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Research paper

Risk-informed evaluation of delivery fleet electrification and vehicle-to-grid economics

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ABSTRACT

Commercial fleet electrification offers various cost optimization options, from smart charging to vehicle-to-grid (V2G) services. The optimal configuration is a function of a particular fleet's attributes and travel obligations. Comprehensive cost-benefit analyses are crucial, considering all costs and uncertainties in the changing electricity market. However, prior fleet electrification studies do not sufficiently capture market-based cause-and-effect relationships in estimating fleets' V2G capabilities and revenues. This study addresses gaps in prior research by using a risk-informed Monte Carlo modeling framework to evaluate electrification costs and benefits under operational uncertainty and changing market conditions. The framework incorporates stochastic optimization for fleet frequency regulation decisions, revenues, and operating costs across seasons and rate designs. By considering market risks, demand charges, and travel needs, the model produces more realistic outcomes. Applying this framework to commercial delivery fleets in California, various electrification options are analyzed and compared to internal combustion engine vehicles (ICEVs), under different market scenarios. Key findings include: (1) V2G frequency regulation revenues are less lucrative than suggested by other studies, providing only marginal benefit (<4 %) over smart charging in some cases when fleet risk and travel obligations are considered (2) Vehicle-to-building (V2B) arbitrage and peak providing 5–6 % and up to 29.8 % operational savings, respectively, relative to smart charging baselines (3) Favorable electrification economics relative to ICEVs, achieving cost parity within 2–3 years and net present costs up to 30–40 % lower. Sensitivity analysis reveals that mileage, energy and vehicle prices, and maintenance costs most influence lifetime costs, while the impact of factors like demand charges and depot load size varies based on the fleet's service type. These findings have significant implications for fleet electrification strategies. Fleet managers should prioritize smart charging and carefully evaluate V2G investments and market structure, given their potentially limited returns. The substantial benefits of V2B services, especially peak shaving, suggest these should be key considerations in electrification planning. Policymakers and utilities can use these insights to develop more effective supportive frameworks and incentives for fleet electrification, focusing on approaches that offer consistent benefits across various scenarios. The robust economic advantage of electric fleets over ICEVs supports accelerated electrification efforts, even in the face of market uncertainties.

1. Introduction

1.1. Background

1.1.1. Commercial fleet electrification

On-road emissions from medium- and heavy-duty vehicles generated 7 % of U.S. greenhouse gases (1555 Million Metric Tons of CO2 equivalent) in 2020 (U.S. EPA, 2022). With many of these vehicles servicing growing logistics industries, transportation emissions pose substantial risks to both the environment and corporate supply chains. For instance, Accenture estimates that global demand for last-mile parcel deliveries will increase by ~78 % by 2030 (from 2021). With no technical interventions, this would result in a ~32 % increase in carbon emissions from urban delivery traffic (Accenture, 2021). Meanwhile, with mounting interest from consumers and financial institutions alike, pressure for large corporations to decarbonize supply chains and operations has never been greater (Clifford, 2022; U.S. SEC, 2022).

Likewise, several companies with large logistics operations have chosen to electrify their vehicle fleets, the benefits of which are twofold.

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Nomenclature

Symbol / Acronym	
EV	Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
V2G	Vehicle-to-Grid
V2B	Vehicle-to-Building
NPC	Net Present Cost
RV	Random Variable
SOC	State of Charge
RU, RD	Regulation Up, Regulation Down
VMT	Vehicle Miles Traveled
OPDC	Off-Peak Demand Charge
SCC	Social Cost of Carbon

(1) Fleet owners are reducing their scope 1 (direct) emissions, and (2) They are reducing the scope 3 (indirect, supply chain) emissions of their customers. To date, fleet electrification has been most prevalent among last mile delivery vehicles, whose predictable schedules and relatively short routes (i.e. lower upfront cost) make them appealing, measurable investments. For instance, Walmart and FedEx plan to have fully electrified delivery fleets by 2040 and Amazon has ordered and committed to have 100,000 electric delivery vehicles on the road by 2030 (Amazon, 2023; "BrightDrop Announces Walmart, FedEx Orders," 2022).

While fleet strategy and economics may be well-established for large, multi-national corporations, the path forward is less certain for smaller fleet owners. Electric Vehicles (EVs) generally have lower operating costs and offer long-term savings via reduced fuel and maintenance expenses, but the initial capital outlay can be a barrier. There are also concerns regarding how concentrated EV charging sessions may impact electricity costs and bottom lines at the commercial scale, as traditional peak demand charges (intended to recover fixed delivery costs) can make up over 70 % of a bill for EV charging stations (CleanEnergyGroup, 2017; Fitzgerald and Nelder, 2019). Smaller fleet owners often operate on tight budgets and may be hesitant to make substantial investments without clear financial incentives or a comprehensive understanding of the potential return on investment. To this end, there are several means by which fleet owners can enhance their bottom lines.

1.1.2. Smart charging

For one, managed or "smart" charging programs have a very low barrier to entry. With smart charging, fleet owners can automatically schedule charging sessions to align with the most cost-effective time-of-use (TOU) electricity rates while considering the vehicles' operational needs, other electric loads (i.e. the demand profile of a depot housing the vehicles), and demand charges. Smart charging also enables fleets to participate in demand response programs, which compensates customers for reducing their electricity consumption during periods of high demand in the broader power system. This helps alleviate strain on the grid and promotes grid reliability (Hale et al., 2035). Similarly, utilities like Pacific Gas & Electric (PG&E) company in California have begun offering electricity rates tailored to commercial fleets ("PG&E Fleets: Business EV Rate Calculator," n.d.).

1.1.3. Vehicle-to-grid services

Another option for commercial fleets is to provide Vehicle-to-Grid (V2G) services. Fleets are compensated for delivering peak shaving and ancillary services to the power system, which augments system stability and can reduce long-run costs (Kempton and Tomić, 2005; Owens et al., 2022). Likewise, they can also provide local peak shaving services (i.e. a building's), behind the meter, which is known as vehicle-to-building (V2B) or vehicle-to-X (V2X). A detailed overview of V2X services and value streams is provided in a review by Thompson and Perez (Thompson and Perez, 2020). Commercial fleets are particularly attractive as V2G and V2B assets given their large batteries, predictable schedules, and overnight co-location. Frequency regulation is seen as a profitable and practical V2G service for commercial fleets due to its low dispatch and cycling requirements (Owens et al., 2024). This is critical to both fulfilling travel obligations and ensuring battery pack longevity. Peng et al. offer a review of studies demonstrating that EVs participating in frequency regulation can increase revenue and savings to helping offset initial electrification expenses (Peng et al., 2017). V2B, on the other hand, offers potential savings via aggregate load peak reduction. A fleet's V2B potential, however, is a function of both travel obligations and when it charges relative to the peak.

Furthermore, the implementation and economic viability of V2G services are significantly influenced by the evolving regulatory landscape and grid codes. In the United States, while there is no comprehensive federal regulation specifically for V2G, the Federal Energy Regulatory Commission (FERC) has issued orders that impact V2G implementation. Order 841 removed barriers for energy storage resources to participate in wholesale electricity markets, while Order 2222 allowed distributed energy resources, including electric vehicles, to aggregate and participate in regional wholesale energy markets (Federal Energy Regulatory Commission, 2018; Zhou et al., 2020). At the state level, California leads with its Rule 21, which sets standards for interconnection, operation, and metering of distributed generation systems, including V2G (California Public Utilities Commission, n.d.). Other states like New York and Massachusetts are developing their own V2G pilot programs and regulations (Commonwealth of Massachusetts Electric Vehicle Infrastructure Coordinating Council, 2023; National Grid, n.d).

