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A Cost Benefit Analysis of Vehicle-to-Grid (V2G) Considering Battery Degradation Under the ACOPF-Based DLMP Framework

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Highlights

What are the main findings?

- Vehicle-to-grid (V2G) implementation does provide additional revenue and/or savings relative to smart charging.
- The costs of V2G implementation more than offset the marginal financial benefits EV owners can generally receive at this current time.

What is the implication of the main finding?

- V2G adoption by individual EV owners, given current costs and benefits, is likely to be challenged despite the overall system benefits prior works find it provides.
- If V2G adoption is going to significantly increase, financial benefits to EV owners must increase—which may ultimately reduce or even eliminate the system benefits prior work estimates V2G provides.

Abstract

This paper seeks to provide a cost benefit analysis of the implementation of a vehicle-to-grid (V2G) charging strategy relative to a smart charging (V1G) strategy from the perspective of an individual electric vehicle (EV) owner with and without solar photovoltaics (PV) located on their roof. This work utilizes a novel AC optimized power flow model (ACOPF) to produce distributed location marginal prices (DLMP) on a modified IEEE-33 node network and uses a complete set of real-world costs and benefits to perform this analysis. Costs, in the form of the addition of a bi-directional charger and the increased vehicle depreciation incurred by a V2G strategy, are calculated using modern reference sources. This produces a more true-to-life comparison of the V1G and V2G strategies from the frame of reference of EV owners, rather than system operators, with parameterization of EV penetration levels performed to look at how the choice of strategy may change over time. Counter to much of the existing literature, when the analysis is performed in this manner it is found that the benefits of implementing a V2G strategy in the U.S.—given current compensation schemes—do not outweigh the incurred costs to the vehicle owner. This result helps explain the gap in findings between the existing literature—which typically finds that a V2G strategy should be favored—and the real world, where V2G is rarely employed by EV owners.

Keywords: AC optimized power flow (ACOPF); distributed energy resources (DER); distribution locational marginal pricing (DLMP); electric vehicles (EV); photovoltaics (PV); vehicle-to-grid (V2G)

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1. Introduction

The rapid decrease in the cost of lithium-ion (Li-ion) batteries over the past decade and an increase in consumer awareness and desire to address carbon dioxide (CO2) emissions has led to rapid growth in the number of electric vehicles (EVs) offerings for light-duty vehicle (LDV) applications. This, in turn, has led to a marked increase in the share of EVs and plug-in hybrid electric vehicles (PHEVs) as a percentage of LDV sales across the globe, with EVs and PHEVs representing 21.4% of new LDV sales in Europe, 9.4% in the U.S., and 33.9% in China in 2023 [1]. Simultaneously, deployment of variable renewable energy (VRE) sources, such as wind and solar photovoltaics (PV), has also grown substantially due to their reduction in cost—and notably for PV, a significant amount of this deployment is in the form of rooftop PV located on single-family homes.

To take advantage of VRE deployment, energy storage is needed to smooth out the variability in generation to better match energy demand. There is also, in certain cases, an interest from homeowners with rooftop PV to store the electricity generated to maximize self-consumption. Historically, rooftop PV owners sold excess electricity generation to the grid, in a process called net-energy metering (NEM), at a rate that was equivalent to the price that they bought electricity from their utility. Several recent policy actions, such as NEM 3.0 in California [2] will or already have significantly reduced the reimbursement rate to the point that storage will be necessary to make the economics of rooftop PV work for homeowners.

It is possible that these storage demands may be met by the batteries in LDVs. This is due to the significant size of LDV EV batteries, which average 72.5 kWh of usable capacity for current fully electric offerings [3] and the large number of LDVs that exist that, on average, are idle 95% of the time [4]. Given these dynamics one can imagine a future where EVs are an important source of storage and reliability services to the grid and there is a large body of research on vehicle grid integration (VGI), with the subset of vehicle-to-grid (V2G) generally receiving the most attention.

Whether V2G is ultimately adopted requires an analysis of competing options and motivations for both the grid operator and the vehicle owner. On the grid operator side, competing centralized storage options include utility-scale Li-ion batteries, thermal energy storage, pumped storage hydropower, compressed and liquified air energy storage, and numerous other earlier-stage long duration energy storage solutions under development. While these options would appear to cost more than utilizing an already purchased battery from an idle vehicle, the typical utility business model, at least in the U.S., incentivizes utility ownership and operation of grid assets. Utilities are likely to own these competing options in most of their forms—but they are unlikely to be an owner of most of the vehicles that are utilized for V2G, which may dampen their desire to enable V2G.

An EV owner considering a V2G program will have to balance revenues against the costs of equipment upgrades required (e.g., to bidirectional chargers) and accelerated degradation of the vehicle battery due to increased cycling. Because the battery also supports their transportation needs, owners will be concerned about state-of-charge (SOC) management to ensure their vehicle can meet their transportation needs. Beyond these straightforward costs (to theorize, not necessarily to calculate), though, there are other potential opportunity costs related to V2G relative to other VGI strategies—which we discuss in greater detail in the VGI Hierarchy section below.

1.1. VGI Hierarchy

To understand these opportunity costs and ultimately compare VGI options, it is necessary to place V2G within the broader VGI framework. Other VGI options include smart charging (i.e., charging during times of lowest cost electricity, often called V1G) or using the vehicle to service energy needs for their own home (referred to as V2H or V2B; here we use V2H). These options form a hierarchy, in terms of complexity and cost to implement that grows from V1G to V2H to V2G. It is critical to consider this hierarchy when evaluating the marginal benefit of each "step up" on the VGI ladder as the value streams that constitute the total V2G value consist of the V1G and V2H value streams while the implementation cost increases with each additional step up. Therefore, from an EV owner's perspective, it is the marginal V2G streams not covered by these other options—and the tradeoff in total marginal value measured against marginal cost—that will determine whether that owner is likely to adopt V2G.

For V1G, the EV owner's largest benefit comes in the form of reduced electricity cost through charging at lower cost hours of the day in areas with variable time-of-use (TOU) electricity rates and/or in managing total electricity demand in areas with demand charges [5,6]. As previously noted, if the owner also has PV on their roof, there may be a form of arbitrage in charging from their PV system if they are in one of the increasing number of locations where NEM rates are below the retail rate of electricity.

If the EV owner allows their automobile to be aggregated into a demand response (DR) program they may receive additional value from capacity payments and/or the provision of a limited set of ancillary services in certain markets [7]. Further, whether aggregated or not, there is some potential transmission and distribution (T&D) deferral value, though this is typically only monetizable by the transmission owner currently.

From the grid operator's perspective, the value of V1G is effectively identical to DR. Therefore, it consists primarily of avoided fuel cost, generation capacity buildout, balancing load, and T&D deferral [8,9].

In V2H, the most well-known additional value for EV owners beyond V1G is as a form of electricity back up if power to their home should go out. However, an EV owner may also be able to reduce their overall electricity bill by charging their car during times of lowest electricity cost and allowing the home to utilize energy from their car battery during times of higher electricity price [10]. Unless the size of the load of the home is considerable, though, most of the value from reducing electricity costs comes from V1G [11]. From a utility perspective, the largest benefit of V2H is the avoidance of additional generation capacity build out and avoided fuel cost [12].

V2G is the broadest step on the VGI ladder in terms of the number of value streams that can be incorporated. For an EV owner, in addition to V1G and V2H value streams they may now be able to arbitrage electricity to an even greater extent by charging during lowest cost times and selling electricity back to the grid at times of highest energy cost. There is also a broader set of ancillary service revenue streams—such as for frequency regulation—that can be received because of the capability to send energy back to the grid when vehicles are integrated as part of a virtual power plant (VPP) [13]. These additional value streams are largely the same ones that could be realized by a utility [14].

1.2. Literature Review and Background

A significant amount of literature comparing V1G and V2G focuses on impacts to the bulk transmission system and, by association, direct benefits to the system at large. These studies usually include some, but typically not all, costs associated with V2G implementation relative to V1G while generally focusing results on the gross benefit of various strategies across a large portion, if not all, of the EV fleet in a geography. They are often conducted using models of the grid that only look at the bulk transmission system, if they consider transmission constraints at all. Studies of this type include [8], which used Lawrence Berkeley Laboratory's V2G-Sim software [15], which incorporates grid-scale system modeling alongside models for vehicle powertrain dynamics, typical driving cycles, and battery degradation models to look at the California grid in a future scenario with high renewable penetration. It was found that V2G reduced ramping requirements to a greater degree than V1G, ultimately reducing the investment that would otherwise be required in grid-scale storage technologies by nearly 7 times.

Reference [16] also looked at V1G and V2G on the California grid in a future high renewable scenario using the Holistic Grid Resource Integration and Deployment Tool (HiGRID), a tool which balances electricity supply and demand on an hourly basis without the consideration of transmission constraints [17]. Powertrain, energy dispatch and vehicle travel pattern models were incorporated into the study as well; it was ultimately found that renewable penetration could be increased from 73% to 84%, with the need for grid storage being 75% lower with V1G and eliminated altogether with V2G relative to immediate charging, assuming 135GW of EV capacity available across the state.

Another volume of V1G to V2G study does consider individual behaviors [18–22]. These studies consider real world revenue from wholesale electricity markets—often including ancillary services and capacity markets in addition to energy prices—and real-world travel patterns to account for time of vehicle availability. These studies, while mentioning concerns about battery degradation, do not consider full cost differences in implementing V2G and often consider fleet ownership consisting of dozens to hundreds of vehicles. These studies do not tend to consider distribution or electrical system constraints more broadly. With those limitations noted, they do find increased revenue from V2G [18,19] or net revenue [20,21].

