. Scenario analysis for frequency regulation prices, non-EV site electricity load, and EV travel requirements are evaluated to see the sensitivity to inputs. Finally, the imposition of symmetric frequency reserve provision is examined for comparison to other market contexts. Results help evaluate the impact of these parameters and inputs on expected economic benefits from V2G activities in the context of the real-world demonstration in the LAAFB EVD project. The paper offers an approach to optimization of small aggregations of electric vehicles fleets, as will likely be seen in near to mid-term applications, and suggests parameters that can help account for uncertain inputs into an aggregator’s optimal scheduling algorithm for V2G offers.

The remaining sections of the paper are structured as follows: Section 2 describes in detail the optimization formulation developed for the LAAFB EVD. Section 3 introduces the design of scenarios that were analyzed. Section 4 presents results and discussion of the scenario results. Lastly, section 5 concludes the paper, highlighting important findings and suggesting opportunities for future work.

2 Day Ahead Optimization Formulation

The optimization formulation minimizes the cost of operation for an EV fleet, subject to constraints that account for the dynamics of energy storage in the vehicles, physical infrastructure constraints, and market participation constraints. The decision variables are the charge/discharge power of each vehicle for each interval in the optimization horizon, the regulation up and down capacity that the fleet may provide for each hour, as well as how the expected impact of regulation is distributed among connected EVs. This leaves the optimization of the form:

$$\begin{aligned} & \min_{(P_i(k), P_i^{reg}(k) \in \mathbb{R}^n; R_D(h), R_U(h) \in \mathbb{R}^+) \forall k, h \in T} \text{Objective Function} \\ & \text{Subject to:} \\ & \quad \text{EV Physical Constraints} \\ & \quad \text{Market Constraints} \\ & \quad \text{Energy Storage Dynamics} \end{aligned}$$

In this application of the model, the horizon of the optimization is 48 hours. Within this horizon, only the first 24 hours are used to generate an actionable bidding plan. The second 24 hours are used only to ensure that the terminal conditions of variables in the actionable horizon (e.g. vehicle states-of-charge) are positioned to satisfy future requirements. The timestep resolution (Δt) is 5 minutes, and the regulation bid interval (Δt_h) is 1 hour. Parameters and decision variables indexed by k are defined on a granularity of Δt ,

whereas those indexed by h are defined by the lower granularity Δt_h . The timescales of EV scheduling vis-à-vis ancillary service markets requires this multi-scale time indexing.

2.1 Objective

The objective of the optimization is to minimize the total cost of charging an electric vehicle fleet while maximizing revenue obtained from participation in the wholesale electricity frequency regulation market, as shown in equation 1a. Energy is procured under a retail tariff that includes both a cost for energy, $\mathcal{C}_e$, and a demand charge, $\mathcal{C}_d$, defined in Equations 1b and 1c, respectively. For frequency regulation, revenue from capacity payments, $\mathcal{R}_{reg}$, is included for expected frequency regulation awards in the wholesale market².

This results in an objective function of the form:

$$J = \mathcal{C}_e + \mathcal{C}_d + \mathcal{C}_{SOC} - \mathcal{R}_{reg} \quad (1a)$$

where:

$$\mathcal{C}_e = \sum_{k=0}^T P_{flt}(k) * c_e(k) * \Delta t \quad (1b)$$

$$\mathcal{C}_d = \sum_{j=1}^m \max \left(\{E_{flt}(\mathcal{K}) + E_{base}(\mathcal{K}); \text{ for all } \mathcal{K} \in I_j\}, E_{max,mo}(I_j) \right) * c_{I_j} / \Delta t_{\mathcal{K}} \quad (1c)$$

$$\mathcal{C}_{SOC} = \sum_{i=1}^n \sum_{k=0}^T c_{SOC} * \Delta t * \left(1 - \frac{E_i(k)}{\mathcal{B}_i} \right) \quad (1d)$$

$$\mathcal{R}_{reg} = \sum_H \left(R_D(h) * c_D(h) + R_U(h) * c_U(h) \right) \quad (1e)$$

$$E_{flt}(\mathcal{K}) = \sum_k P_{flt}(k) * \Delta t; \text{ for all } k \in \mathcal{K} \quad (1f)$$

In this formulation, $P_{flt}(k)$ is the power consumed by the fleet of electric vehicles for interval k , $p_e(k)$ is the price of energy in that interval, Δt is the time step between intervals, $E_{flt}(\mathcal{K})$ is the total energy consumed in the time intervals contained in set $\mathcal{K}$ as shown in Equation 1f. For example, the each interval k may be 5 minutes long, but demand charges are calculated as energy consumption over fifteen minutes, so each set $\mathcal{K}$ will contain three intervals of the optimization. $E_{base}(\mathcal{K})$ is the forecast base demand for all uncontrolled, non-EV loads. I_i are the m separate demand charge intervals in the retail tariff, these typically span hours. $E_{max,mo}$ is the previously set, or forecast, monthly maximum demand. $\mathcal{R}_{reg}$ is the sum over all hours of regulation capacity bids ($R_U(h)$, $R_D(h)$) multiplied by the hourly prices ($c_U(h)$, $c_D(h)$) for up and down, respectively (Equation 1e).

The objective also includes a SOC penalty cost $\mathcal{C}_{SOC}$, which incentivizes the model to charge vehicles above the minimum SOC required for trips (Equation 1d). The total SOC penalty cost is the sum over all intervals and EVs of the empty usable energy capacity of each EV multiplied by a user defined SOC penalty value c_{SOC} . Additional details on the application of the SOC penalty are provided in Section 3.3.