Internationally, the European Union is working on standardizing V2G technologies and regulations across member states, with the European Network of Transmission System Operators for Electricity (ENTSO-E) updating its grid codes to accommodate V2G (ENTSO-E, 2021). The United Kingdom is actively promoting V2G through various pilot projects and regulatory sandboxes (Aydın and Yardımcı, 2024). Japan, a pioneer in V2G technology, has supportive regulations in place and widely adopts the CHAdeMO charging standard, which supports bidirectional charging (CHAdeMO, n.d.).

1.1.4. Evolution and state of V2G research

The research landscape of vehicle-to-grid (V2G) technology has undergone a remarkable transformation over the past two decades, evolving from initial feasibility assessments to sophisticated analyses of system-wide impacts. Kempton and Tomić laid the theoretical groundwork for V2G services and economic valuation with their seminal analysis developing frameworks for calculating capacity and net revenue from various grid services (Kempton and Tomić, 2005). This work provided the economic rationale that would shape V2G research for years to come. Soon after, researchers focused on validating V2G's technical and economic potential in real-world contexts. Early real-world feasibility studies of V2G frameworks revealed stark regional differences, with Andersson et al. finding potential revenues of €30–80 per vehicle monthly in German markets with high-capacity payments, while Swedish markets showed minimal to no profit potential due to competition from low-cost hydropower regulation (Andersson et al., 2010). Ma et al. furthered this work by modeling specific power system benefits, demonstrating V2G's ability to reduce both peak loads and operating costs while improving voltage profiles, and highlighting the potential for significant cost savings to vehicle owners through load balancing and optimized energy deployment strategies (Ma et al., 2012). In 2013, the University of Delaware and NRG Energy together became official participants in the PJM Interconnection's frequency regulation market, marking the first time that electric vehicles sold power services to the power grid (Gleason, 2013).

As renewable energy penetration increased, researchers began examining V2G's potential role in grid stability and renewable integration. Pillai and Bak-Jensen provided one of the first comprehensive analyses of V2G integration into an existing power system, studying Western Denmark's grid. Their research demonstrated that V2G could support significant levels of wind power penetration (~50 %) by enabling flexible charging and discharging of electric vehicles, which helped stabilize the grid. They observed that V2G integration could reduce power system operating costs by managing imbalances in renewable generation, though they also highlighted critical challenges such as the need for reliable communication infrastructure and effective aggregation strategies for distributed resources (Pillai and Bak-Jensen, 2011). This work was complemented by Schuller et al., who demonstrated that coordinated EV charging could more than double VRE utilization, but also detecting limitations of limited lookahead periods (Schuller et al., 2015). Likewise, both Carrión and Zárate-Miñano and Nezamoddini and Wang provided key insights into how coordinated EV charging and V2G services could support high renewables penetration by managing the technical risks from uncertainties in wind and solar generation, load patterns, parking patterns and grid reliability (Carrión and Zárate-Miñano, 2015; Nezamoddini and Wang, 2016). The former demonstrated that while V2G services could effectively reduce renewable energy curtailment, the benefits varied significantly based on area type (residential, commercial, industrial) and EV availability patterns. Mehrjerdi and Rakhshani further built upon this for local distribution networks, using stochastic programming to optimize EV charging and discharging in a 33-bus distribution grid and successfully demonstrating how to dampen VRE intermittency while minimizing battery cycling impacts (Mehrjerdi and Rakhshani, 2019).

Direct environmental impact studies emerged as another important research direction. Sioshansi and Denholm demonstrated that V2G from plug-in hybrid vehicles could reduce CO_2 and NOx charging emissions by approximately 31 % and 77 % respectively in the ERCOT grid (Sioshansi and Denholm, 2009). More recently, Zhao and Baker employed life cycle assessment methodology to evaluate V2G's environmental impacts in a future UK system, finding that V2G can effectively mitigate electricity generation's environmental footprint when properly deployed in high-renewable scenarios (Zhao and Baker, 2022).

As V2G research matured, attention shifted toward understanding market opportunities and optimizing economic outcomes for systems and consumers. Among other studies emphasizing control schemes and economic benefits from services like peak shaving (Wang and Wang, 2013) and participation in ramping markets (Zhang and Kezunovic, 2016), Debnath et al. developed an energy storage model incorporating battery degradation costs and transparent cost-benefit analysis for vehicle-to-grid programs. Their approach prevented vehicles from operating at a loss during grid discharge (compared to up to 52 % losses in conventional models) while optimizing system-wide economic dispatch, addressing a key consumer barrier to V2G participation (Debnath et al., 2015). For regional and national electricity markets, Staudt et al. developed a decentralized, local V2G flexibility market heuristic for using V2G to resolve transmission congestion in Germany (Staudt et al., 2018). Their model showed potential congestion cost reductions of 18–56 € per EV, but revealed highly localized benefits, emphasizing the importance of spatial considerations in V2G market design. And while studies show potential for financial V2G benefits being passed onto vehicle owners, Wang et al. warn that previous research significantly overestimates V2G revenues by not accounting for fleet-wide effects and price interactions - their analysis shows that when properly modeling millions of EVs, actual average annual net revenues are modest at $23 to $10 per vehicle, rather than the thousands of dollars suggested by single-vehicle studies, highlighting the critical need to consider long-term market dynamics in V2G planning (Wang et al., 2021).

Finally, research within the last decade has increasingly focused on the complex dynamics of large-scale V2G deployment. Brinkel et al. demonstrate that for a Dutch case study, while grid reinforcements offer electric vehicles more V2G flexibility in minimizing charging costs and emissions, the associated costs and emissions of infrastructure upgrades often outweigh the potential benefits, with higher transformer capacity limits rarely justifying the expenses of transformer upgrades (Brinkel et al., 2020). Another significant advancement in understanding V2G's capabilities in achieving low-carbon energy system targets came from Tarroja et al., who analyzed how different EV charging strategies affect the scale of stationary energy storage needed to reach high renewable integration levels in California. For an 80 % renewable portfolio standard in 2050, they found that immediate charging of PEVs requires an aggregate energy storage system with a power capacity of 60 % of installed renewable capacity and an energy capacity of 2.3 % of annual renewable generation. With smart charging, the required power capacity drops to 16 % and energy capacity to 0.6 %. Most notably, with vehicle-to-grid (V2G) charging, non-vehicle energy storage systems are no longer required to meet the renewable target (Tarroja et al., 2016). Similarly, Nunes and Brito examined V2G's potential to displace natural gas generation for grid stabilization, finding 30 % fleet participation to eliminate the baseline 10.2 % gas generation share in a 2050 Portuguese power system (Nunes and Brito, 2017). Recent capacity expansion modeling by the authors has provided new insight into V2G's long-run value for deep decarbonization, examining its potential to displace both stationary storage and other generators at scale. The analysis of a New England-sized power system demonstrated that participation from just 13.9 % of the light-duty vehicle fleet could displace 14.7 GW of stationary storage, yielding over $700 million in capital savings (Owens et al., 2022).

The current research frontier encompasses several critical areas requiring further investigation: integration of V2G into capacity expansion planning, analysis of V2G's role in deep decarbonization scenarios, assessment of spatial and temporal value variation, development of robust market mechanisms and regulatory frameworks, and investigation of synergies with other emerging technologies like long-duration storage.