This paper fills the gap between studies focused on system level impacts in V1G to V2G comparisons, which misses the importance of costs to the individuals that own the EVs, and studies that consider individuals or fleet owners but assume unrealistic conditions—such as individual EV owner access to wholesale market pricing—while omitting physical grid implications and/or additional EV owner costs for the implementation of V2G. To do this, we focus on single homeowners as they are the most likely owner of an EV in the near-term and, therefore, will be the decision-maker as to how the vehicle is used. We also only consider the total costs that EV owners are likely to (1) be aware of and (2) have a meaningful impact on their decision making between selection of a V1G or V2G strategy and do not count benefits for things like emissions reduction, which most EV owners cannot receive direct compensation for. Additionally, we only consider near-term value in the form of energy arbitrage that EV owners can likely receive and avoid ancillary service compensation, which EV owners cannot access unless they join a virtual power plant (and thereby forego much of the revenue to the virtual power plant operator). In this arbitrage calculation we add the under explored consideration of the case where the EV owner has solar PV on their roof, which is increasingly relevant due to the relatively high overlap between EV and solar PV owners. Finally, we utilize a DLMP methodology which has not been widely applied to the study of V2G though it is not yet (to our knowledge) utilized in a commercial setting. However, it allows the implementation of real-world TOU rates while modeling the physical limitations of the distribution grid and likely provides a best-case scenario for individual EV owner compensation when implementing V2G.

It should be noted that in this discussion of value we have focused on those that can be monetized, at least in some form, by either the EV owner or the utility across most of the world. Much of the literature around VGI also focuses on the potential climate benefits this technology can provide. Climate is a significant driver in the adoption of DER and EV technology to this point, so this value is non-trivial. However, much of this support has come in the form of government incentives or mandates. There are carbon markets in some parts of the world, but most of these markets are limited to large industrial players and, therefore, do not directly incorporate residential power and transportation related emissions.

Many studies of VGI include a value for carbon emissions avoidance based upon local carbon market pricing or various avoided cost of carbon calculations. This study will not include a carbon emission value stream due to the general inability for stakeholders—that is EV owners or utilities—to directly monetize this benefit in the U.S., which likely keeps these potential value streams outside of the decision making process when selecting between V1G and V2G.

The remainder of this paper is laid out as follows. Section 2 will cover the methodology used to model the distribution system and how costs and values associated with EV ownership have been determined. Section 3 will present the results of the modeling effort. Section 4 contains a discussion of the results while Section 5 provides a conclusion and discusses next steps.

2. Theory

To look at the impacts of EV ownership, the choice of VGI strategy, and determine the ultimate value that choice will have, an AC optimal power flow (ACOPF) model is utilized under a distributed locational marginal pricing (DLMP) framework. While the DLMP framework creates some differential pricing at the various nodes on the circuit that would not typically be seen by EV owners today (due to the congestion pricing aspect of DLMP), it does serve to highlight where equipment limitations may exist on the distribution grid and the grid operator would incur costs to upgrade the system due to EV deployment. Therefore, the DLMP methodology does serve as a reasonable proxy for total costs that would be realized in the near term to allow for greater penetration of EVs.

The remainder of this section will highlight the ACOPF and DLMP framework, the ACOPF model used, and how costs and value are determined for the EV owner.

2.1. DLMP and ACOPF Modeling Approach

DLMP is an extension of the traditional locational marginal price (LMP) methodology typically used by independent system operators (ISOs) or regional transmission operators (RTOs) for the bulk transmission systems [22]. To move the LMP framework on to the distribution system the congestion had traditionally been removed [23], resulting in DLMP being composed solely of energy and energy loss. However, to reflect the operational constraints specific to distribution systems, recent improvements to the modeling methodology and increasing congestion on the distribution system have allowed for the addition of congestion and voltage components to DLMP [24]. For example, Reference [25] utilized a DLMP method inclusive of congestion to examine demand response. Reference [26] takes a similar approach to look at EV charging management on the distribution system. More recent work such as [27] has brought together DLMP and OPF to look at an active distribution network. Reference [28] used a linearized formulation of an ACOPF to calculate DLMPs and a more wholistic distribution system operation by also considering active power, reactive power, congestion, voltage support, and loss. The model used here builds off the more wholistic approach and considers each of these pieces of the electric system.

We have chosen to adopt the DLMP approach to evaluate EV integration into the distribution system as increasing EV penetration is likely to increase the probability that congestion and voltage constraints will be the binding technical factors limiting EV integration. The reason for this belief is the fact that a singular EV with a level 2 charger represents a load that is greater than or equal to the maximum power draw from most homes in the U.S.—and with average households owning more than two cars, large-scale EV adoption is effectively equivalent to tripling the housing stock on the existing distribution system from the perspective of potential maximum power draw. DLMP incorporating voltage constraints and congestion would, therefore, provide effective price signals to EVs and households generally that would maximize the capabilities of the existing grid.

In adopting a DLMP framework, we require that the distribution grid operates similar to ISOs/RTOs in that those homeowners generating electricity via DERs or those with storage technologies, such as EVs, must provide bids at which they are willing to sell electricity ahead of time. The market price is then set—at each individual node—at the price where the marginal bid for supply meets demand, with all sellers receiving and electricity consumers paying the market clearing price. In this study we do not specify a bidding protocol or specific market maker as the relative comparison of VxG strategies should not be significantly affected by those choices, but the assumed bidding and clearing operation would be most closely aligned to a day-ahead market with perfect demand and supply foresight. Bids to deliver power from EVs are set equivalent to their cost of charging (i.e., the cost paid for electricity divided by the battery round trip efficiency) and the bids for PV generated electricity are assumed to be equivalent to the levelized cost of electricity of the PV. parentheses to avoid ambiguities in denominators.

2.1.1. Distribution Market-Clearing Model for Joint Active and Reactive Power Pricing to Value VGI

The ACOPF model utilized here has been previously described in [29], with modification to account for EV batteries in addition to PV systems. For this study, the focus is on the active and reactive power value of each VGI option under study and we assume that the EV charger can provide reactive power. The distribution market clearing is defined as:

$$min b_s^p p^s + b_s^q q^s + \sum_{i \in EV} \left(b_i^{p,EVc} p_i^{c,EV} + b_i^{p,EVd} p_i^{d,EV} + b_i^{q,EV} q_i^{EV} \right) \tag{1}$$

$$\sum_{k \in \Phi(i)} \left(p_{ki}^f - r_{ki} w_{ki} \right) - \sum_{j \in \Psi(i)} p_{ij}^f = p_i^d - \sum_{i \in EV} \left(p_i^{c,EV} - p_i^{d,EV} \right), \forall i \in \frac{N}{N_f} : \left(\lambda_i^p \right) \tag{2}$$

$$\sum_{k \in \Phi(i)} \left(q_{ki}^f - x_{ki} w_{ki} - \sum_{j \in \Psi(i)} q_{ij}^f = q_i^d - \sum_{i \in EV} q_i^{EV}, \forall i \in \frac{N}{N_f} : \left(\lambda_i^q \right) \right. \tag{3}$$

$$p_i^g - \sum_{j \in \Psi(i)} p_{ij}^f = p_i^d - \sum_{i \in EV} p_i^g, i \in N_f \tag{4}$$

$$q_i^s - \sum_{j \in \Psi(i)} q_{ij}^f = q_i^d - \sum_{i \in EV} q_i^g, i \in N_f \tag{5}$$

$$u_i - u_j = 2\left(r_{ij} p_{ij}^f + x_{ij} q_{ij}^f \right) + \left(r_{ij}^2 + x_{ij}^2 \right) w_{ij}, \forall j \in \Psi(i),\ \forall i \in \mathcal{N} \tag{6}$$

$$\left\| 2p_{ij}^f\ 2q_{ij}^f\ w_{ij} - u_i \right\|_2 \leq w_{ij} + u_i \tag{7}$$

$$V_{i,min}^2 \leq u_i \leq V_{i,max}^2 \tag{8}$$

$$0 \leq w_{ij} \leq I_{ij,max}^2 \tag{9}$$

$$p_{i,min}^{EV} \leq p_i^{EV} \leq p_{i,max}^{EV} \tag{10}$$

$$-p_i^{EV} \frac{\sqrt{1-\kappa^2}}{\kappa} \ \leq\ q_i^{EV} \ \leq\ p_i^{EV} \frac{\sqrt{1-\kappa^2}}{\kappa} \tag{11}$$

$$\left(p_i^{EV} \right)^2 + \left(q_i^{EV} \right)^2 \leq \left(S_{i,\ max}^{EV} \right)^2 \tag{12}$$

$$(p^s)^2 + (q^s)^2 \leq (S_{max}^s)^2 \tag{13}$$

where p^s and q^s are the active power and reactive power imported from the transmission network through the substation, respectively; b_p^s and b_q^s are the LMPs at the substation node for active power and reactive power, respectively, $b_i^{p,\ EVc}$ and $b_i^{p,EVd}$ are the bidding prices of active power while charging and discharging the EV (when applicable) and b_i^q is the reactive power from EV i; $p_i^{c,EV}$ and $p_i^{d,EV}$ are the active charging and discharging power and q_i^{EV} is the reactive power of EV i (either charging or discharging); $p_{i,min}^{EV}$ and $p_{i,max}^{EV}$ are the minimum and maximum limits for active power from the EVs (assumed to be equivalent for charge and discharge); $S_{i,max}^{EV}$ is the nameplate power capacity of EV i; p_i^d and q_i^d are the active power and reactive power load demand at node i; p_{ij}^f and q_{ij}^f are the active and reactive power flow in the line from node i to j; $\Phi(i)$ and $\Psi(i)$ are denoted as the sets of parent and children nodes of node i, respectively; r and x are the line impedance; u and w are the variables representing the square of nodal voltage and line current; $V_{i,min}$ and $V_{i,max}$ are the minimum and maximum voltage limits of node i; $I_{ij,max}$ is the maximum current limit of line i-j; S_{max}^s is the power capacity of the substation; and, κ is the power factor of the EVs.