2.2 Electric Vehicle Constraints and Dynamics

Electric Vehicles are constrained both in their energy storage capacity and their power capacity.

$$b_i^{av}(k)P_i^{min} \leq P_i(k) + P_i^{reg}(k) \leq b_i^{av}(k)P_i^{max} \quad (2)$$

²Although the Federal Energy Regulatory Commission stipulates a "performance" or "mileage" payment from frequency regulation participation [24], it is not included in this analysis. The authors believe this is acceptable based on the its historical prices in the California market, but acknowledge the importance of including it for fleets participating in other markets throughout the United States.

$$\mathcal{B}_i \times SOC_i^{min} \leq E_i(k) \leq \mathcal{B}_i \times SOC_i^{max} \quad (3)$$

In equation 2 $P_i(k)$, the power delivered to/from EV i , is constrained. $P_i(k)$ is defined as the power on the meter side of the EV inverter, and is positive when the EV is charging. $b_i^{av}(k)$ is a binary input parameter indicating whether EV i is connected to its EVSE, P_i^{min} and P_i^{max} are the minimum and maximum power capacity of the i^{th} EVSE/EV pair as measured at the electricity grid interconnection. Equation 3 constrains the energy stored in EV i during interval k , $E_i(k)$. $\mathcal{B}_i$ is the rated battery capacity of EV i , and SOC_i^{min} and SOC_i^{max} are the minimum and maximum allowable energy state of charges for the battery during operation.

The previous equations constrained the absolute ranges in which the state variables of each EV can operate, but we need to add the dynamics of those state variables to our constraints, particularly for energy storage:

$$E_i(k) = E_i(k-1) + \left(b_i^{ch}(k) \times \eta_i^{ch} P_i(k) + (1 - b_i^{ch}(k)) \frac{1}{\eta_i^{dis}} P_i(k) + P_i^{tr}(k) - P_i^{reg} \right) \Delta t \quad (4)$$

where:

$$b_i^{ch}(k) = \begin{cases} 1 & \text{if } P_i \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Equation 4 is a compact form of a set of linear equations that introduces a binary variable, $b_i^{ch}(k)$, that is dependent on the charging/discharging decision variable for each vehicle. This effectively allows the system to differentiate between charging and discharging efficiency, while also ensuring that individual EVs cannot charge and discharge within the same timestep k . Charging and discharging efficiencies are modeled as fixed input parameters: η_i^{ch} and η_i^{dis} .

Equation 4 also introduces two new power terms: $P_i^{tr}(k)$ is an input parameter that represents the average power consumed during interval k of a vehicle that is on a trip, and P_i^{reg} is the expectation of average power provided during an interval in which the vehicle provides frequency regulation. Because P_i^{reg} is defined as power provided from the fleet, it given a negative sign in Equation 4 to indicate discharging. This value will be further defined when we describe the requirements of frequency regulation. The inclusion of $P_i^{tr}(k)$ in this constraint ensures that the EVs are always charged in a manner that satisfies their mobility energy requirements.

2.3 California Regulation Market Constraints

In order to ensure that the capacity available from the fleet for frequency regulation is properly bounded it must be constrained by the vehicles that are expected to be connected during any hour, h .

$$P_{flt}(k) = \sum_{i=1}^n P_i(k) \quad (5)$$

$$R_U^h \leq R_U(k), \forall k \in h \quad (6)$$

$$R_D^h \leq R_D(k), \forall k \in h \quad (7)$$

$$R_U(k) \leq \sum_{i=1}^n (P_i^{min} \times b_i^{av}(k)) + P_{flt}(k) \quad (8)$$

$$R_D(k) \leq \sum_{i=1}^n (P_i^{max} \times b_i^{av}(k)) - P_{flt}(k) \quad (9)$$

Equations 6 and 7 ensures that the up/down regulation capacity (R_U^h or R_D^h) offered for hour h , is the minimum available regulation capacity ($R_U(k)$ or $R_D(k)$) for all intervals in

the hour. Further, equations 8 and 9 limits capacity to the sum of power capacity (P_i^{min} , P_i^{max}) of vehicles that are connected in an interval, as indicated by availability parameter $b_i^{av}(k)$. These constraints are appropriate for any market context, however, there are also constraints that are specific to the CAISO context:

$$R_D(k) \leq \sum_{i=1}^n \left((SOC_i^{max} \times \mathcal{B}_i - E_i(k)) \times b_i^{av} \right) / \Delta t_h - P_{flt}(k) \quad (10)$$

$$R_U(k) \leq \sum_{i=1}^n \left((E_i(k) - SOC_i^{min} \times \mathcal{B}_i) \times b_i^{av} \right) / \Delta t_h + P_{flt}(k) \quad (11)$$

$$R_U^h \geq R_U^{min} \text{ or } R_U^h = 0 \quad (12)$$

$$R_D^h \geq R_D^{min} \text{ or } R_D^h = 0 \quad (13)$$

In the California wholesale market, a resource must maintain enough energy capacity to provide the intended frequency regulation at full dispatch for the entire hour of an award. This is represented in equations (10) and (11), which use the available energy capacity for charging and discharging to constrain hourly regulation capacity. The bid time interval Δt_h in this case is 1 hour. Further, every ISO has a minimum reserve quantity that a resource may bid, represented by R_U^{min} and R_D^{min} . In CAISO, that quantity is 0.1 MW-h for ancillary service reserves.

Equation 5 defines the fleet charging level, which determines the baseline around which the resource provides regulation. As such, the scheduled charging baseline must be considered in determining available regulation capacities (e.g. Equations 8, 9, 10, and 11) and acts effectively as a capacity offset. For instance, scheduled charging $P_{flt}(k)$ can be shed to increase up regulation capacity, whereas the same scheduled charging diminishes the available capacity to absorb energy via down regulation.

$$f_U(h) * R_{U,bid}(h) - f_D(h) * R_{D,bid}(h) = \frac{1}{\Delta t_h} \sum_{i=1}^n P_i^{reg}(k), \forall k \in h \quad (14)$$

Finally, the model takes into account the expected impact of participating in regulation to ensure the EV SOC's are not depleted, and that the resource maintains sufficient capacity when providing regulation for multiple continuous hours. To do this, the model requires hourly AGC utilization factors for up $f_U(h)$ and down $f_D(h)$ regulation, which estimate how much the resource will be exercised in each direction during each hour of reserve provision. Figure 1 is provided as an illustrative representation of these AGC factors for better understanding. It shows a generic AGC signal over an hour of reserve provision in both up and down regulation (R_U^h , R_D^h) that includes non-zero scheduled charging for the fleet (P_{flt}). In this example, the dimensionless AGC factors are calculated as the ratio of the shaded AGC dispatch energy over the total possible energy that could have been dispatched throughout the reserve provision period (R_U^h or R_D^h multiplied by the one hour period).