1.1.5. Operational considerations of V2G ancillary services

The present work focuses on market opportunities and economic considerations for vehicle fleets offering ancillary services to the grid, particularly frequency regulation. Frequency regulation is dispatched to precisely match generation with load at a high resolution (i.e. seconds). "Regulation-up" is the increase of net power generation, whereas "regulation-down" is storing excess power on demand. These services are contracted both together and separately depending on the power system operator.

In the context of an electric vehicle fleet, an aggregator/operator will typically contract capacity for certain hours in the day-ahead market (e.g. 100 kW of down regulation from 9 to 10 AM, meaning the fleet will provide up to 100 kW of instantaneous excess load when called upon during the hour). In real-time, the aggregator will use onboard controllers to instantaneously adjust the charge and discharge rates of individual vehicles such that the fleet's net dispatch/consumption matches the system signal to maintain the interconnection frequency.

Note that the fraction of contracted capacity dispatched in real-time is stochastic with low autocorrelation (i.e. random), making the net dispatch or charge of energy within an hour highly uncertain (Gehbauer et al., 2020). Hence, there are inherent risks to over-committing capacity in the day-ahead market, including out-of-commission vehicles if batteries are too depleted to fulfill travel obligations and financial penalties if the aggregator does not have enough real-time capacity to fulfill its day-ahead commitments. These risks are elaborated on in 2.4.2. Likewise, fleet operators are likely to hedge capacity commitments to avoid these pitfalls, and so it is critical to capture these considerations in the estimation of a fleet's potential V2G revenues.

1.1.6. The bottom line

With several electrification options available to fleet owners, it is critical for decision makers to have access to rigorous cost-benefit analysis capabilities that fully captures all capital, operational, and external considerations, particularly accounting for future uncertainties and risk considering an ever-changing electricity landscape. The uncertainty and range of future market scenarios (e.g. electricity costs, regulation capacity costs, carbon externalities) are especially key to capture, as charging decisions and financial outcomes can greatly vary from one scenario to the next. Previous studies on fleet electrification and V2G/V2B have not fully addressed these market dynamics. The present work addresses this gap with a systematic, risk-informed cost modeling framework and demonstrates its utility in informing electrification investment strategies for a daytime delivery fleet.

1.2. Prior study of fleet V2G economics and grid integration

To motivate the present work, we first provide context of V2G economic analysis in the literature and where we stand to build upon prior studies. Technoeconomic analyses of commercial fleets have centered on identifying key costs sensitivities and payback periods relative to incumbent diesel and gasoline powertrains. For example, Lal et al. evaluate the total cost of ownership and lifecycle emissions impacts of delivery vehicles with internal combustion engine, battery electric, and hydrogen fuel cell electric powertrains in Germany and California (Lal et al., 2023). Their results indicate that EVs are already cost-competitive in both the studied regions and stand to reduce greenhouse gas emissions by 15 %–48 % over the vehicle's lifetime. Specifically focusing on charging infrastructure and strategy, Hsieh et al. address charging time constraints for electrifying a Beijing taxi fleet and identify several cost-effective options and parity scenarios (Hsieh et al., 2020). A range of other studies have provided insight to the costs and benefits of fleet electrification in different contexts (Barkh et al., 2022; Smith et al., 2020; Zhao et al., 2019). However, these studies do not address the possibility of V2G in their analyses.

Several elements have been identified as key cost and benefit drivers for EV and V2G economics. In a report from the National Renewable Energy Laboratory, Steward delineates the primary physical elements of V2G systems: EVs and their battery assets equipped with bidirectional charging capabilities and software, communications devices enabling interaction with grid operators, and electrical vehicle supply equipment that connects the EV with the grid (Steward, 2017). The author also notes that installed costs can vary significantly from site to site for commercial fleets due to site circuit upgrades and equipment configurations (e.g. on-board or off-board AC-DC conversion, Level 2 vs DC fast charging). As for operational costs, a study by Hill et al. focuses on the risks that fleet operators take on with V2G and identified the extent of accelerated battery degradation as a critical parameter in determining whether different business models are viable (Hill et al., 2012). Thus, it is prudent for future studies to consider degradation and battery replacement scenarios. With regards to perceived benefits and large variations among studies, Heilmann and Friedl performed a meta-analysis of 340 published cases to identify key economic drivers. In addition to identifying peak shaving and frequency regulation as the most lucrative opportunities, the authors find significant financial influence rooted in the availability of vehicle and charging technologies (e.g. unidirectional vs. bidirectional capabilities) (Heilmann and Friedl, 2021).

Among fleet electrification studies that do consider V2G and ancillary services, several evaluate the technology through a systems lens. Coban et al. and Lewicki et al. both examine V2G benefits throughout the Turkish power system, demonstrating technical feasibility and highlighting benefits in stabilizing high renewable penetration rates. The former poses a strategy optimizing for co-optimizing aggregator profits and EV owner energy costs, while the latter compares the costs and benefits of different EV charging and dispatch strategies across the entire power system. However, neither considers uncertainties or changing circumstances at the individual fleet/vehicle level, which often lends to overestimations in fleet flexibility and, ultimately, system performance (Coban et al., 2022; Lewicki et al., 2024).

Others take a bottom-up approach in capturing these costs and benefits on a fleet's financial bottom line. Noel and McCormack analyze the cost and benefits of a V2G-enabled school bus relative to traditional diesel alternatives (Noel and McCormack, 2014). Considering factors like fuel, electricity and battery replacement costs, maintenance, health externalities, and regulation market prices, they find a net benefit is achieved within 5 years for investment in 2014. For scaled, fleet-wide analysis, the authors do not explicitly consider electrical losses or local circuit limitations, meaning the cost model does not capture important limitations that would likely prohibit large fleets capturing the same per-vehicle benefit as smaller fleets. In a separate study by Shirazi et al., the marginal and fleet-wide net costs of school buses providing frequency regulation are examined for a fleet in Philadelphia, PA (Shirazi et al., 2015). Their model captures the impact of seasonality on regulation revenues – as EVs may not reliably provide V2G service at the extremely cold temperatures (thermal limits) coincident with the highest prices. Results indicate that temperature considerations (using a 20 °F cutoff) reduces expected revenues by 22 % relative to the no cut-off case. However, they conduct this analysis irrespective of typical commercial tariff structures and the service limitations demand charges are known to impose. In all, despite valuable advances in methodology, both studies do not consider the implications of (1) Demand charges, (2) Fleet operating risks, (3) Changing electricity markets, and (4) How EV charging and bidding behavior respond to (1)-(3).

Demand charges are imposed by utilities to recoup fixed delivery costs and are typically determined by the peak consumption over a 15-minute period during a one-month billing period. While demand charges recover the cost of infrastructure (i.e. transformer and/or line upgrades) built out to accommodate peak loads, studies indicate that they can inadvertently disincentivize opportune EV charging patterns and V2G strategies by imposing limits when there is not a coincident peak load (i.e. the system cost-driver) straining the system (Fitzgerald and Nelder, 2019; Owens et al., 2024). Further, in consideration of regulation signal uncertainty and primary vehicle duties, fleet owners must also formulate hedged charging and bidding strategies that reflect the operational risks of out-of-commission vehicles (if a vehicle is not sufficiently charged ahead of scheduled departure) and penalties for violating frequency regulation capacity commitments.