Equation (1) is the objective function that minimizes the total power purchase cost across the entire system. Equations (2)–(5) are the nodal power balance equations in the distribution network. Voltage drop is defined in Equation (6) while Equation (7) is the second order cone-relaxed line flow constraint. Details for the second order cone relaxation can be found in [30]. Equations (8) and (9) set the nodal voltage and line current limits. The operating limits of EVs are provided in Equations (10)–(12). Equation (11) imposes the power factor constraints (i.e., the ratio of real to reactive power), which range from 0.95 lagging to 1.05 leading. The imported power is subject to the substation capacity limit in Equation (13).

2.1.2. PV Addition to Model

For the cases where PV is added to homes with EVs, Equations (1)–(5) are modified to Equations (14)–(18), respectively, and additional constraints (19)–(21) are added:

$$min b_s^p p^s + b_s^q q^s + \sum\nolimits_{i\in EV}\left(b_i^{p,c} p_i^{c,\ EV} + b_i^{p,d} p_i^{d,EV} + b_i^q q_i^{EV}\right) + \sum\nolimits_{i\in PV}\left(b_i^p p_i^{PV} + b_i^q q_i^{PV}\right) \tag{14}$$

$$\sum\nolimits_{k\in\Phi(i)}\left(p_{ki}^f - r_{ki}w_{ki}\right) - \sum_{j\in\Psi(i)} p_{ij}^f = p_i^d - \sum\nolimits_{i\in EV}\left(p_i^{c,EV} - p_i^{d,EV}\right) - \sum\nolimits_{i\in PV} p_i^{PV}, \forall i \in \frac{N}{N_f} : \left(\lambda_i^p\right) \tag{15}$$

$$\sum\nolimits_{k\in\Phi(i)}\left(q_{ki}^f - x_{ki}w_{ki} - \sum\nolimits_{j\in\Psi(i)} q_{ij}^f = q_i^d - \sum\nolimits_{i\in EV} q_i^{EV} - \sum\nolimits_{i\in PV} q_i^{PV}, \forall i \in \frac{N}{N_f} : \left(\lambda_i^q\right)\right. \tag{16}$$

$$p_i^g - \sum\nolimits_{j\in\Psi(i)} p_{ij}^f = p_i^d - \sum\nolimits_{i\in EV} p_i^g - \sum\nolimits_{i\in PV} p_i^g, i \in N_f \tag{17}$$

$$q_i^s - \sum\nolimits_{j\in\Psi(i)} q_{ij}^f = q_i^d - \sum\nolimits_{i\in EV} q_i^g - \sum\nolimits_{i\in PV} q_i^g, i \in N_f \tag{18}$$

$$p_{i,min}^{PV} \le p_i^{PV} \le p_{i,max}^{PV} \tag{19}$$

$$-p_i^{PV}\frac{\sqrt{1-\kappa^2}}{\kappa} \le q_i^{PV} \le p_i^{PV}\frac{\sqrt{1-\kappa^2}}{\kappa} \tag{20}$$

$$\left(p_i^{PV}\right)^2 + \left(q_i^{PV}\right)^2 \le \left(S_{i,\ max}^{PV}\right)^2 \tag{21}$$

where $b_i^{p,PV}$ and $b_i^{q,PV}$ are the bidding prices of active power and reactive power from PV i; p_i^{PV} and q_i^{PV} are the active and reactive power of PV i; $p_{i,min}^{PV}$ and $p_{i,max}^{PV}$ are the minimum and maximum limits for active power from the PVs; $S_{i,max}^{PV}$ is the nameplate power capacity of PV i; and, κ is expanded to cover the power factor of the PVs as well as the EVs.

The dual values, or shadow prices, of the active and reactive power balance equations represent the additional system cost for serving the marginal unit of active and reactive power. Thus, after solving the above distribution-market clearing model, the DLMPs at each node can be obtained as λ_i^p and λ_i^q.

2.2. Determination of VGI and PV Cost and VGI Value

The total package of costs that could be included in a study on VGI is massive and many are non-obvious and complex to calculate. This complexity is owed to the vast number of differing situations that EV owners might find themselves in. Therefore, to begin the calculation of VGI for this study we must first define the condition of the EV owner and explicitly state which costs will and will not be considered.

VGI costs depend on the type of residence that the owner lives in. If the EV owner lives in and owns a single-family home, it is likely that they are responsible for the cost of ownership for an EV charger. However, if the EV owner is a renter, it is likely that their landlord is responsible for the cost of an EV charger. Further, at least currently, if the EV owner lives in multi-family housing they may not pay for the electricity used to charge the car—but then they are also unlikely to be able to benefit from any VGI value the EV provides. Given the complexity and uncertainty of these renter relationships today, this study focuses on a VGI situation that assumes that the EV owner owns the charging infrastructure, is responsible for charging costs, and can benefit from any VGI value associated with energy services.

On the cost side, there is also a potential type of opportunity cost that many EV owners must face if utilizing any VGI strategy—the ability, or lack thereof, to make their next trip. Often referred to as range anxiety, any EV owner implementing a VGI strategy incurs this cost by moving from a single goal in their charging—filling up the battery as quickly as possible—to an optimization strategy that adds a lowest cost charging and/or highest revenue generation target to the goal of filling the battery.

Determining the cost of range anxiety is complex and multi-variable. Several studies have been conducted on this topic, generally with a focus on the cost of charging infrastructure to alleviate these concerns [31–33]. These studies, however, are not particularly useful when it comes to day-to-day charging at home. Therefore, to alleviate the need to calculate these costs we have chosen to ensure a minimum SOC in the vehicle based upon the average daily miles driven by a light-duty vehicle driver in the U.S., which was 36.9 miles as of May 2022 [34], and limit any VGI usage subject to the constraint that enough energy has been added to the battery to account for traveling that distance by 8 AM in the morning, regardless of the initial state of charge of the battery. Although this is an oversimplification, because it ignores changes in week versus weekend and seasonal driving patterns, it is still useful to estimate the relative differences between V1G and V2G.

Finally, the initial capital expense of the vehicle itself is ignored. It may be true that those with more expensive EVs are less inclined to participate in V2G generally, as the associated depreciation on their vehicle due to battery degradation would be higher. However, there is also reason to believe that EV depreciation unrelated to the battery is a function dominated by time from manufacture and miles driven, which is not impacted by battery cycling for V2G. There appears to be a lack of literature that has explored these conjectures—there has been a comparison of EV depreciation to internal combustion engine (ICE) vehicles, but this focused on the aforementioned variables of age of vehicle and miles driven as the drivers of depreciation [35]. There are also a few studies that include the cost of an EV when analyzing the total cost of ownership (TCO) for participation in V2G generally [36,37]. However, these studies focused on V2G alone and therefore do not account for the differing battery cycle pattern between V1G and V2G. Therefore, we assume that marginal depreciation of the EV is solely driven by increased cycling of the battery pack and the associated increase in battery degradation.

On the value side of the ledger the relatively straightforward value to understand is that accrued from charging at times of lower cost energy. In this study it is assumed that all vehicle charging is performed at home so that a "best-case" value of V1G can be calculated. As previously noted, there may also be the ability for an EV operating in a V1G mode to receive some amount of capacity value and value from T&D deferral. However, EVs are a relatively unique resource to the grid in that they are potentially unconnected, or at least connected in different locations, frequently. This makes the calculation of capacity value and T&D value much more complex; however, this behavior and associated challenge is true regardless of VGI operational strategy. Therefore, for simplicity, any capacity and T&D value has been ignored in this study.

In addition to the previously discussed V1G opportunity to charge at lower cost times, V2G adds the ability to sell electricity back to the grid at times of higher energy prices. Additionally, there is also potential for V2G to provide ancillary services, such as frequency regulation. However, the rules allowing a resource to qualify to bid into ancillary service markets varies widely in differing ISO territories in the U.S., the total revenue from these services is <5% of total electricity market revenue in the U.S., and the value of these services has generally been falling over the past decade—even as penetration of renewables has increased [38]. The value of these services is therefore ignored here due to the complexity in calculation and their relatively small value.

2.2.1. VGI Cost Methodology

To calculate the marginal cost of going from V1G to V2G one must first baseline the cost of implementing V1G. For V1G, the costs included in this study only consist of a level 2 EV charger. For V2G, costs will include the cost of a bidirectional level 2 EV charger and costs associated with the increased degradation of the vehicle battery due to additional cycling to provide V2G services. Note that there is also some work highlighting that V1G could degrade battery lifetime due to the potential for extended time spent at a lower SOC [39], but this can be mitigated if the battery is kept at or near room temperature.