To incorporate the AGC utilization factors in the model, the factor values are applied to their corresponding bids to estimated a net energy flow to or from the resource in each hour. For instance, in an hour where $f_U(h) = 0.25$ and $R_{U,bid}(h) = 100$ kW, a net discharge of 25 kWh would be estimated for the hour. This net impact is then distributed among the fleet in the form power flows to or from individual EVs $P_i^{reg}(k)$, which are linked to each EV's energy balance in Equation 4. Additional details on the application of the AGC utilization factors are provided in Section 3.4.

3 Scenario Design

Regulation bidding strategies and charging schedules generated by the model are dependent on the availability and energy requirements of the vehicles. They are also driven to a lesser

Figure 1: Visualization of the relationship between actual AGC signal and corresponding AGC utilization factors ($f_U(h)$, $f_D(h)$). AGC signal is unknown during day-ahead optimization, so factors must be forecast from historic data or other sources.

extent by other inputs, such as the forecasted hourly regulation prices, AGC utilization, and building loads, as well as other, user defined model parameters such as the SOC penalty. The scenario analyses presented in this paper are used to evaluate the sensitivity of model outputs to several key input parameters. In these exercises, as individual parameter values are varied, the remaining parameters are held to their base case values, described in Section 3.1. Unless explicitly stated, the parameters of a scenario are given by the base case values, indicated in Table 1. Parametric analyses will be used to assess the impact of the following inputs:

- Hourly regulation prices
- Building load (peak day vs. non-peak day)
- SOC penalty cost
- AGC utilization factors
- Symmetric bidding constraints

3.1 Base Case Input Values

The base values of parameters for every scenario evaluated are presented in Table 1. All scenarios analysis exercises use the same EV fleet, described in Section 3.1.1. For each exercise 30 unique usage schedules as described in Section 3.1.2 are evaluated. Further, each exercise evaluates five regulation price profiles scenarios as described in Section 3.1.3. For three of the five scenario analysis exercises, these are the only variable parameters, resulting in 150 total runs per exercise. Exercises that examine SOC penalty and AGC utilization parameters each vary an additional parameter, resulting in 900 and 1200 total runs per exercise, respectively.

3.1.1 EV fleet composition

The EV fleet simulated in this investigation is similar to the fleet that is currently installed and under testing at L.A. Air Force Base as part of the demonstration project. It is composed of several vehicle types, including sedans, vans, trucks, and a shuttle bus, each with varied vehicle properties. In total, the simulated fleet has a total usable energy capacity of 591 kWh, a total maximum charging rate of 568 kW, and a total maximum discharge rate of 555 kW. The composition of the fleet and individual vehicle type properties are given in Table 2. Vehicles of the same type are assumed to be identical models, with properties defined to approximate real, currently available EV models. For all EVs, charging and discharging

parameter	basecase values
day type	weekday
season	summer
building load	non-peak
Δ from peak load	200 kW
EV usage	30 scenarios
regulation prices	5 scenarios
bid symmetry	unconstrained
SOC penalty	0.004 \$/%-hr
AGC up utilization	0.5
AGC down utilization	0.5

Table 1: Parameters evaluated in the scenario analysis and their base case values

efficiencies are assumed to be 0.92. In application, it is likely that usage and scheduling patterns would vary across vehicle types (e.g. the daily usage pattern of a shuttle bus would be distinct from that of a sedan). The simulated EV trips used in investigation do not take this into account, however, due to lack of sufficient usage data by vehicle type.

vehicle type	number	usable capacity [kWh]	max charge rate [kW]	max discharge rate [kW]
sedan	13	13	15	15
van	11	15	13	14
truck	4	43	47	42
shuttle	1	85	42	38
total	29	591	568	555

Table 2: summary of simulated EV fleet at L.A. Air Force Base

3.1.2 EV Availability and Charging Requirements

A vehicle’s trip schedules define its availability for charging and ancillary service provision. To adequately capture the sensitivity to the other input parameters of interest, a range of EV use patterns have been randomly generated. In total 30 unique EV fleet schedules have been generated, where each fleet schedule consists of 29 schedules of individual EV availability (i.e. connection to a charging station) and trip load (i.e. energy required for travel). Each schedule has been randomly generated from normal distributions of start time ($\mu=10:30$, $\sigma=2$ hours), trip duration ($\mu = 4$ hours, $\sigma = 1.5$ hours), and energy use fraction ($\mu=0.5$, $\sigma=0.2$), which describes the fraction of usable energy capacity required for the trip. The distribution values have been selected to approximate the trip patterns observed at the test site. Ten schedules are generated at each of three usage levels: high, medium, and low, under which the likelihood of an individual vehicle being scheduled for a daily trip is 25%, 50%, and 75%, respectively. If a vehicle is not selected for a trip, it is fully available for the day with no trip load. The result is 30 sets of 29 EV usage schedules. For this investigation, these 30 sets of schedules are generated once and remain fixed for all subsequent analyses. The use of different schedule parameters or distributions would likely have a significant impact on the resulting bidding and charging behaviors, but has not been investigated in this paper.

3.1.3 Regulations prices

Regulation prices should significantly impact optimization results and is the first parameter set explored in the scenario analysis. To analyze the impact of hourly regulation prices on bidding behavior, five price scenarios, as outlined in Table 3, have been modeled. The profiles are based on CAISO market clearing prices from summer 2012. The medium price

case is based on median values for weekday prices. The high price case is given by the 90th percentile of hourly prices, while the low price case is given by the 10th percentile of hourly prices. Because these statistics are taken from data for each hour independently, neither the high nor low price profile is likely to be representative of the variance of an actual day, but have been nonetheless selected for use here to illustrate how prices drive certain outcomes within the optimization model. Price profiles for each scenario are also given in Figure 2.