To this end, we previously introduced a risk-conscious stochastic optimization to advise fleets on how much regulation service to offer the grid in the day-ahead market and demonstrate that other, deterministic approaches greatly overestimate fleet flexibility and revenue potential. For instance, we demonstrate that while a deterministic formulation (perfect foresight of regulation signal) and its aggressive bid strategy boast 15–20 % lower net costs than the expected stochastic (which bids less) outcome, they do not hold up when faced with random signals. In fact, when exposed to 100 random signals, the fleet violates 40–50 % of its regulation capacity bids commitments in the median case, while the stochastic solution expected to violate less than 1 %. Other results indicate that simple rate modifications like demand charge relaxation or elimination during off-peak, overnight periods can increased V2G activity by 10-fold and net operating saving by 8–20 % in a single month.

Likewise, not accounting for the above and the other considerations discussed in Section 1.1.4, Noel and McCormack and Shirazi et al. both oversimplify calculations of annual V2G revenues (taking the product of hours, capacity offered, and an average, effective capacity price) and thus overstate the benefits to net ownership costs. For instance, mapping the reductions in bid capacity observed between deterministic and stochastic approaches in our prior work (Owens et al., 2024), we would expect potential revenues to be as much as 50–100 % less, depending on the size of the fleet (the upper bound coming from scenarios where a large fleet's charging obligations outweigh the risk of bidding into the market). Furthermore, both studies (using ~15-year horizons) also overlook sensitivities to how electricity and regulation prices may change independent of general inflation. Hence, it is critical that financial analyses of fleet investments take a more measured modeling approach.

These gaps also highlight the critical importance of risk- and price-sensitive models because regulation markets are already quite thin and hypothesized by many to saturate and cannibalize in coming years as more storage projects and distributed energy resources come online (Charles River Associates, 2019; Colthorpe, 2022). For example, Xu et al. point out that the PJM RegD market became saturated in 2016 and that by 2018 its capacity clearing prices had dropped by over two-thirds since 2014 (Xu et al., 2018); and in areas like California, battery projects now provide the majority share of regulation service capacity, from providing ~15 % in 2020 to ~60 % in 2022 (California ISO, 2023). A 2012 study by Hill et al. does reflect ancillary service rate decreases over time (1–3 % annually), but their simplified financial model again does not reflect practical fleet scheduling and tariff (i.e. demand charge) limitations (Hill et al., 2012). Finally, while studies by De Los Ríos et al. and Gough et al. do employ a form of market or bidding model to consider scheduling externalities, neither captures changes to future market conditions (De Los Ríos et al., 2012; Gough et al., 2017). For example, De Los Ríos et al. do not consider the implications of other loads local to the fleet (i.e. a depot) nor demand charges in their revenue simulation model; and further, Gough et al. use vehicle and market models and evaluate revenue sensitivities to regulation and energy prices, but do not evaluate long-run changes. As more renewables and new energy technologies continue to come online, evaluating sensitivities to both utility rates and changes in long-run market conditions is critical to a robust cost-benefit analysis.

1.3. Research questions

Ultimately, we address the following key research questions:

1. What are the effects of demand charges and operational uncertainties on financial V2G benefits?
2. How do potential long-term risks (i.e. market saturation) impact fleet electrification and V2G economics?
3. How do adaptive charging and bidding behaviors evolve with changing market conditions?

Thus, the subject of the present work is to obtain a more accurate assessment of the economic viability of fleet electrification and vehicle-to-grid (V2G) strategies, particularly accounting for future uncertainties in electricity markets and regulatory environments. The scientific aim of this work is to develop a comprehensive, risk-informed cost modeling framework for commercial fleet electrification that fully captures capital, operational, and external considerations. This study extends the existing research in several key ways: by incorporating demand charges, fleet operating risks, changing electricity markets, and adaptive EV charging and bidding behaviors in response to these factors. Furthermore, it addresses the gap in current literature by providing a systematic approach to evaluate long-term investment strategies for daytime delivery fleets considering V2G capabilities, while accounting for the dynamic nature of regulation markets and potential saturation effects. Table 1 summarizes the key similarities and differences of existing literature and the present work.

1.4. Research contribution

This research introduces a novel risk-informed Monte Carlo modeling framework that addresses critical gaps in fleet electrification cost analysis. The key methodological advance is the integration of stochastic optimization to capture how fleets realistically respond to uncertainties in demand charges, regulation market participation, and operational constraints - factors that previous studies have over-simplified or ignored. Unlike prior work that has overstated V2G revenues through deterministic approaches (some by as much as 60–70 %), this framework provides more accurate cost-benefit projections by modeling how charging and bidding strategies adapt to changing market conditions over time.

To demonstrate the framework's practical value, we apply it to delivery fleets in California - a particularly relevant test case given the state's high renewable penetration and significant potential for V2G applications. Through this case study, we evaluate how fleets optimize their charging and bidding strategies under various market scenarios. By analyzing fleet behavior under various electricity cost and frequency regulation market scenarios, we provide more accurate estimates of electrification costs than previous studies which did not account for stochastic elements.

2. Materials and methods

To address questions regarding the effects of demand charges, operational uncertainties, and changing market conditions on fleet electrification and V2G economics, the present work introduces a comprehensive, risk-informed modeling framework. The approach integrates stochastic optimization with Monte Carlo simulations to capture the complex interplay of factors affecting fleet operations and market dynamics. The methodology enables the study of adaptive charging and bidding behaviors under various scenarios, providing insights into the long-term economic viability of fleet electrification and V2G strategies. The following sections detail our analytical approach, beginning with an overview of the modeling framework and progressing through its key components.

Table 1
Attributes of select fleet electrification studies compared to present work.

Study	Total Fleet Cost Analysis	V2G Freq. Regulation	Vehicle-to-Building	Tariff / Price Sensitive Optimization of Cost and Revenues	Stochastic / Risk-Informed Model	Considers Demand Charges	Considers Changing V2G Market
This study	✓	✓	✓	✓	✓	✓	✓
Lewicki et al. (2024)		✓					
Coban et al. (2022)		✓		✓	✓		
Hsieh et al. (2020)	✓						
Gough et al. (2017)		✓	✓	✓	✓	✓	
Shirazi et al. (2015)	✓	✓					
Noel and McCormack (2014)	✓	✓					
De Los Ríos et al. (2012)	✓	✓		✓			
Hill et al. (2012)		✓					✓

2.1. A dynamic, risk-informed modeling framework

The lifetime cost of fleet electrification is evaluated using a comprehensive Monte Carlo simulation approach of the net present cost (NPC). A 15-year investment horizon is evaluated using a 3 % discount rate (Boardman et al., 2018) as a base case. While previous studies have often relied on simplified assumptions about future V2G revenues, our framework introduces a more nuanced and dynamic approach. The framework offers several key innovations over existing methods.

First, unlike deterministic models, our framework incorporates a stochastic charging and V2G strategy model, allowing for more realistic and adaptive decision-making in the face of day-ahead signal uncertainties. Second, the model accounts for changing market conditions over time, providing a more accurate representation of long-term fleet economics. Third, by using Monte Carlo simulations, our method provides a fuller picture of potential outcomes and associated risks, going beyond point estimates. Fourth, the framework explicitly models seasonal variations in electricity prices and regulation markets, capturing important temporal dynamics often overlooked in simpler models. Finally, our model incorporates practical constraints such as demand charges and daily travel obligations, providing results more aligned with real-world conditions. Overall, this integration allows for a more realistic assessment of fleet decisions, seasonal revenues, and annual net operating costs throughout the investment period.