The cost to install a level 2 EV charger in the U.S. is highly variable, dependent upon local labor rates, the condition of the home it is to be installed in, and the brand of charger purchased. On average, however, the cost in mid-2022 of an installation was $1100. There are also a wide variety of offerings for level 2 chargers ranging in price from $260–$2100, with an average cost of $833. Both these average values include data on single port and dual port chargers, with the latter being a considerably more expensive option [40].

Bi-directional chargers are a more nascent technology, and it is therefore difficult to pinpoint current costs. Relative to standard level 2 chargers, bi-directional chargers contain an inverter to convert the electricity returning from the vehicle battery from DC to AC. Numerous companies have announced that they will soon offer bi-directional chargers to the U.S. market, but only the Ford Charge Station Pro appears to be for sale currently. Because the Ford offering relies on an inverter internal to the Ford F-150 for DC to AC conversion—a function currently unique to that vehicle—it is not a good representation of the likely cost of a universal bi-directional charger. There are some bi-directional models for sale overseas currently, with the Wallbox Quasar ranging in price from $4500–$8000 depending upon location. There have not been formal price announcements for many of the upcoming offerings, though Emporia Energy has stated that they estimate their cost will be ~$1500 [41].

With a lack of solid data on bi-directional charger costs in the U.S., a more basic assumption on cost must be made. As a bi-directional charger is analogous to a level 2 charger combined with an inverter, here it is estimated that a bi-directional charger cost is the sum of current commercial offerings of these components. The average level 2 charger cost in the U.S. was previously given. For inverter costs, a proxy of the cost of residential solar inverters is used as an estimate. In 2019, SolarEdge had over 50% of the market share for U.S. residential solar inverters [42]. SolarEdge residential inverters can be purchased online for prices ranging from ~$1300–$2800 depending upon size and features [43]. The midpoint of this range is used and added to the average cost of a level 2 EV charger to estimate a bi-directional charger cost of $2883. As power specs appear to generally be similar between level 2 EV chargers and bi-directional EV chargers, it is assumed the cost of installation is the same for both options.

The final cost to consider for V2G is the increased degradation of the vehicle battery due to additional cycling. There are numerous charging and discharging factors that have been found to impact battery lifetime, including battery temperature, SOC, and depth-of-discharge; the impact these factors have varies with battery chemistry and battery life [44]. Therefore, the impact that V2G will have on battery lifetime will vary accordingly with the control constraints and electricity services the owner chooses to provide (e.g., frequency regulation, energy arbitrage).

Generally, increasing the time that the battery is in service increases degradation. For example, ref. [45] utilized an Arrhenius equation model to calculate battery capacity fade for lithium iron phosphate (LFP) batteries and found that daily frequency regulation service increased capacity fade by 14.3%, allowing the battery to serve as a peak shaving asset for 2 h daily increased fade by 22.8%, and allowing both led to 35.6% decreased capacity. Reference [46] uses similar methodologies and finds directionally similar impacts to battery degradation while also finding increased degradation from use of level 2 chargers relative to level 1 chargers, primarily because of the greater amount of energy that can by cycled through the battery with a level 2 charger.

There are more limited studies that physically cycle batteries using patterns similar to what would be seen on the road alongside usage that V2G would entail. In [47] the current dominant EV battery chemistry, lithium nickel-cobalt-aluminum oxide (NCA), was cycled in actual physical tests that mimicked real driving conditions and grid operations. It found that providing V2G services two times per day could bring the lifetime of the battery down to under 5 years while performing V2G services only once per day more than halved the impact V2G had on battery degradation. An older, but similarly constructed, study was performed on LFP, which is becoming increasingly popular in EVs. This study—like the strict modeling efforts above—found battery degradation was most dependent on the total energy cycled through the battery, meaning that V2G again increased the degradation rate of the EV battery [39].

Reference [48] investigated the cost of cycling, inclusive of these degradation modes, using various charging strategies on Li-ion battery. The cases most relevant to the charging strategies proposed for this study find the cost of battery degradation—in one specific case—to be $4.28 when adding 20 kWh to the battery, or $0.214/kWh. The authors note this value changes based upon the SoC and state of health of the battery, the charging power input into the battery, and a host of other factors. While noting the conditions of this case will not—and cannot—match the variety of charging conditions that will be found in this study, this value is used as the baseline degradation value in the cost/benefit comparison between V1G and V2G scenarios.

2.2.2. PV Cost Calculation

To determine what an EV owner with PV on their roof might choose to do with their PV generated electricity it is necessary to calculate the cost of that electricity. To do this, it is assumed that the EV owner has installed PV at the average cost of an installation in San Francisco in March 2023, $3.00/W [49], and can receive the full 30% ITC available in the

U.S. [50]. Additionally, it is assumed that the size of the installation is 6.4 kWDC, which is the median size of a residential solar installation in California for a homeowner making between $100k and $150k per year [51].

NREL SAM 2022.11.21 [52] was used for calculating the LCOE of a residential PV system. The PVWatts model with the Distributed and Residential Owner settings were selected. The typical meteorological year (TMY) file for San Francisco at latitude 37.7771 and longitude −122.42 was chosen to be representative of a general location in San Francisco. Outside of the values defined above, all other parameters were left equal to the default values in SAM. SAM calculated the LCOE of this system, as described, to be $0.092/kWh in real 2023 dollars.

3. Calculation

The model was implemented and case studies were conducted on a modified IEEE 33-node distribution system. The modification includes the addition of EV load and PV production at each node, as relevant per the case descriptions below, coupled with an adjustment to make daily demand equivalent to average daily load shape in the PG&E region in July 2023 [53]. The proposed optimization model was implemented in MATLAB R2024a and Yalmip and solved by Gurobi. The base case of the IEEE 33-node system can be found in [54]. The topology is shown in Figure 1.

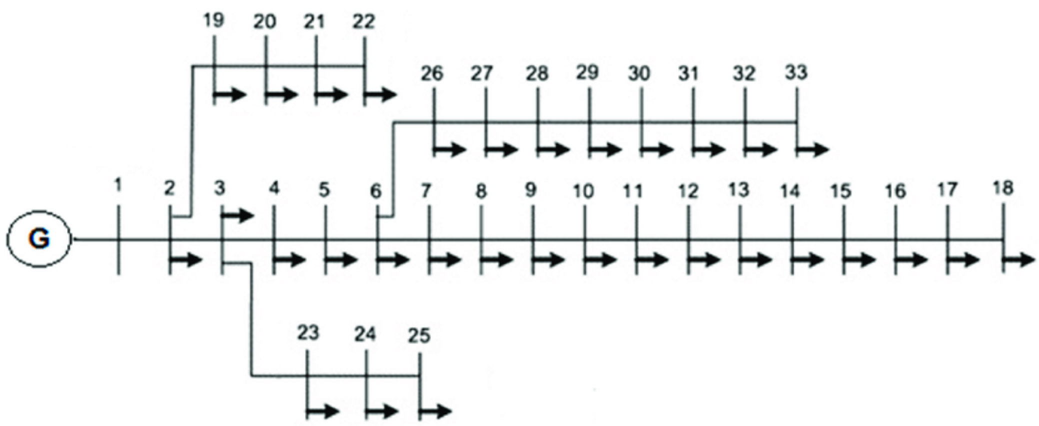

Figure 1. IEEE 33-node Distribution Network.

To baseline VGI value, an initial scenario (dubbed V0G) is run for each case. In this scenario an EV starts charging once plugged in and does not stop until the endpoint charging value is hit (akin to most charging done today in the U.S.). Additionally, to make the case more representative of a potential near future for much of the U.S., the price of electricity available at the substation is defined by the PG&E EV-2A TOU rates as defined in March 2023, which are provided in Table 1 below. Note these rates are much higher than most of the U.S., but the relative pricing of hours given by the TOU schedule is likely representative of TOU schedules that could be implemented across greater portions of the U.S.

Table 1. PG&E EV-2A TOU Rate Schedule [55].

Time of Day	Electricity Price
12 a.m.–3 p.m.	$0.26/kWh
3 p.m.–4 p.m.	$0.46/kWh
4 p.m.–9 p.m.	$0.57/kWh
9 p.m.–12 a.m.	$0.46/kWh

To parameterize EV and PV penetration for the separate cases and scenarios, the number of households at each node in the IEEE 33-node case was defined by looking at the baseline demand at each node and dividing it by the average hourly power consumption of a U.S. household, which was 1.23 kW in 2022 [56]. This U.S. value was used, rather than California, as existing U.S. datasets contain electricity sold by utilities, which omits electricity generation from rooftop solar. This understates residential electricity usage across the U.S., but given the relatively large amount of rooftop solar in California it is likely to be even further impacted by this omission if only looking at data for the state alone. Additionally, this methodology does not account for daily and seasonal demand variance—but as this study is using TOU pricing and focused on the comparison of VGI methodologies this oversight should not bias the results.

The EV characteristics utilized are the equivalent of a Tesla Model Y, which was the EV with the greatest number of unit sales in the U.S. in 2023 [57]. The specific Model Y assumed is the extended range version, which has a battery with 75.0 kWh of usable capacity [58]. Finally, it is assumed that the rate of charge/discharge is limited by the EV charger and we ignore any impacts that battery SOC, environment, or other factors have on real-time power draw or power supply. The charger is assumed to be operating at 240 V and 40 A, for 9.6 kW of power, a relatively common level 2 configuration in the U.S. [59].