Figure 2: Hourly regulation price profiles derived from CAISO summer weekday 2012 data.

price scenario	up regulation	down regulation
1	low	low
2	median	median
3	high	high
4	high	low
5	low	high

Table 3: Regulation price scenarios for parametric investigations. Hourly prices for each price level can be found in Figure 2

3.2 Building load

In the application of this model at LA Air Force Base, the cost of charging the EV fleet falls under a retail time-of-use tariff. Furthermore, for billing, EV charging is aggregated with building consumption. The billed consumption profile includes both direct EV charging as well as EV charging resulting from responses to AGC. Because down regulation likely involves increased charging, the model must take into account the potential additional costs due to regulation bidding, particularly as they relate to monthly power demand charges. As a consequence of this, the bidding strategy produced by the model will likely be substantially different when operating on a peak day (i.e. electricity consumption is at or near the peak for the billing cycle) versus a non-peak day. To capture this effect, the results of the regulation price scenarios are replicated for both a peak and non-peak day-type. In the non-peak scenarios, it is assumed that the model has already encountered a higher load day and has a uniform 200 kW buffer between expected building loads and previously encountered peak loads in all timesteps. As the base load profile is fixed within the problem, this simplified representation of a non-peak load is appropriately illustrative for demonstrating this application. In the peak-day scenario, this buffer is reduced to zero. Relative to the size of the fleet load, the size of the building load is high (approximately 2.9 MW). This presents the model with opportunities to charge EVs (on both peak and non-peak days) without incurring significant additional demand charges. The results of this will be seen in subsequent sections. The building load used in this investigation is shown in Figure 3 with the TOU demand periods also indicated. The shape of the building load profile will be important in determining the opportunities for low cost charging.

Figure 3: Sample L.A. Air Force Base building load profile. Time-of-use billing periods are highlighted. Fill indicates the previously observed demand levels. Lines indicate load profiles for the peak day and non-peak day load scenarios.

3.3 SOC Penalty

A natural consequence of deterministic optimization is that the vehicles will only buy exactly enough energy to meet their expected trip requirements and market participation. However, in reality the on-road vehicle consumption is uncertain. The SOC penalty, described in Equation 1a, is an incentive meant to drive higher states-of-charges in the fleet, which increases the tolerable margins for error in forecasting and operation and reduces risk of battery depletion during trips. SOC penalty c_{SOC} is defined as dollars per percent empty usable capacity per hour. Because the penalty is imposed in percent units rather than energy units, it can be applied to large and small capacity EVs with comparable magnitude. To illustrate the sensitivity of the model to the SOC penalty, a range of values from \$0 to \$0.01 per % SOC per hour is modeled, while maintaining all other base case values as described in Table 1. The base case SOC penalty value (0.004\$/% - hr) has been selected based on iterative testing to elicit an adequately strong response by the model.

3.4 AGC utilization factor

AGC utilization factor is the forecasted usage of the resource during the regulation event. Factors are defined independently for up and down regulation for a given hour. It is expected that in an application, hourly utilization factors can be predicted with reasonable accuracy based on historical AGC for the same resource. These factors provide an estimate for how much a resource will be exercised in each direction when bidding and are an indirect measure of the cost of participating in regulation. To capture the model's sensitivity to AGC utilization factor, eight scenarios have been modeled. Each of these scenarios has uniform AGC factors for a given direction throughout the day. In actuality, it is likely that the AGC factors derived from real data will be highly variable throughout a single day, as the need for either up or down regulation fluctuate. Model AGC factor scenarios are provided in Table 4. This exercise will evaluate each AGC scenario while maintaining all other base case values as described in Table 1.

Market rules effectively dictate that the sum of up and down AGC utilization factors for a given hour should be less than or equal to 1. To violate this, the resource would have to be exercised beyond the capacity it had bid. With this in mind, it should be noted that AGC scenario 4 violates the market rules, while scenarios 3, 5-8 all describe full utilization of the resource. While these values are unlikely to be encountered in a real market application, they are modeled here to investigate the model's response to extreme cases of resource utilization in balanced or biased directions.

AGC scenario	Description	AGC factor up	AGC factor down
1	no AGC	0	0
2	balance low	0.25	0.25
3	balance medium	0.5	0.5
4	balance high	0.75	0.75
5	biased up	0.75	0.25
6	biased down	0.25	0.75
7	all up	1	0
8	all down	0	1

Table 4: AGC utilization factor scenarios.

3.5 Bidding Symmetry

While some frequency regulation markets, such as in CAISO, allow resources to bid in regulation up and regulation down separately, many markets expect that regulation resources must provide their capacity symmetrically in both directions. To examine the impact of this constraint on bidding strategy and revenue from regulation, the base case inputs (Table 1) are reevaluated while constraining hourly regulation to be symmetric in up and down.

4 Results and Discussion

4.1 Base Scenario Results

The base case scenario run set is composed of 150 optimization results corresponding to the 30 EV fleet schedules and five regulation price scenarios described above. Figure 4 illustrates the impact of regulation price on hourly bidding behavior of the base case parameters by plotting the range of values in each hour for up regulation, down regulation, and energy bidding. In each of these plots, the solid line indicates the median hourly values for the runs within that subset. The colored shaded regions indicates the 25th to 75th percentile range, while the lighter shaded region indicates the maximum to minimum range of values.

As this figure illustrates, different regulation price scenarios drive significantly different bidding behaviors. Within any single price scenario, the range of bidding behaviors is not highly variable, particularly in hours when vehicle usage is low (e.g. early morning and late evening periods). The model appears to favor up regulation bidding, particularly during on-peak periods. The model also appears to avoid bidding down regulation above 200 kW during on-peak periods. Bidding above this value creates the potential to set new demand charges, which are significantly higher than revenue potentials from regulation. When up regulation prices are low (e.g. scenarios 1 and 5), the model reduces up bidding hours, particularly in the morning. It remains in the market for hours when up prices peak (13:00-18:00) in all price scenarios. For all price scenarios, the up regulation capacity between 11:00 and 12:00 appears to fall significantly. The precise reason for this depends on the interplay of input data and model constraints, but is likely driven by the confluence of a number of factors: (1) the loss of connected EV capacity as vehicles leave for midday trips, (2) relatively high tariff rates to replace energy lost due to up regulation discharging, (3) the risk of depleting SOC of EVs scheduled for afternoon trips, and (4) the opportunity cost of depleting resource SOC prior to afternoon and evening hours, where up regulation prices increase significantly.