Under the Monte Carlo approach, the NPC is iteratively simulated with randomly assigned model variables that are sampled from external probability density functions. To approximate key cost and scenario uncertainties, the model samples from triangular distributions, which are simple continuous distributions defined by a lower limit, an upper limit, and a mode. The model has both random variables (RVs) and fixed/sensitivity parameters. For example, infrastructure costs are sampled while fleet size is fixed. Given the computational expense of the stochastic charging and V2G simulation being run for 15 years, the electricity and regulation price scenarios are not sampled as continuous RVs, but instead as sensitivity parameters/scenarios. Fig. 1 shows how these pieces fit together. For each scenario, the 15-year horizon of electricity and regulation prices are fed into the stochastic charging and V2G model, which simulates thirty independent seasons (summer and winter each year) and returns annual net operating costs for the fleet to the NPC model. Random, fixed, and sensitivity parameters that do not influence the charging outcomes are fed directly to the NPC model. The formulation and utility of the strategy model is detailed further below. A full accounting of variables, their types, and values is provided in 3.

The computational complexity of our proposed method is primarily driven by two factors: the number of Monte Carlo iterations and the stochastic optimization problem solved within each iteration. The overall complexity scales linearly with the number of Monte Carlo iterations (N), with each iteration involving a full 15-year simulation. Within each year of each iteration, the stochastic charging and V2G optimization problem is solved for 30 representative days (15 summer, 15 winter). This mixed-integer linear programming problem has a worst-case complexity of O(2^n), where n is the number of independent integer variables (n = 20 for the below case study, which uses a 10-hour charging window). In practice, per the sequential algorithm, overall simulation runtime is constrained by the stochastic optimization, taking a representative day approximately 20 minutes to converge using Gurobi 8.1.1 on a cloud computing cluster. For a given case study scenario, the 30 representative days can be run in parallel on the computing cluster.

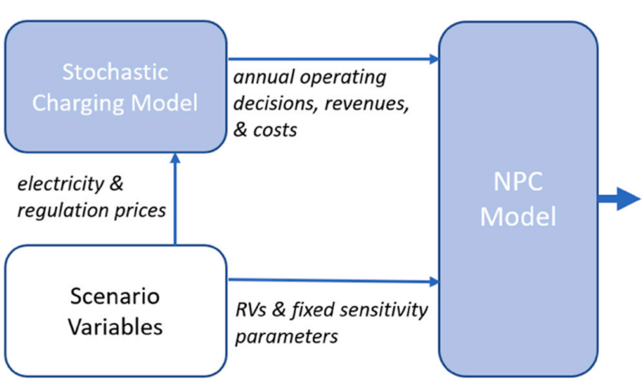

Fig. 1. : Risk-informed modeling framework input and output flows.

2.2. Net present cost calculation

The net present cost (NPC) (Zizlavsky, 2014) of fleet electrification is calculated using Eq. (1):

$$NPC_{EV} = Capital\ Costs + \sum_{y} \frac{Net\ Operating_y + Maintenance_y + Emissions_y}{(1 + discount\ rate)^y} \tag{1}$$

Where *Capital Costs* include the upfront costs of the vehicles, charging equipment, and site upgrades. Annual *Net Operating* costs is the net of V2G revenues minus associated service costs and penalties and energy costs (see 2.4.2). *Maintenance* both vehicle and infrastructure repair fees. Annual *Emissions* costs are derived from the cost of purchasing offsets for vehicle operating emissions, which in this case is the electricity production.

The calculation is similar for determining the NPC of gasoline-powered fleets, using Eq. (2). *Capital Costs* include the upfront costs of just the vehicles and annual *Fuel* and *Maintenance* costs only depend on vehicle mileage.

$$NPC_{ICEV} = Capital\ Costs + \sum_{y} \frac{Fuel_y + Maintenance_y + Emissions_y}{(1 + discount\ rate)^y} \tag{2}$$

2.3. Capital costs: vehicle and infrastructure costs

The fleets modeled in this study are based on the approximate size and make of the last-mile delivery vehicles employed by Amazon and other delivery services. The base case considers a Ram ProMaster Cargo Van for diesel powertrains and Ford E Transit for electric powertrains (68 kWh battery capacity, 126-mile range). Both have ~500 ft^3 storage volumes and retail for $49,495 and $56,000 respectively ("Ford Pro," n.d.; "RAM Trucks," n.d.). The final financed costs are sampled from a triangular distribution 5 % above and below these prices. Varying widely from one state to the next, tax incentives and rebates are not considered in this analysis. While real-time battery degradation is not explicitly modeled, it is reflected as a utilization cost in the charging and V2G model's objective function (see below). Thus, there is no cost assigned to battery replacement in the base case. However, the overall cost sensitivity of a one-time battery pack replacement is examined (conservatively priced at the 2022 cost of 151 $/kWh to account for associated maintenance) (BloombergNEF, 2022).

It is assumed that fueling infrastructure for ICEVs already exists and does not require additional site installations. For electrified fleets, it is assumed that each vehicle is equipped with a ~30 kW three phase charger, having an installed cost of $5,000-$8000. A triangular distribution with a mode, minimum, and maximum of $6500, $5000, and $8000 is sampled in the simulation. For vehicles equipped to perform V2G, there are additional costs of $400 for power electronic and $100 for communications and controls per vehicle (Willet Kempton, personal communication, June 2023).

At scale, it is assumed that fleet electrification will also cost owners in the form of circuit/panel upgrades and even costs of local transformer upgrades passed on by the utility. These can vary significantly from site to site and range from a few thousand dollars for local electric work to over $100,000 if the utility passes on the cost of transformer upgrades to the consumer (this is not the case in California, the location of the case study). In short, these costs are highly uncertain and, whether high or low, are relatively small compared to overall lifetime fleet costs. Thus, they are not included in the NPC calculation for this case study.

2.4. Net operating costs

2.4.1. A generic, fleet and building metering case

The fleet cost model and framework are applicable to a wide range of scenarios. The core formulations are meant to reflect a ubiquitous fleet scenario: a fleet housed at a depot or warehouse. This is because commercial delivery fleets are often co-located with distribution centers and it is thus common for both to be on the same electricity meter, as shown in Fig. 2. From the perspective of the meter (and thus system operator), the building and EV loads are intrinsically linked as the net aggregate load is what drives monthly demand charges. Thus, smart charging fleet strategies and V2B peak shaving can be leveraged to reduce peak demand charges.

As for V2G participation in frequency regulation markets, down regulation corresponds to increased load relative to a baseline and up regulation corresponds to a net decrease of load or injection relative to a baseline. This model assumes that the building load cannot be instantaneously adjusted to dispatch frequency regulation. Therefore, it the EV fleet responds to the dispatch signal. To dispatch down regulation, the fleet can increase its demand, or, to dispatch up regulation, the fleet can inject energy into the building/depot and grid. In dispatching up regulation, the fleet generates more savings by first injecting electricity to the local building/depot (peak load reduction and retail rate savings) rather than directly into the grid (paid the lower, wholesale rate).

If there is no building load or if the fleet is separately metered, the building load profile can simply be set to zero within the model and the formulation will still hold.

2.4.2. EVs: stochastic fleet charging and V2X optimization with seasonality

Here we employ our previously reported stochastic, two-stage charging and ancillary service model to determine optimal charging and regulation bidding strategy, so as to provide realistic expectations of net fleet operating costs in future years and under different market scenarios (Owens et al., 2024).