In all cases, it is assumed that all EV owners leave their home at 8:00 AM and return home at 5:00 p.m., plug in the EV, and the EV is then available for whichever charging strategy is being evaluated. In all cases it is assumed each individual car is driven 36.9 miles daily, aligned with the daily average driving amount in the U.S. noted above, and that the car is achieving an efficiency of 240 Wh/mi, equivalent to the spec for a Model Y driving in mixed (road and highway) conditions in mild weather [57]. This results in an estimate of 8.86 kWh/day of energy used per day for travel, and in all cases and scenarios this is the amount of net energy the car must be supplied with between the time it returns home (i.e., 5 p.m.) and when it leaves in the morning (i.e., 8 a.m.).

Finally, for V2G scenarios it is assumed that the EV owners bid—and thereby charging-behavior is driven by the TOU rate schedule. The bids ignore potential impacts of congestion as that cannot be predicted before the market clears. The discharge bids do account for roundtrip efficiency losses, however. Therefore, the bid behavior is one where owners only offer to charge their cars when the TOU scheduled rate is \$0.26/kWh and offer to discharge at all other times with higher TOU pricing. Additionally, it is assumed that the battery is at a 50% state-of-charge upon the EVs return home at 5 p.m. and that all existing energy in the battery was charged at an electricity cost of \$0.26/kWh.

4. Results

4.1. No PV Case

In the baseline V0G scenario, the power demanded from the system looks like one would expect—simply a large spike at 5 p.m. when the EVs return home plug in. This spike lasts for a singular hour (Figure 2) as all the power needed for a daily drive cycle can be delivered in one-hour from each individual EV charger. As there is no ability to shift charging time in this scenario, the overall power demand at the 5 p.m. hour increases nearly linearly—with some minor deviation caused by congestion and associated line losses—as EV penetration increases. This behavior limits the system to max out at 78% penetration (i.e., 78% of households have one EV) before the distribution system limitations are no longer able to service any further EV demand.

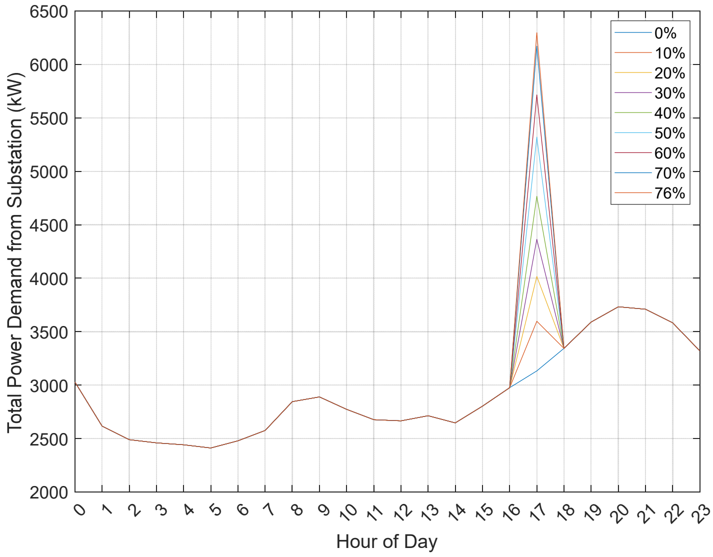

Figure 2. Substation Power Demand, V0G, No PV.

As the substation is the only source of energy supply in this case, nodal DLMPs change little even as EV penetration increases, solely driven by slight increases in congestion along the distribution system. No node shows significantly different behavior, so DLMPs for nodes covering representative points along the length of the system are shown in Figure 3. Note that the hourly pricing differences are driven by the TOU schedule outlined in Table 1.

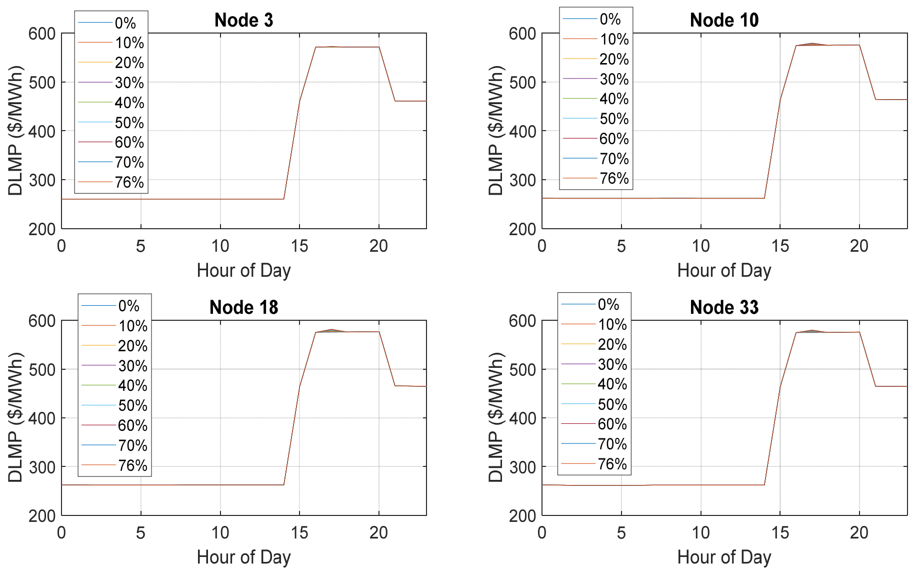

Figure 3. Representative Nodal DLMPs Throughout the Day, V0G, No PV.

Once V1G charging is enabled the demand from the charging vehicles gets evenly spread across the low-cost night hours before the car must leave at 8 a.m. (Figure 4). This allows the system to now reach 200% penetration (i.e., every home has 2 EVs) without any need for system upgrade. Note that further EVs could have been added, but 200% was the chosen end point for this analysis as this is approximately how many cars the average American household owns.

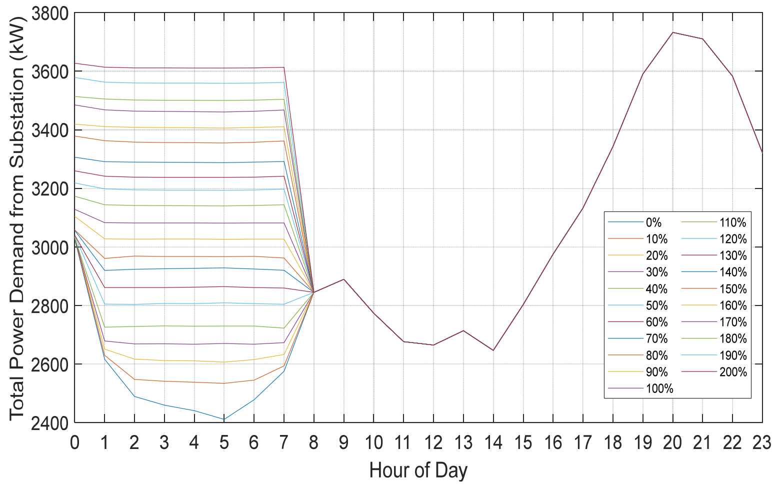

Figure 4. Substation Power Demand, V1G, No PV.

As the substation is still the only source of energy supply in this scenario, nodal DLMPs show little change with EV penetration in the V1G scenario. Similarly to the V0G, No PV scenario, no node shows unique behavior—there still only minor variances node-to-node caused by congestion.Therefore, DLMPs for the same four representative nodes are shown in Figure 5.

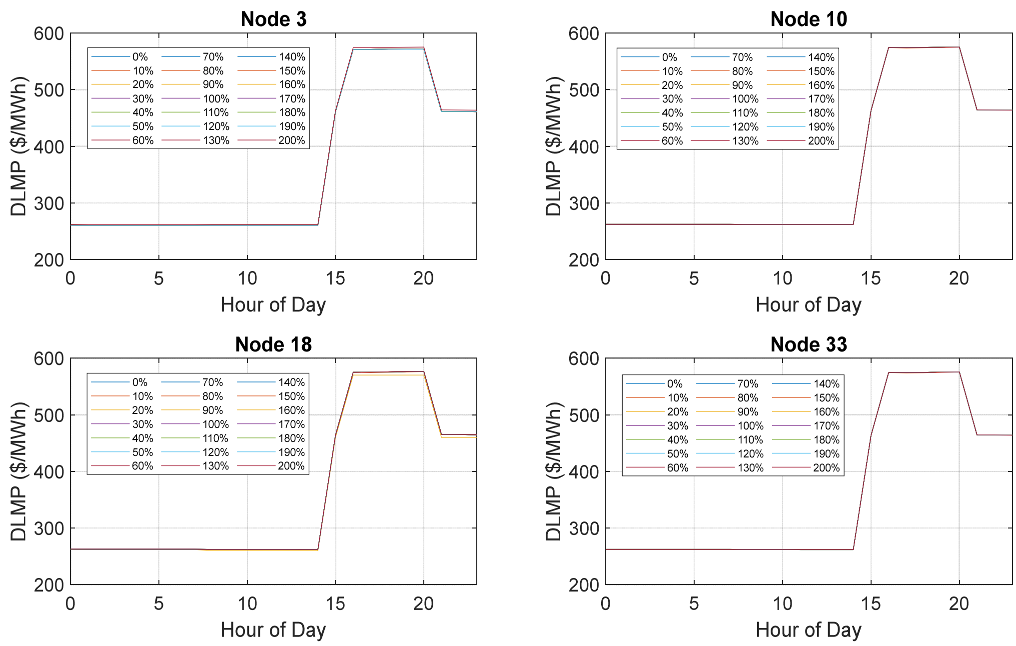

Figure 5. Representative Nodal DLMPs Throughout the Day, V1G, No PV.