For each individual optimization, the objective function is composed of a number of cost components. These include energy costs, demand costs, SOC penalty costs, and regulation revenue. Table 5 gives the mean values of the objective function components for each price scenarios³. Due to the relatively larger variability in the prices for up regulation, the high

³The total objective value includes fixed costs for building energy costs (\$11,673). These have been removed to illustrate the impact on EV decision variables alone. The presence or absence of fixed costs from the model do

Figure 4: Impact of regulation price scenario on range of bidding and charging behaviors for base case parameters.

price scenarios in up regulation have a dramatic impact on total regulation revenue. Further, larger differentials between up and down regulation prices lead to larger energy purchases. This is likely due to the fact that the charging energy can be shed to provide additional up regulation capacity beyond the discharging capacity available in vehicle batteries. Additionally, scenarios with higher regulation revenue also have higher energy costs, indicating higher levels EV charging and discharging to position the resource for regulation and to satisfy expected AGC signals. However, regulation participation yields a net benefit to the objective, despite the higher energy costs. For scenarios where up regulation prices are high, the model is able to achieve net revenues from regulation versus energy and penalty costs. In general, the model must balance several competing incentives: maximizing regulation revenue, minimizing charging costs, and managing EV SOC to reduce SOC penalty costs. Given the interaction of these various strategies, the model can often achieve solutions with comparable total objectives, even when scenarios and inputs vary substantially.

4.2 Demand Charge Impact

Demand charges are a significant cost for commercial building owners. Because this particular resource is billed in combination with a larger facility load, the non-EV demand levels may have an impact on bidding behavior due to the potential for increased demand charges when total facility load is near the monthly peak. To investigate this impact, the above investigation has been replicated with the 200 kW load buffer removed. This simulates the impact of bidding during a peak-day, where tariff demand charges are expected to be set for the entire month during the simulated day.

The optimization results ensure that any vehicle charging or discharging does not impact not impact the optimal values of the variables.

Table 5: Objective function components of daily costs and revenues - Regulation price scenarios for non-peak weekdays

up regulation price scenario	down regulation price scenario	objective	EV energy costs	EV demand costs	regulation revenue	SOC penalty costs
high	high	\$-83.72	\$75.48	\$0.00	\$223	\$64.12
high	low	\$-65.22	\$91.80	\$0.00	\$212	\$55.07
low	high	\$27.19	\$38.26	\$0.00	\$73.52	\$62.44
low	low	\$60.94	\$34.17	\$0.00	\$13.19	\$39.97
medium	medium	\$34.88	\$38.91	\$0.00	\$64.50	\$60.48

Table 6: Objective function components of daily costs and revenues - Regulation price scenarios for peak weekdays. Note: negative values indicate net revenue from EV charging and regulation.

up regulation price scenario	down regulation price scenario	objective	EV energy costs	EV demand costs	regulation revenue	SOC penalty costs
high	high	\$-70.61	\$74.55	\$0.00	\$206.37	\$61.20
high	low	\$-52.45	\$88.02	\$0.00	\$193.91	\$53.42
low	high	\$31.24	\$35.33	\$0.00	\$59.50	\$55.37
low	low	\$61.49	\$34.22	\$0.00	\$12.98	\$40.26
medium	medium	\$36.36	\$30.04	\$0.00	\$60.16	\$56.48

the demand charge, as seen in both Tables 5 and 6³. To accomplish this, the regulation bid quantities are generally reduced. Figure 5 illustrates the range of peak-day bidding behavior for each price scenarios. Compared with Figure 4, the change in up regulation and energy bids are minor. Conversely, down regulation bidding is diminished significantly, particularly during mid-peak and on-peak demand periods. During the hours of 8:00 to 15:00 no down regulation bids are submitted. Because down regulation is less lucrative in the price scenarios presented, the impact to regulation revenue is relatively small as shown in Table 6. Reductions in daily revenue range from \$0.21 to \$18, which typically comprise less than 10% of total daily regulation revenue in each scenario. As with the non-peak results, total objective values (Table 6) appear to be driven primarily by up regulation prices, and less so by down prices.

4.3 SOC Penalty

The model has an incentive to maintain a fleet average SOC significantly below 100%. This reserves capacity to participate in both up and down regulations simultaneously and thus maximize regulation revenue. Requirements of the fleet (i.e. trips) may push the SOC higher in daytime hours, but otherwise the optimal average SOC should be nearer to 50% depending on the price spread in regulation. In a deterministic optimization, the system is allowed to jeopardize the mobility of fleet users by minimizing the stored energy in EV batteries due to this incentive. The introduction of the SOC penalty changes this. By creating a penalty incurred when SOC is maintained below maximum, this penalty drives the model away from a near 50% SOC target. The SOC penalty is thus a useful way of reducing risk of battery depletion due to uncertainty in vehicle trip input data and reduce the risk of failure to provide mobility services.

The general impact of increasing the SOC penalty can be seen in Figure 6, which shows the average SOC profiles for each SOC penalty value investigated here. In all optimizations, the initial SOC for individual EVs is 0.5. The impact of the SOC penalty can be seen clearly in the initial time intervals, where the aggregate SOC rises sharply for the higher penalty

Figure 5: Impact of regulation price scenario on range of bidding and charging behaviors for peak demand day.

scenarios. This behavior is consistent with the formulation of the penalty. Because SOC penalty costs accrue proportional with both empty capacity and duration, the model has an incentive to fill empty capacity early in the optimization horizon. Increases in the SOC penalty result in increased fleet average SOC.