To contextualize our approach within the existing literature, it's important to note the advancements made by our stochastic, two-stage model. We improve upon studies like that of DeForest et al. by incorporating regulation dispatch uncertainty and potential capacity commitment violations (DeForest et al., 2018). In contrast to De Los Ríos et al. and Gough et al., our model optimizes performance with respect to net fleet profit and captures real-time frequency regulation dispatch, providing a more comprehensive view of performance uncertainty and financial risk (De Los Ríos et al., 2012; Gough et al., 2017). While some studies on EV aggregators, e.g. (Rafique et al., 2022), use similar two-stage stochastic models, our approach is unique in its consideration of commercial rate designs and the linking of daily demand limits within each month, which is crucial for long-term financial performance simulation. These advancements allow our model to more accurately represent the complex decision-making environment faced by commercial EV fleets participating in V2G services.

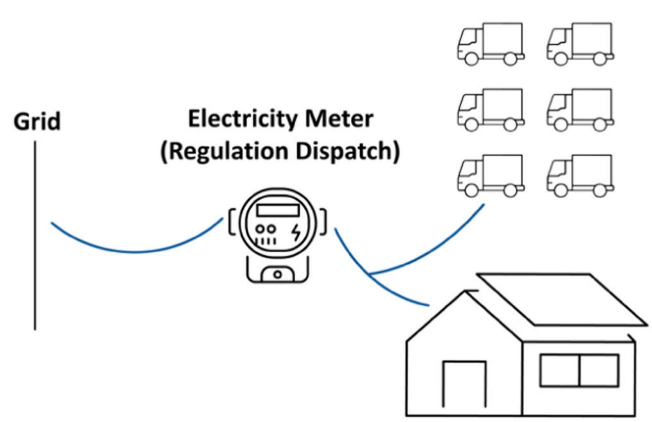

Fig. 2. : Conceptual configuration of an EV delivery fleet and fulfillment depot behind a single meter. (Figure credit: Heather Hodgkins).

The model simulates outcomes for a single month at a time, segmented by day. For each day, the model stages correspond to (1) the day-ahead charging and regulation bid commitments and (2) the real-time charging and regulation dispatch of the contracted capacity. The key uncertainty is the dispatch signal, which is generally random and can vary from 0 % to 100 % dispatch at a 4 second resolution. Making capacity bids that reflect this uncertainty is key to avoiding financial penalties for violating commitments or fleets with insufficient charge for their daily routes. This can happen when, for example, a large quantity of up or down regulation capacity is dispatched for a prolonged period, leaving the EV batteries either too depleted (i.e. cannot provide sufficient up regulation or not enough charge to complete route) or full (i.e. cannot provide sufficient down regulation) for upcoming regulation and travel commitments. If a fleet aggregator does not physically have enough energy to dispatch or free capacity to charge, the shortfall will be covered by a generator in the real-time market and the aggregator will face steep penalties commensurate with the service disruption. It may also have its certification as an ancillary service provider reassessed ("California Independent System Operator Corporation Fifth Replacement Electronic Tariff," 2023). Hence, the model explicitly considers the uncertainty of regulation dispatch and scheduling and energy requirements for travel to inform hedged bidding strategies and real-time charging adjustments that will maximize its ability to fulfill its day-ahead obligations and ensure the EVs can fulfill their primary travel duties.

Model inputs include depot fleet travel parameters and infrastructure information, tariff time-of-use prices and demand charges, hourly regulation prices, and regulation signal data derived from V2G field demonstrations (the key uncertainty). The objective maximizes capacity revenues and peak shaving savings minus costs with respect to regulation signal uncertainty, travel obligations, and day-ahead market commitments, with slack penalty terms for missed SOC targets or unfulfilled capacity commitments. Consistent with the prior California study, capacity commitment and departure SOC target violation penalties are tuned to three times the DA rate and \$0.38/kWh, respectively. The former yields an expected of capacity violations for less than 1 % of hours and at quantities $<<1$ % of contracted capacity. Cost of degradation from increased battery cycling is accounted for in the objective. In simulating the whole month, the model uses a heuristic to approximately link the demand charges across days. Different constraint settings are used to evaluate regulation, V2B, and smart charging scenarios separately. Previous works detail the objective function, formulation, and use cases(Owens et al., 2023; Owens and Gençer, 2023).

In this study, the model is used to simulate two representative months per year, one in the summer and one in the winter (a total of 30 simulated months per modeled scenario). In California, PG&E defines winter as 8 months and summer as 4 months. The outcomes of these two simulations are scaled accordingly to approximate annual fleet V2G activity and net operating costs. Tariff specifications and electricity and regulation prices are exogenous inputs determined by the scenario being explored. Fleet and price scenario specifications are detailed in 3.

2.4.3. ICEVs: gasoline fuel

The on-road efficiency of the Ram ProMaster is sampled annually in the Monte Carlo simulation. Using a triangular distribution, the model is taken to be 14 miles per gallon, with a minimum of 12 miles per gallon and maximum of 16 miles per gallon ("RAM Trucks," n.d.).

Fuel costs are based on the Energy Information Administration's

2023 Annual Energy Outlook projection for motor gasoline prices, including local taxes and fees ("Annual Energy Outlook, 2023," 2023). In the Monte Carlo simulation, a triangular distribution is used to sample the long-run outcome in the West South-Central region. The Reference case, in terms of average annual percent price change over 15 years, is taken to be the mode, while the changes in the Low Oil Price and High Oil Price scenarios are the minimum and maximum, respectively. These price scenarios are further detailed in 3.

2.5. Maintenance costs

Annual delivery vehicle maintenance is priced per mile according to estimates from Argonne National Laboratory (Burnham et al., 2021). The mode cost is \$0.30/mile and \$0.20/mile for ICEVs and EVs, respectively. A 25 % contingency is applied in both directions to establish a distribution.

It is also assumed that the electric vehicle charging infrastructure will require upkeep. A conservative cost of \$300 (\$200 material, \$100 labor) is assumed per charger every five years (Willet Kempton, personal communication).

2.6. Emissions externalities

To remain consistent with capital and operating costs, the model reflects emissions externalities as they are priced in carbon markets. This work uses the clearing price of the California cap-and-trade auction (\$32/mtCO2 as of Q2 2023) and, based on the last 10 years, sample around an assumed 1 % annual increase (California Air Resources Board, n.d.), 0.8 %-1.2 %.

For ICEVs, a carbon cost is assigned to on-road tailpipe emissions. For electric vehicles, carbon costs are assigned to scope 2 electricity emissions. Varying by both time of day and season, CAISO emissions factors are obtained from the Electricity Maps database ("Electricity Maps | Data Portal," n.d.). The seasonal average is computed for each overnight period and the Sustainable Energy Systems Analysis and Modeling Environment (SESAME) is used to project electricity emissions reduction over the 15-year simulation horizon (Gençer et al., 2020). For CAISO in 2022, electricity consumed between 8PM-6AM on-average generated 204.3 gCO_2eq/kWh and 196.7 gCO_2eq/kWh during the summer and winter, respectively. This yields a weighted annual average of 199.2 gCO_2eq/kWh for the first simulated year. Based on SESAME projections, the electricity emissions factor is assumed decline, on average, by 2.38 % per year.