When V2G control is enabled, the demand curve for power from the substation changes markedly. As the EV returns home at 5 p.m.. it begins offering electricity—from the remaining energy in the battery—at a price significantly below the evening TOU rate. Therefore, as EV penetration grows evening demand is increasingly serviced by the EVs, with all power demand in the evening delivered by the vehicles once EV penetration hits 80% (Figure 6). To return to the necessary SOC for daily transport at 8 a.m., the EVs increasingly demand power during the low-cost night-time hours. Once EV penetration hits 170%, power demand reaches the maximum delivery capability of the substation during the low-cost nighttime hours. Notably, above this level of penetration the EVs must begin to reduce the evening load they service to ensure that there is enough power available from the substation during the night to meet the daily transport needs for all EVs. As in the V1G, No PV scenario the analysis is stopped at 200% penetration though the system could handle a higher amount of EVs.

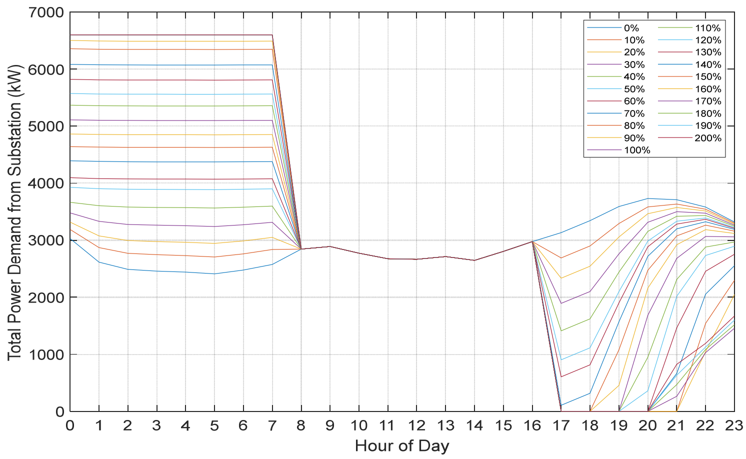

Figure 6. Substation Power Demand, V2G, No PV.

As EVs supply 100% of system electricity demand in the evening hours, they become a portion of the marginal generation and cause a shift in DLMP relative to the prior scenarios. As EV penetration increases, DLMP increasingly falls from the substation TOU prices during these hours to a value closer to that of the bid price from the EV—notably, it does stay above that value as meeting the marginal energy demand requires shifting some portion of total demand to earlier in the day via the EVs. This behavior is similar across all nodes, so there is not significant variation in nodal DLMP in this case either. A representative set of nodal DLMPs for the V2G, No PV case is shown in Figure 7.

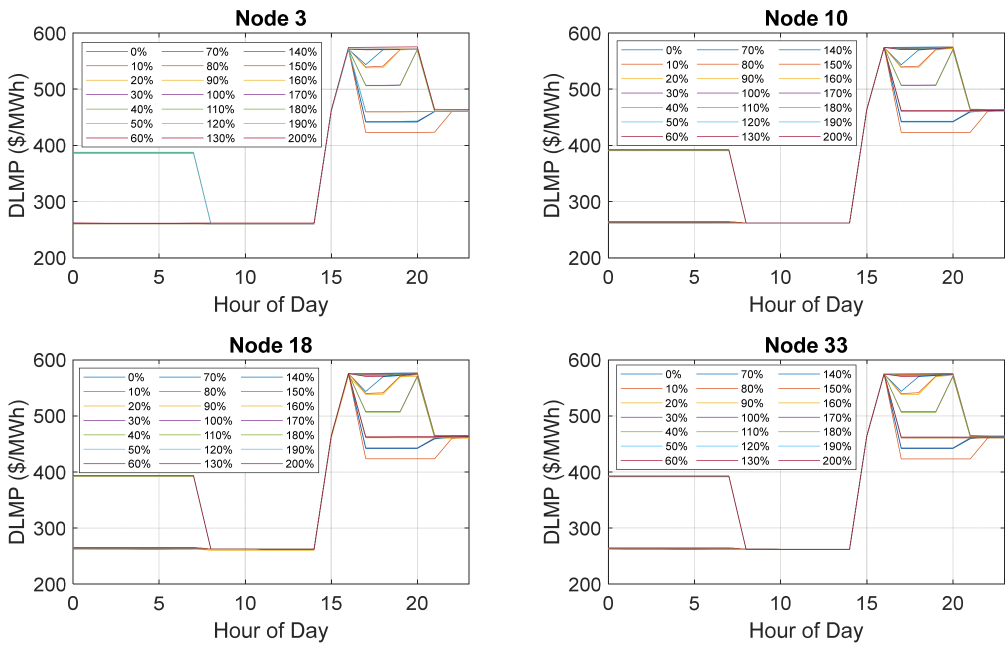

Figure 7. Representative Nodal DLMPs Throughout the Day, V2G, No PV.

4.2. PV + EV Case

In the PV + EV case, the V0G, V1G, and V2G scenarios are repeated with PV installations alongside the EVs. In all cases PV penetration is made to be equivalent to the stated

EV penetration up to 100%, after which EV penetration is increased up to 200% while PV penetration remains fixed at 100%.

In the PV + V0G scenario a similar demand spike to the No PV, V0G scenario at 5 p.m. is found (Figure 8). Additionally, PV demand is found to significantly reduce demand for electricity from the substation during daylight hours as PV penetration increases. However, very little PV generation overlaps with the hours when the vehicle is home and available for charging. Therefore, the EV penetration that can be achieved in this scenario only slightly increases over the correlating scenario with no PV, to 89%, before limitations of the distribution system allow for no more EVs.

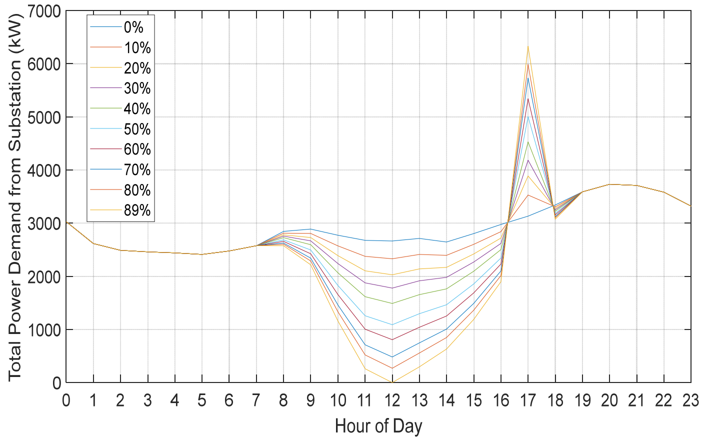

Figure 8. Substation Power Demand, PV + V0G.

Once the PV penetration reaches 89% PV does meet all demand for one hour—otherwise, for all other penetration levels and hours of the day the substation remains the marginal generator. In that singular hour—noon—PV generation drops the DLMP down to the PV price of generation, as seen in Figure 9. In all other hours the substation remains the source of marginal electricity and, therefore, outside of the noon hour at 89% EV penetration the plot of DLMP looks very similar to the V0G, No PV scenario.

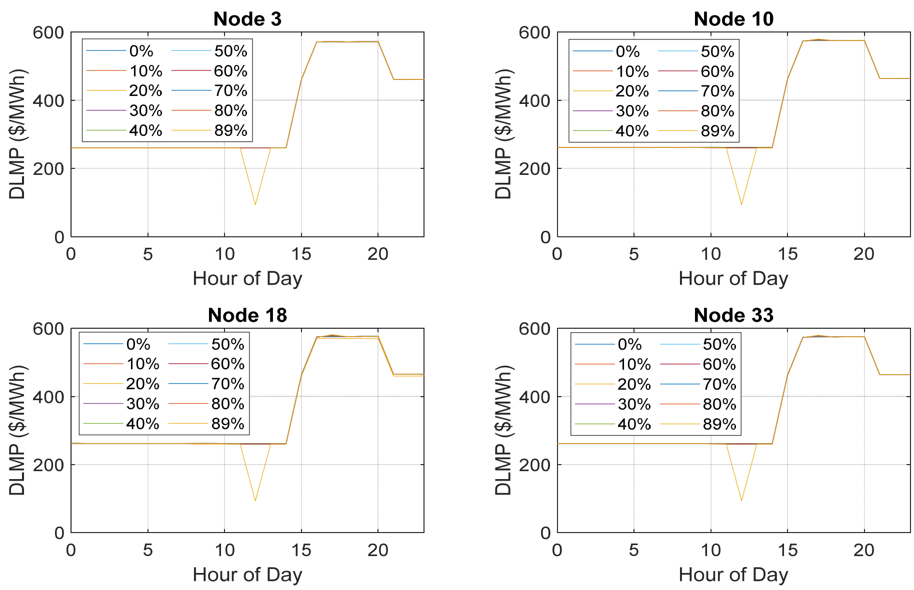

Figure 9. Representative Nodal DLMPs Throughout the Day, V0G + PV.