The impact of the SOC penalty value on the regulation bidding strategies can be seen in Figures 7 and 8 for up and down, respectively. These "violin" plots simply show the distribution of all hourly regulation bids for each value of the SOC penalty. For up regulation, the bids appear to vary between 0 and 0.6 MW with the highest frequency of bids in the range of 0.2 to 0.4 MW. As the the SOC penalty increases in value, the peak at 0.3 MW falls, while bidding frequency at the extremes of the range appears to increase, particularly at 0 MW. The observed range of bidding does not appear to change substantially.

Down regulation bidding appears to be much more sensitive to the SOC penalty. As Figure 8 shows, increasing the penalty value reduces the range of observed down bids, while significantly increasing the frequency of 0 MW bids. As higher SOC penalty values increase the average SOC across all time intervals, the fleet has less empty capacity to apply to down regulation. Hourly energy bids do not appear to change substantially between SOC penalty scenarios, and have therefore been omitted. As Figure 6 shows, outside of the high charging during initial intervals, the shapes of the SOC profiles are largely similar, indicating comparable levels of charging and discharging.

Table 7 summarizes the impact to the optimization objective function from variable SOC penalty values³. The relationship between the SOC penalty value and the total SOC penalty cost is clear: higher penalty values drive higher costs due to the increased vehicle charging and lower regulation revenues. However, the relationship between the penalty value and cost is non-linear, implying that the model becomes more responsive to reducing the penalty cost as the penalty value grows. Higher penalty values also drive lower regulation revenue, but again the relationship is not linear. In fact, the regulation revenue when the penalty is

Figure 6: Impact of SOC penalty value on fleet average SOC across all modeled usage and regulation price scenarios.

Figure 7: Distribution of all hourly up regulation bids by SOC Penalty value.

\$0.002 is higher than when it is \$0. From this peak, the total regulation revenue falls only 23% as the SOC penalty increases by 400%.

4.4 AGC Utilization Factor

As mentioned earlier, AGC utilization factor can be seen as corresponding to the cost of participating in either up or down regulation in a given hour. For up regulation, discharged energy will need to be replaced, either for future trips or to reduce SOC penalty costs. Additional charging from down regulation drives additional energy purchases which must be paid for under the retail tariff. In either case, higher utilization creates the potential for higher costs.

Bidding behaviors for each of the eight AGC scenarios are plotted in Figure 9. For AGC scenarios 1-4, the utilization of both up and down regulations is balanced. However, the relative benefits are potentially much different. The typical market prices of up regulation are significantly higher, as such the model engages in behaviors that favor bidding in the up direction. This is particularly true in the case where utilization is zero. Under this case, there is no energy impact from AGC, and so the model heavily favors the more lucrative up regulation. As utilization grows in scenarios 2-4, up regulation falls, and down regulation grows, and are closely balanced in the high usage scenario 4. This indicates that the model is driving towards bidding strategies that mitigate costly energy impacts from responding to AGC by bidding in a more symmetric fashion. In balanced usage scenarios, symmetric bidding reduces the adverse impact of AGC because energy lost to up regulation is replaced through down regulation within each hour.

For scenarios 5-8, AGC utilization are no longer balanced between up and down. In these

Figure 8: Distribution of all hourly down regulation bids by SOC Penalty value.

Table 7: Objective function components of daily costs and revenues - SOC penalty scenarios

SOC penalty [\$/%-hr per EV]	objective	EV energy costs	EV demand costs	regulation revenue	SOC penalty costs
0	\$-104.55	\$10.02	\$0.00	\$114.58	\$0.00
0.002	\$-36.73	\$48.06	\$0.00	\$121.29	\$36.49
0.004	\$-5.19	\$55.73	\$0.00	\$117.33	\$56.42
0.006	\$21.15	\$58.03	\$0.00	\$109.22	\$72.34
0.008	\$43.16	\$65.97	\$0.00	\$101.97	\$79.16
0.01	\$61.60	\$68.30	\$0.00	\$94.33	\$87.63

cases, the models tend to favor the lower utilized direction. In the fully biased scenarios (7,8) the model mostly elects to avoid the biased direction entirely. Without utilization of both directions the model has no mechanism to balance out the energy impacts. Of course, such level of bias over the course of an entire event day is unlikely to occur in a real-world application. In nearly all AGC scenarios, the model elects not to bid down regulation above 200 kW to avoid the potential for additional retail demand charges.

Table 8 provides a summary of average objective values for each of these scenarios³. Overall, total regulation revenue appears to be correlated with lower AGC usage of up regulation, since up is the higher priced direction. Total objective values varying by approximately \$100 between scenarios with comparable energy costs and SOC penalty costs.

4.5 Bid Symmetry

While the previous bidding range figures provide some insight into the relative tendency to bid up and down regulation, it obscures the symmetry or asymmetry of any given up/down bid pair. To shed light on this, scatter plots of hourly up and down regulation bid pairs have been made for each of the AGC scenarios discussed in section 4.4. These plots shown in Figure 10 illustrate the frequency and magnitude of asymmetry in the bids. In each subplot, a point represents a single hourly bid pair from each of the 150 optimizations per AGC scenario. The value of up regulation is given as the vertical position, while the down regulation is given by the horizontal position. To understand the influence of demand charges, which may reduce the model's propensity to bid down regulation, subplots have been further divided by retail TOU period as indicated on the right of the figure.

In this figure, a symmetric bid will fall along the line $x=y$. As the figure illustrates, in many scenarios, bidding tends to be highly asymmetric. As scenarios progress from 1-4 with increasing, but balanced utilization, more bids tend to appear along the $x=y$ line. However, bids off this line, and completely asymmetric bids (e.g. either up bid = 0 or down bid = 0) still appear frequently. For the unbalanced AGC scenarios (5-6) bidding is highly asymmetric and favors the lesser used direction. In the totally biased scenarios (7-8) bidding tends to be almost exclusively the unutilized direction.

Figure 9: Impact of AGC utilization factor scenarios on hourly regulation and energy bidding behaviors.