3. Case study and scenarios

This case study examines a commercial delivery fleet in California. By exploring various fleet sizes, charging strategies, and market scenarios, the study provides insights into how adaptive charging and bidding behaviors evolve under different conditions. The following sections detail the fleet scenario, service options, and market projections used in the analysis, enabling the evaluation of long-term economic viability of fleet electrification and V2G strategies in a real-world context.

3.1. Fleet scenario

This case study examines ownership cost outcomes for the same fleet scenario studied in our group's analysis of rate designs in California (Owens et al., 2023). It considers a commercial delivery fleet of varying size, 20–60 vehicles, housed at a depot in California and subject to Pacific Gas & Electric company (PG&E). Both daily mileage and charging windows are based on National Renewable Energy Laboratory's Fleet DNA dataset for delivery vans on daytime routes(National Renewable Energy Laboratory, n.d.). The dataset is comprised of data from 94 reporting vehicles across 974 days. The daily operating of reporting vehicles spans ~10 to ~270 miles, with most individual vehicle operating days spanning 40–80 miles in delivery service per vehicle (the median being approximately 55–60 miles per day). Summary statistics and vehicle-level data are available in the publicly available dataset. In the base case, each vehicle travels 60 miles per day and is made available for charging and other services strictly between the hours of 8PM and 6AM, seven days per week. The ten-hour charging window is derived from the Fleet DNA data, assuming 1-hour margins around periods when most, 70 % in this case, of vehicles are present at the depot. For EVs, each vehicle is assumed to have a dedicated 30 kW charger and require 32.4 kWh of charging in the overnight base case (1.85 mi/kWh for the Ford E Transit). Based on the battery management findings of Kostpoulos et al., an 80 % SOC target is used for the departure set point (Kostopoulos et al., 2020).

The base load profile of the depot is identical to that described in the aforementioned study, modeling California warehouse demand using ComStock for the load profile shape (location-specific details in Fig. 3 caption) and ENERGY STAR consumption data to an 800,000 square foot fulfillment center (ComStock - NREL, n.d; Energy Star, n.d.). The peak load of this profile is 820 kW, and a 1500 kW feeder line limit is applied as a physical constraint. Fig. 3 shows the baseload profile overlaid with the EV charging window in the base case.

As price scenarios are being projected well into the future, the case study scenarios employ a straightforward B-10 schedule from PG&E as the basis for scaling future demand charges and volumetric energy prices. The B-10 schedule has a single, floating demand charge rate for overall peak demand in a 15-minute period and three time-of-use (TOU) rates for volumetric energy consumption (Pacific Gas and Electric Company, 2021). The TOU rates vary with season while the demand charge rates remain fixed. "Summer" rates apply June 1 through September 30 and "Winter" rates October 1 through May 31. The demand rates and relevant TOU charges are detailed in Table 3 below.

3.2. Fleet service scenarios

The outcomes of several charging and bidirectional service strategies available to the EV fleets are studied. As one baseline, the study evaluates the implications of EV fleets going without intelligent, or "smart", charging capabilities and simply charging immediately, at maximum capacity upon returning to the depot. A step up from this is smart charging, for which the EV load is managed, perhaps charging just a few vehicles at a time to keep demand peaks low, to minimize costs. The study separately evaluates frequency regulation and V2B services for vehicles with bidirectional charging. This means that when frequency regulation services are being bid into the market, V2B arbitrage or peak shaving is not explicitly (beyond what occurs in dispatching up regulation) and vice versa. The modeling and optimization of frequency regulation and peak shaving are purposely decoupled to analyze their

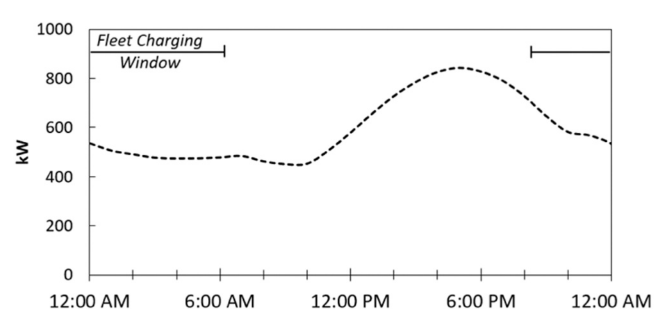

Fig. 3. : Depot load profile and fleet charging window relative to one another. The load shape profile was downloaded from comstock.nrel.gov/dataviewer using the TMY3 dataset from Release 2021_1 (representing the U.S. commercial sector in 2018). The following data viewer filters were applied: Fuel type = electricity, Building type = warehouse, ISO region = CAISO, Month constraints = May to Sep, Aggregation type = Average.

economics independently. Two scenarios are explored for V2B: one for which only price arbitrage is available (the aggregate load peak occurs outside fleet charging hours) and another for which the fleet can shave the overall peak load of the depot. For the latter, a hypothetical case is posed, in which the base load profile (Fig. 3) is simply shifted three hours back to such that the peak coincides with vehicle charging. While it is also possible for additional market participation via V2G peak shaving, the market landscape and compensation are largely unknown, and so it is beyond the scope of the present work.

3.3. Future market scenarios

Regulation and net cost outcomes are assessed as a function of several market scenarios. The base case uses the current PG&E B-10 rates in the first model year and applies an annual inflation rate of 2.26 % (based on historical EIA data for delivered costs to commercial sector customers) to project future years (U.S. Energy Information Administration, n.d.). A high growth rate of 3.39 % (1.5x) is tested as a sensitivity. Specific values are detailed below. Revenue sensitivities to a tariff modification, by which overnight demand charges are eliminated, are also tested. As posited in previous work, timing-independent demand charges can obstruct win-wins for the fleet owners and the grid, as overnight peaks (whether from charging or regulation) are not expected to drive additional local network costs. With no off-peak demand charge (no OPDC, as referred to it here), fleets can shift loads and services more productively (Owens et al., 2023).

As noted in the literature review, regulation markets are at risk of cannibalization in coming years as more energy resources come online and some markets have already experience steep declines in capacity clearing price(Charles River Associates, 2019; Colthorpe, 2022; Xu et al., 2018). However, exact regulation market outcomes remain highly uncertain, and so several cases are considered. In the base cases a −5 % annual capacity price decline is assumed. Additional scenarios include static prices (no change relative to the first year) and a −15 % annual price decline (consistent with the aforementioned PJM saturation and reduction observed by Xu et al. (Xu et al., 2018). In 2022, median CAISO prices during the overnight charging period (8PM-6AM) were 3.09 \$/MW-h and 4.34 \$/MW-h for up regulation and down regulation, respectively. Fig. 4 shows how these change over time in the different scenarios.

3.4. Key parameters, scenarios, and assumptions

The Tables 2 and 3 summarize the discussed model inputs used to simulate vehicle operations and compute net present costs.

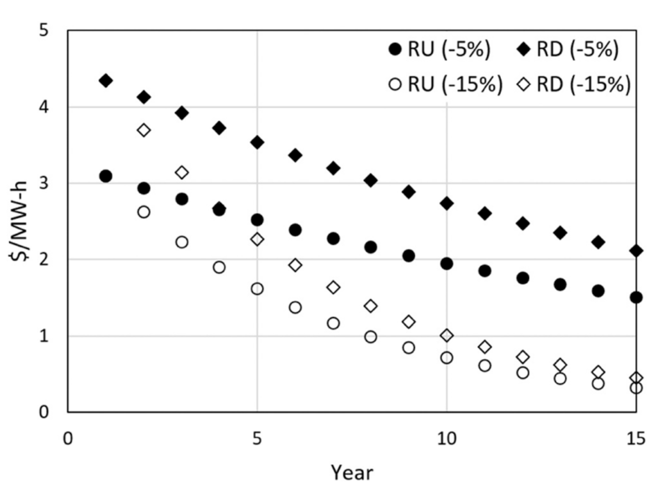

Fig. 4. : Change in regulation capacity clearing price over time for −5 % and −15 % annual capacity price decline scenarios.