EV charging in the PV + V1G scenario exhibits similar behavior to the V1G, No PV scenario in that power demand for charging is evenly spread throughout the night (Figure 10). Once 90% PV + EV penetration is reached, PV generation meets all demand during the noon hour. At 100% penetration, PV services all demand from the hours of 11 a.m. to 1 p.m. (note that in cases labeled greater than 100%, only EV penetration exceeds 100% while PV penetration stays at 100%). However, similar to the V0G + PV case, as the EVs are not home to charge during these hours they cannot take advantage of this lower cost energy supply.

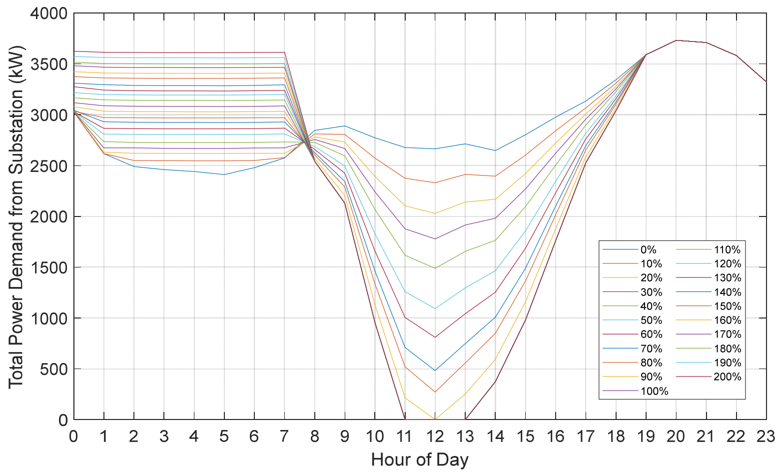

Figure 10. Substation Power Demand, PV + V1G.

DLMP behavior in this scenario is similar to the V1G, No PV as PV becomes the marginal generator only at noon once PV penetration reaches 90% and from 11 a.m. to 1 p.m. when PV reaches 100% penetration. At all other PV penetration levels and at all other hours the substation remains the marginal generator and this is reflected in the resulting DLMP, as seen in Figure 11.

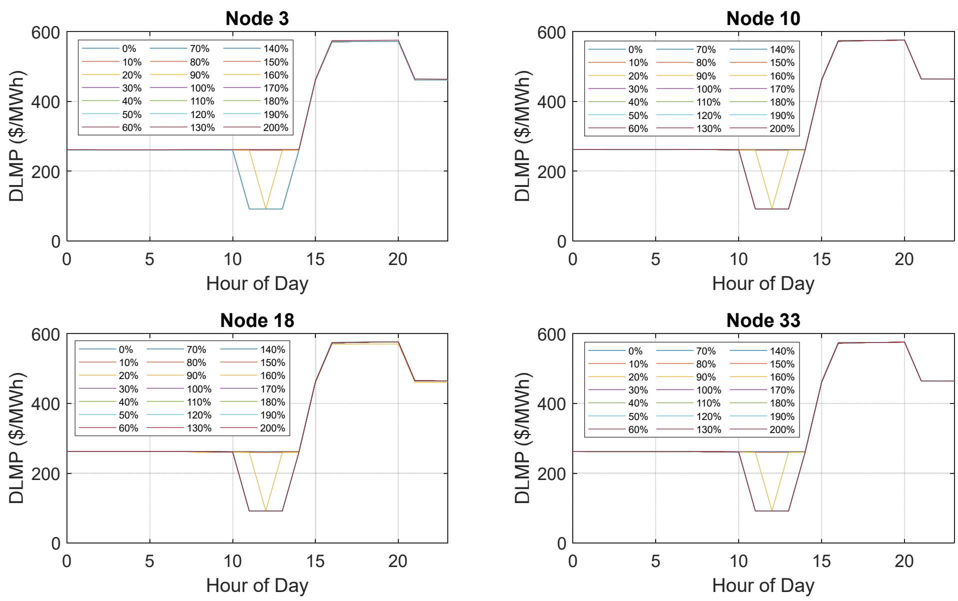

Figure 11. Representative Nodal DLMPs Throughout the Day, V1G + PV.

In the V2G + PV scenario power demand from the substation inverts as EV and PV penetration increases, meaning that peak demand moves from the middle of the day to the night with increasing penetration. As EV + PV penetration increases, demand from the substation is reduced to nearly zero during the day and evening due to PV generation servicing demand during the day and EVs meeting demand during the evening. There is a small spike in substation demand from 2 to 5 p.m. as PV generation subsides and the EVs have not yet returned home. Additionally, as penetration increases nighttime becomes the time of greatest demand for the substation as the EVs take advantage of the lower-cost power, with substation delivery being maxed out during the night once EV penetration hits 170% (Figure 12).

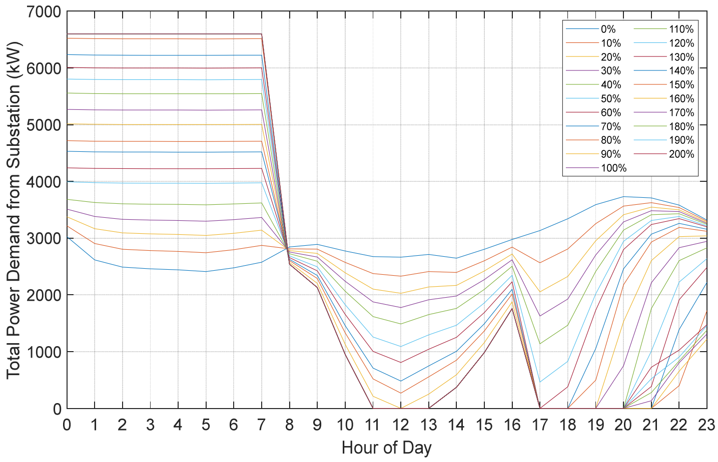

Figure 12. Substation Power Demand, PV + V2G.

In this scenario DLMP behavior essentially combines what is seen in the V2G, No PV scenario with the V1G + PV scenario, caused by PV serving as the marginal supplier during the middle of the day once penetration exceeds 90% and EVs being the marginal supplier during the evening, with nighttime DLMP being driven by the same behavior noted in the No PV, V2G case. We again do not see significant shifts in DLMP behavior across the nodes and representative nodal DLMPs for this case are shown in Figure 13.

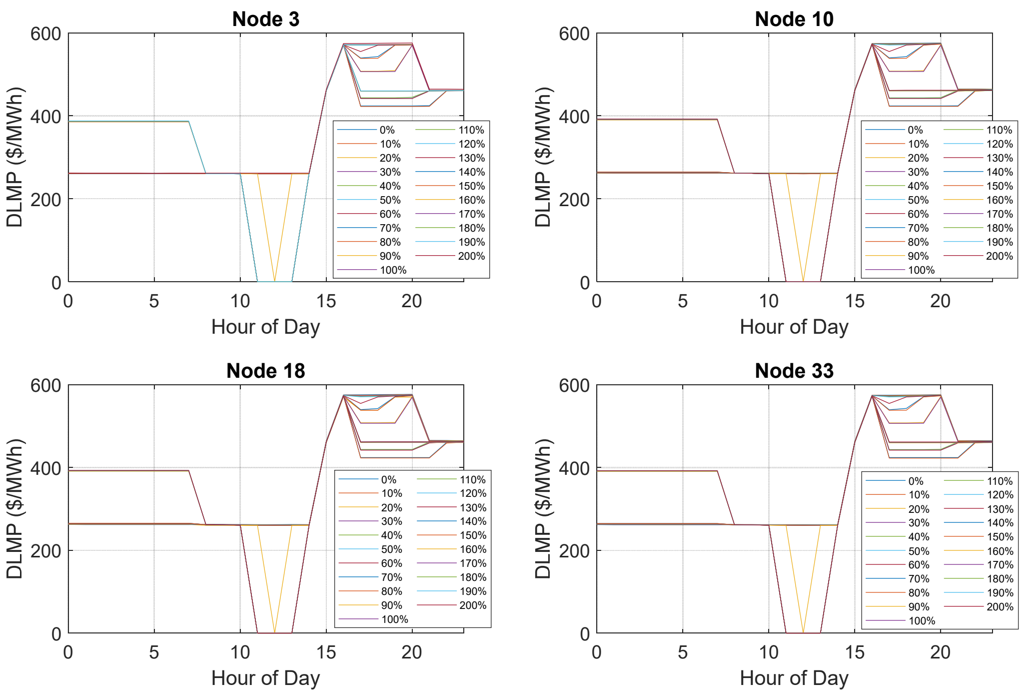

Figure 13. Representative Nodal DLMPs Throughout the Day, V2G + PV.

In comparing the No PV scenarios (Figure 14), it is clear that the addition of PV reduces total system cost generally and that V1G reduces total system cost relative to V0G. However, in each of the V0G and V1G scenarios without PV total system cost increases linearly with

EV penetration increases. In the V2G, No PV case, however, V2G implementation reduces total system cost relative to the corresponding V1G scenario with costs actually falling until EV penetration reaches 100%. After this point system cost does start to increase, though it stays below the baseline system cost (i.e., 0% EV penetration) even as penetration rises to 200%. This behavior is a clear result of the arbitrage behavior V2G allows, replacing more expensive evening electricity with lower cost nighttime electricity.