Table 8: Objective function components - Regulation price scenarios for peak weekdays

up regulation usage factor	down regulation usage factor	objective	EV energy costs	EV demand costs	regulation revenue	SOC penalty costs
0	0	\$-45.24	\$44.43	\$0.00	\$121.23	\$31.35
0.25	0.25	\$-5.19	\$55.73	\$0.00	\$117.33	\$56.42
0.5	0.5	\$15.05	\$39.66	\$0.00	\$88.60	\$63.99
0.75	0.75	\$16.06	\$36.77	\$0.00	\$84.07	\$63.36
0.75	0.25	\$43.22	\$35.51	\$0.00	\$50.68	\$58.39
0.25	0.75	\$-20.37	\$44.34	\$0.00	\$112.14	\$47.43
1	0	\$52.33	\$31.93	\$0.00	\$30.00	\$50.39
0	1	\$-42.49	\$44.69	\$0.00	\$113.90	\$31.55

Figure 10: Symmetry of optimized hourly up and down regulation bids under various AGC usage scenarios indicates high asymmetry. Bids are also disaggregated by TOU period, indicated on the right.

In regulation markets where bidding and AGC impacts are not assured to be symmetric, it is clear that effective asymmetric bidding will be a key feature for a model to capture optimal regulation revenue. However, understanding and predicting AGC utilization factors is a critical prerequisite to accomplishing this. Bidding asymmetrically does present risks however, especially in cases where the AGC utilization factor cannot be accurately forecasted. In these cases, or when market rules dictate so, bidding may be constrained to be symmetric only.

To illustrate the impact of such a constraint, the base case inputs of section 4.1 are replicated with forced symmetric bidding in each hour. Objective values by price scenario are presented in Table 9³. Comparing these results with those from the base case (Table 5), there is a clear difference between total objective and total regulation revenue for the first two price scenarios. In these cases, up regulation prices are high. Because of the forced symmetry constraint, the model is unable to pursue higher up bidding, and therefore loses out on 20%-50% of the revenue opportunity if it were unconstrained. The difference is far lower in the scenarios where up regulation prices are more similar to down regulation prices.

Finally, to understand the general impact of peak-day conditions and forced symmetric bidding, the results of the base case, peak-day, and symmetric bidding exercises have been averaged for all regulation price scenarios in Table 10³. Examining this it is clear that forcing symmetric bidding has a more significant downward impact on regulation revenue

than bidding during a peak day, with average total daily revenue falling more than 27% relative to the base case, versus a 9% drop for the peak day. The average total objective for the symmetric case is comparable to the other cases however, implying that a forced-symmetry fleet participates less in the market, but reduces its overall EV charging costs to offset this loss in revenue.

Table 9: Objective function components of daily costs and revenues - Regulation price scenarios for non-peak weekdays with forced bid symmetry

up regulation price scenario	down regulation price scenario	objective	EV energy costs	EV demand costs	regulation revenue	SOC penalty costs
high	high	\$-49.32	\$43.23	\$0.00	\$176.75	\$84.20
high	low	\$7.46	\$42.28	\$0.00	\$107.58	\$72.76
low	high	\$32.39	\$41.86	\$0.00	\$74.45	\$64.98
low	low	\$67.93	\$40.06	\$0.00	\$4.54	\$32.40
medium	medium	\$43.99	\$41.38	\$0.00	\$61.65	\$64.26

Table 10: Objective function components of daily costs and revenues - average over all price scenarios.

scenario	objective	EV energy costs	EV demand costs	regulation revenue	SOC penalty costs
non-peak day	\$-5.19	\$55.73	\$0.00	\$117.33	\$56.42
peak day	\$1.20	\$54.34	\$0.00	\$106.58	\$53.34
symmetric bids	\$20.49	\$41.76	\$0.00	\$84.99	\$63.72

5 Conclusion

This paper presents an overview and mathematical formulation of the day-ahead optimization model being deployed at the Los Angeles Air Force Base Electric Vehicle Demonstration. This optimization identifies economically optimal charging patterns and frequency regulation bidding strategies for the approximately 30 bi-directional charging capable EVs in the LAAFB EVD. It requires input data that include forecasts of CAISO market prices, building load, and intended EV fleet trip requirements captured through the on-base fleet management system.

The optimization model presented in this paper provides a practical deterministic approach to optimization with the ability to be resilient to limited and uncertain data, and supports smaller aggregation sizes than has been previously discussed in the literature. It explicitly includes parameters to handle uncertainty in the energy requirements on the vehicle batteries, both for mobility and inherent in the AGC commands from the CAISO. These parameters allow users to tune the behavior of the model to better match real-world conditions.

To assess the impact of these parameters on high level model behavior and resulting bid strategy, a series of scenario analysis exercises are undertaken. These assess the impact of hourly regulation prices, local load conditions, forced symmetry constraints for regulation bids, SOC penalty values to reserve higher states-of-charge in vehicles, and predicted resource utilization scenarios. The scenario analysis yielded the following insights:

- The model shows significant sensitivity to regulation price conditions, with large differentials between regulation up and down pricing causing the model to attempt to max-

imize its available capacity through energy purchases that effectively shift the baseline from which regulation up and down are provided.

- In all conditions, any increase in retail demand charges should be avoided due to their extremely high cost. This tends to lead to reduced regulation revenue as down regulation is entirely ignored at times that may result in increased demand charges.
- Overall fleet average SOC targets can be met by applying a small penalty for holding low SOC that has limited negative impact on the net cost of operation.
- The AGC Utilization parameter, or the expectation of energy charged/discharged while providing regulation reserve, had the most dramatic effects on both the quantity of regulation bidding offered and the degree of symmetry in the bids for up and down regulation.
- Enforcing regulation bidding symmetry significantly impacts the revenue opportunity in providing regulation when there is a large disparity between regulation up prices and regulation down prices, having as much as a 65% reduction in revenue.

Given the clear sensitivity of the bidding strategy and charging profiles to the predicted AGC utilization, future work will be focused on developing a stochastic optimization around these inputs. Additional focus will also be given to quantifying and incorporating expected costs of providing V2G services, namely those related to battery degradation. Ongoing work on this project also allows for the collection of valuable data related to both fleet operation and CAISO AGC instructions. Statistical analysis of these growing datasets will allow us to better understand this application, develop generalized insights for EV regulation participation, and modify our approach accordingly.