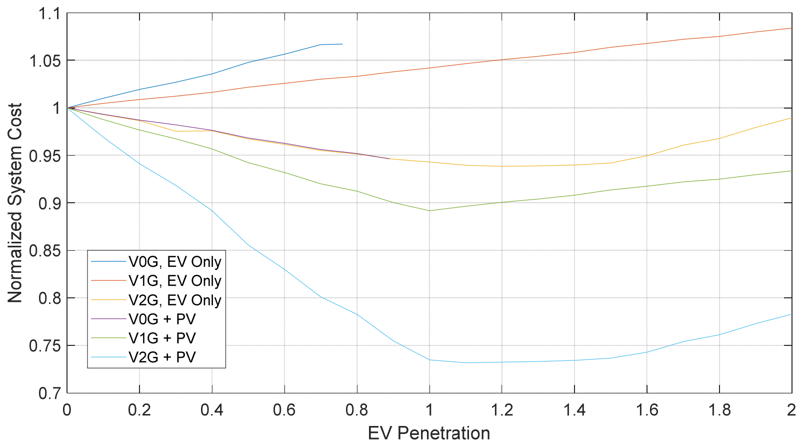

Figure 14. Normalized System Cost.

For the V0G and V1G scenarios with PV, costs fall with increasing PV penetration until 100% of rooftops have PV. In the V1G scenario, after 100% penetration no more PV can be added and, therefore, costs begin to increase due to the increase in power demand from the EVs—though costs do stay below the initial baseline level. The V2G scenario sees cost fall even more deeply almost entirely due to EV driven arbitrage—as the time of EV availability does not significantly overlap with PV generation V2G capability only enables a negligible amount of additional PV generation. V2G scenario cost is essentially flat from 100% to 160% EV penetration before a mild increase up to about 78% of the baseline cost when EV penetration reaches 200%.

A cost-to-benefit ratio for the implementation of V2G relative to V1G in the No PV scenario is shown in Figure 15 from the perspective of an individual EV owner. This analysis assumes a 5-year ownership period for the vehicle, assumes that cycling behavior each day over that time is identical to the single day calculation here, and the calculation is performed using nominal cash flows. The Base Case has the costs for a level 2 charger and battery degradation as previously specified. Given the uncertainty of current bidirectional EV charger cost, two additional cases were run that parameterize this cost. The Mid Case assumes the cost premium is reduced by half and the Parity Case assumes that a bidirectional level 2 charger is at cost parity with a current standard level 2 charger.

In the Base Case, the increased cost in battery degradation coupled with the cost of a bidirectional charger results in costs exceeding benefits by at least 1.39 times, with the cost-to-benefit ratio rising as EV penetration increases due to EV competition reducing the electricity arbitrage opportunity for each individual vehicle. The Mid Case finds costs exceed benefits by at least 1.3 time and the Parity cases reduces the cost-to-benefit ratio even further, but it remains greater than 1.2 for all EV penetrations. The ratio also rises with EV penetration in each of these cases, for the same reason specified for the Base Case. As previously noted, in the scenario with PV the V2G case allows for a minimal amount of additional PV generation—no more than 380 kWh, or less than 1% of total demand, over the course of the day at any level of EV penetration. Therefore, the cost-to-benefit ratio is largely unchanged in the PV scenario.

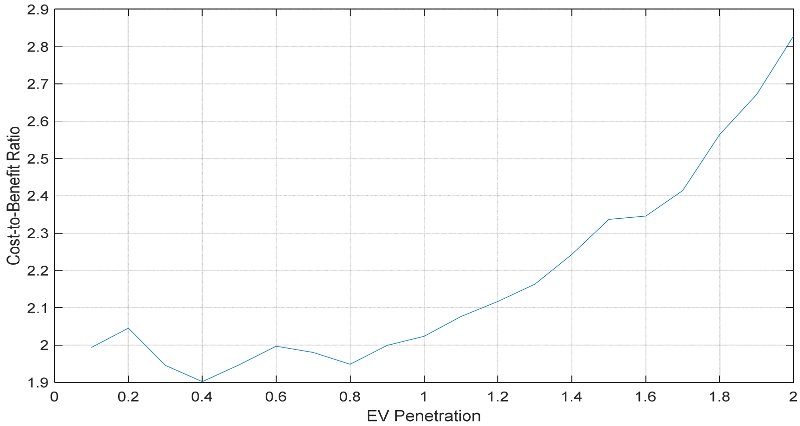

Figure 15. V2G, No PV Cost-to-Benefit Ratio.

5. Conclusions

This study utilized a novel ACOPF model to examine the relative value of V1G and V2G charging strategies for EVs located in residences with and without solar PV. The model utilizes numerical values for energy and equipment cost based upon recent data for San Francisco, CA, for the U.S., and for real equipment as appropriate, whereas much of the existing literature uses assumed values for some or all of these inputs. The value streams available to EV owners were also based upon their general current ability to access these streams and do not include benefits that cannot be received by EV owners, unlike much of the current literature. These considerations are input into the model so that we can evaluate whether the additional cost required to implement a V2G strategy is sufficiently compensated by the additional value it can provide. Within the limitations of the study assumptions, it is found that the cost to implement V2G, relative to V1G, is roughly 1.2 times or greater than the benefits captured even under the most optimistic scenarios for V2G implementation cost. This presents a challenge for the grid of the future, as many citing the promise of V2G rightly note the lower overall system costs enabled by its implementation—consistent with the findings here—without fully considering the cost of implementation to the asset owners.

While we view this study to be grounded in the real-world at a greater extent than much of the existing literature, there are still limitations to the approach taken. For example, this work has focused on energy price conditions in San Francisco, CA and the use of other geographies or market conditions could change the magnitude of the V1G to V2G comparison, though we believe that the overall conclusion is robust across most geographies given the level of commonality among current energy market structures in the U.S., Europe, and Australia. Additionally, this study utilized simplified assumptions of driving behavior and only considered EV ownership from the perspective of a single-family homeowner. To improve the fidelity of the study to real world behavior, future studies could include more real-world informed driving patterns (and, by association, EV availability) as well as expand the EV ownership structures represented in the study. Finally, including other potential value streams such as ancillary services may improve fidelity of the analysis, though the relatively small value of these services and the limitations to EV owner access to these value streams is unlikely to change the conclusion found here. With that said, expansion of the study fidelity and validation or refutation of these beliefs are interesting areas for future research.

Author Contributions: Conceptualization, J.S. and U.C.; methodology, J.S. and A.R.; soft-ware, J.S. and A.R.; formal analysis, J.S.; investigation, J.S.; data curation, J.S.; writing—original draft preparation, J.S.; writing—review and editing, U.C.; supervision, U.C. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ACOPF	AC Optimized Power Flow
CO2	Carbon Dioxide
DER	Distributed Energy Resources
DLMP	Distributed Location Marginal Pricing
DR	Demand Response
EV	Electric Vehicle
HiGRID	Holistic Grid Resource Integration and Deployment Tool
ICE	Internal Combustion Engine
ISO	Integrated System Operator
LDV	Light-Duty Vehicles
Li-ion	Lithium-ion
LMP	Locational Marginal Pricing
PHEV	Plug-in Hybrid Electric Vehicles
PV	Photovoltaics
NEM	Net Energy Metering
NREL	National Renewable Energy Laboratory
RTO	Regional Transmission Operator
SAM	System Advisor Model
SOC	State-of-Charge
T&D	Transmission and Distribution
TCO	Total Cost of Ownership
TOU	Time-of-Use
V1G	Smart charging
V2B	Vehicle-to-Building
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home
VGI	Vehicle Grid Integration
VPP	Virtual Power Plant
VRE	Variable Renewable Energy

Nomenclature

$b_i^{p,\ EVc}$	bidding prices of active power while charging and discharging EV i
$b_i^{p,EVd}$	bidding prices of active power while discharging EV i
$b_i^{p,PV}$	bidding prices of active power from PV i
b_i^{q}	reactive power from EV i
$b_i^{q,PV}$	bidding price of reactive power from PV i
b_p^{s}	LMP at the substation node for active power
b_q^{s}	LMP at the substation node for reactive power
$I_{ij,max}$	maximum current limit of line *i-j*

$p_i^{c,EV}$	active charging power of EV i
$I_{ij,max}$	maximum current limit of line *i-j*
$p_i^{c,EV}$	active charging power of EV i
$p_i^{d,EV}$	active discharging power of EV i
p_i^d	active power load demand at node i
$p_{i,max}^{EV}$	maximum active power limit for EV i
$p_{i,min}^{EV}$	minimum active power limit for EV i
p_{ij}^f	active power flow in the line from node i to j
p_i^{PV}	active power of PV i
$p_{i,max}^{PV}$	maximum limit for active power from PV i
$p_{i,min}^{PV}$	minimum limit for active power from PV i
p^s	active power imported from the transmission network through the substation
q_i^d	reactive power load demand at node i
q_i^{EV}	the reactive power of EV i
q_{ij}^f	reactive power flow in the line from node i to j
q_i^{PV}	reactive power of PV i
q^s	reactive power imported from the transmission network through the substation
r	resistance portion of line impedance
$S_{i,max}^{EV}$	nameplate power capacity of EV i
$S_{i,max}^{PV}$	nameplate power capacity of PV i
S_{max}^s	power capacity of the substation
u	square of nodal voltage
$V_{i,max}$	maximum voltage limit of node i
$V_{i,min}$	minimum voltage limit of node i
w	square of line current
x	reactive component of line impedance
λ_i^p	active power DLMP at node i
λ_i^q	reactive power DLMP at node i
κ	EV and PV power factor
$\Phi(i)$	parent node of node i
$\Psi(i)$	children node of node i

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