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References

- [1] USDOE, “EV Everywhere Grand Challenge: Road to Success,” Tech. Rep. DOE/EE-1024, United States Department of Energy, Washington, DC, Jan. 2014.
- [2] M. D. Galus, M. G. Vayá, T. Krause, and G. Andersson, “The role of electric vehicles in smart grids,” *Wiley Interdisciplinary Reviews: Energy and Environment*, vol. 2, no. 4, pp. 384–400, 2013.
- [3] S. o. California, “Assembly bill 2514: Energy storage systems,” Sept. 2010.
- [4] C. Marnay, T. Chan, N. DeForest, J. Lai, J. MacDonald, and M. Stadler, “Los angeles air force base vehicle to grid pilot project,” *ECEEE 2013 Summer Study on Energy Efficiency, Club Belambra Les Criques, Presqu’ Ile de Giens, Toulon/Hyères, France, 3-8 June 2013*, 2013.
- [5] C. Marnay, M. Stadler, A. Siddiqui, N. DeForest, J. Donadee, P. Bhattacharya, and J. Lai, “Applications of optimal building energy system selection and operation,” *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy*, vol. 227, no. 1, pp. 82–93, 2013.

- [6] S. Mashayekh, M. Stadler, G. Cardoso, and M. Heleno, "A mixed integer linear programming approach for optimal der portfolio, sizing, and placement in multi-energy microgrids," *Applied Energy*, vol. 187, pp. 154–168, 2017.
- [7] G. Wenzel, M. Negrete-Pincetic, D. E. Olivares, J. MacDonald, and D. S. Callaway, "Real-Time Charging Strategies for an Electric Vehicle Aggregator to Provide Ancillary Services," *IEEE Transactions on Smart Grid*, pp. 1–1, 2017.
- [8] J. MacDonald, P. Cappers, D. Callaway, and S. Kiliccote, "Demand Response Providing Ancillary Services: A Comparison of Opportunities and Challenges in the US Wholesale Markets," in *Proceedings of the 2012 Grid Interop Conference*, (Irving, TX), Dec. 2012.
- [9] J. Donadee and M. D. Ilic, "Stochastic Optimization of Grid to Vehicle Frequency Regulation Capacity Bids," *IEEE Transactions on Smart Grid*, vol. 5, pp. 1061–1069, Mar. 2014.
- [10] S. I. Vagropoulos and A. G. Bakirtzis, "Optimal Bidding Strategy for Electric Vehicle Aggregators in Electricity Markets," *IEEE Transactions on Power Systems*, vol. 28, pp. 4031–4041, Nov. 2013.
- [11] M. Ansari, A. T. Al-Awami, E. Sortomme, and M. A. Abido, "Coordinated bidding of ancillary services for vehicle-to-grid using fuzzy optimization," *IEEE Transactions on Smart Grid*, vol. 6, pp. 261–270, Jan. 2015.
- [12] M. Shafie-khah, E. Heydarian-Forushani, M. Golshan, P. Siano, M. Moghaddam, M. Sheikh-El-Eslami, and J. Catalão, "Optimal trading of plug-in electric vehicle aggregation agents in a market environment for sustainability," *Applied Energy*, vol. 162, pp. 601 – 612, 2016.
- [13] R. J. Bessa, M. A. Matos, F. J. Soares, and J. A. P. Lopes, "Optimized Bidding of a EV Aggregation Agent in the Electricity Market," *IEEE Transactions on Smart Grid*, vol. 3, pp. 443–452, Mar. 2012.
- [14] E. Yao, V. W. S. Wong, and R. Schober, "Robust Frequency Regulation Capacity Scheduling Algorithm for Electric Vehicles," *IEEE Transactions on Smart Grid*, pp. 1–14, 2016.
- [15] W. Kempton and J. Tomić, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *Journal of Power Sources*, vol. 144, pp. 280–294, June 2005.
- [16] E. Sortomme and M. A. El-Sharkawi, "Optimal Charging Strategies for Unidirectional Vehicle-to-Grid," *IEEE Transactions on Smart Grid*, vol. 2, pp. 131–138, Mar. 2011.
- [17] A. Subramanian, M. J. Garcia, D. S. Callaway, K. Poolla, and P. Varaiya, "Real-Time Scheduling of Distributed Resources," *IEEE Transactions on Smart Grid*, vol. 4, pp. 2122–2130, Dec. 2013.
- [18] P. Sanchez-Martin, G. Sanchez, and G. Morales-Espana, "Direct Load Control Decision Model for Aggregated EV Charging Points," *IEEE Transactions on Power Systems*, vol. 27, pp. 1577–1584, Aug. 2012.
- [19] O. Sundstrom and C. Binding, "Flexible Charging Optimization for Electric Vehicles Considering Distribution Grid Constraints," *IEEE Transactions on Smart Grid*, vol. 3, pp. 26–37, Mar. 2012.
- [20] F. Fazelpour, M. Vafaeipour, O. Rahbari, and M. A. Rosen, "Intelligent optimization to integrate a plug-in hybrid electric vehicle smart parking lot with renewable energy resources and enhance grid characteristics," *Energy Conversion and Management*, vol. 77, pp. 250–261, Jan. 2014.
- [21] E. Sortomme and M. A. El-Sharkawi, "Optimal Combined Bidding of Vehicle-to-Grid Ancillary Services," *IEEE Transactions on Smart Grid*, vol. 3, pp. 70–79, Mar. 2012.
- [22] J. Lopes, F. Soares, and P. Almeida, "Integration of Electric Vehicles in the Electric Power System," *Proceedings of the IEEE*, vol. 99, pp. 168–183, Jan. 2011.

- [23] N. Rotering and M. Ilic, “Optimal Charge Control of Plug-In Hybrid Electric Vehicles in Deregulated Electricity Markets,” *IEEE Transactions on Power Systems*, vol. 26, pp. 1021–1029, Aug. 2011.
- [24] FERC, “Order 755 - Frequency Regulation Compensation in the Organized Wholesale Power Markets.,” Oct. 2011.