Table 2
Key cost and input parameters for simulating costs of ICEV fleets.

Fleet Data					
Parameter	**Type**	**Units**	**Min**	**Mode (base)**	**Max**
Vehicle Cost	RV	2022$	47,020	49,495	51,970
Discount Rate	Sensitivity	%	2	3	6
Vehicle Lifetime	Static	Years		15	
Fuel and Maintenance					
Parameter	**Type**		**Min**	**Mode (base)**	**Max**
Daily VMT	Sensitivity	miles		60	90
Fuel Economy	Static	mpg		14	
Fuel Price	Static	2022$		3.85	
Fuel Inflation Rate	RV	%	−3.2	−1.69	1
Maintenance Rate	RV	$/mile	0.225	0.3	0.375
Externalities					
Parameter	**Type**	**Units**	**Min**	**Mode (base)**	**Max**
Carbon Cost	Static	2022 $/mtCO2		29.15	
Carbon Cost Inflation	RV	%	0.8	1	1.2
Gasoline Carbon Intensity	Static	mtCO2/ gallon		8.89E−03	

In addition to the prescribed base case parameters, several sensitivity scenarios are simulated for each fleet to evaluate relative impact on regulation revenues, operating expenses, and overall fleet costs. Summarized along with the charging and V2G strategies, they are as follows:

Parameter Sensitivities:

- **Base:** All parameters of type "sensitivity" are set to their base values, as indicated in Tables 2 and 3.
- **Static:** Regulation prices change 0 % year over year. All other parameters are consistent with base case.
- **Low Reg:** Instead of −5 %, regulation prices change −15 % year over year. All other parameters are consistent with base case.
- **High Electric:** Electricity inflation rate is 1.5x that of the base case. All other parameters are consistent with base case.
- **No OPDC:** The demand charge is eliminated during EV charging hours (effectively set to 0 \$/kW), coinciding with the off-peak hours for the PG&E system. All other parameters are consistent with base case.
- **High Mileage:** Vehicle mileage is 1.5x that of the base case. All other parameters are consistent with base case.

Charging Strategies

- **Regulation Base:** The fleet bids into the frequency regulation market. All other parameters are consistent with base case.
- **Smart Charging:** The fleet does not provide frequency regulation or V2B services, only optimizes for least-cost charging. All other parameters are consistent with base case.
- **Flat Profile:** The fleet does not provide frequency regulation or V2B services. The charging load is set equal across all hours. All other parameters are consistent with base case.
- **Unmanaged, Immediate:** The fleet does not provide frequency regulation or V2B services. The Fleet charges immediately, at maximum capacity upon returning to the depot. All other parameters are consistent with base case.
- **V2B Arbitrage:** Only price arbitrage is available (the peak occurs outside fleet charging hours) No regulation is performed. With no regulation signal to consider, the average building load profile is assumed known/fixed and the formulation is deterministic. All other parameters are consistent with base case.
- **V2B with Peak Shaving:** Peak shaving and price arbitrage are available. The depot base load profile is shifted such that its peak

Table 3
Key cost and input parameters for simulating costs of electric vehicle fleets.

Parameter	Type	Units	Min	Mode (base)	Max
Fleet Data					
Parameter	**Type**	**Units**	**Min**	**Mode (base)**	**Max**
Vehicle Cost	Sensitivity	2022$	53200	56,000	58800
Charging Infrastructure Costs	RV	2022 $/EV	5000	6500	8000
V2G Infrastructure Premium		2022 $/EV		400	
Infrastructure Maintenance	Static	2022 $/5 yrs		300	
Battery Replacement	Sensitivity	2022 $/EV		0	10,268
Discount Rate	Sensitivity	%	2	3	6
Vehicle Lifetime	Static	Years		15	
Fuel and Maintenance					
Parameter	**Type**		**Min**	**Mode (base)**	**Max**
Daily VMT	Sensitivity	miles		60	90
Fuel Economy	Static	mi/kWh		1.85	
Round Trip Charger Efficiency	Static	%		88	
B−10 Demand Charge, 2022	Static	2022 $/kW		18.65	
B−10 volumetric rates winter, 2022, (8−9)/(9−11)/(11−6)	Static	2022 $/kWh		0.33/ 0.28/ 0.24	
B−10 volumetric rates summer, 2022, (8−9)/(9−11)/(11−6)	Static	2022 $/kWh		0.26/ 0.23/ 0.23	
Electricity Inflation Rate	Sensitivity	%		2.26	3.39
Regulation Prices	Sensitivity	%	−15	−5	0
SOC Target Penalty	Static	2022 $/kWh		0.38	
Capacity Commitment Violation	Static	Multiple of DA Price		3	
Maintenance Rate	RV	$/mile	0.15	0.2	0.25
Externalities					
Parameter	**Type**	**Units**	**Min**	**Mode (base)**	**Max**
Carbon Cost	Static	2022 $/mtCO2		29.15	
Carbon Cost Inflation	RV	%	0.8	1	1.2
Electricity Carbon Intensity, 2022	Static	gCO2eq/ kWh		199.2	
Carbon Intensity Rate of Change	Static	%		−2.38	

occurs over the first two hours of the fleet charging session. No regulation is performed. With no regulation signal to consider, the average building load profile is assumed known/fixed and the formulation is deterministic. All other parameters are consistent with base case.

3.5. Key assumptions and model validation

3.5.1. Key assumptions

The following summarizes key study assumptions regarding market conditions and fleet operations, which are crucial for interpreting results and ensuring reproducibility. The implications of these assumptions, as well as key sensitivities, are addressed in Sections 4 and 5 to provide a more comprehensive understanding of potential outcomes under varied circumstances.

For market conditions, a 2.26 % annual increase in electricity prices is assumed, based on historical EIA data for commercial sector customers. The regulation market is modeled with a base case of −5 % annual capacity price decline, with additional scenarios exploring 0 % and −15 % annual changes to capture potential market dynamics. Carbon pricing is projected to increase by 1 % annually, reflecting trends in California's cap-and-trade program, while demand charges are assumed to remain constant in real terms over the study period. Current policies and incentives for fleet electrification are assumed to remain stable, and competition in V2G markets is expected to gradually increase over time.

Regarding fleet operations, vehicles are modeled as being available for charging and V2G services between 8 PM and 6 AM daily, with a base case daily mileage of 60 miles per vehicle. While this consistent charging window is a simplification of real-world conditions, it allows for clear comparisons across scenarios and is appropriate for this aggregate fleet-level analysis. Exploring variable fleet availability patterns is beyond the scope of this study and is noted as a limitation.

Each vehicle is assumed to have access to a dedicated 30 kW charger. Battery performance and charging efficiency are considered constant over the study period. The fleet size is assumed to remain stable over the 15-year study period, and regular maintenance is presumed to occur outside of the charging window, not impacting V2G availability. Consistent driver behavior with predictable return times and charging patterns, and stable weather conditions year-round are also assumed. Additionally, the model assumes consistent grid reliability without major outages or constraints and perfect market participation is posited when profitable for the fleet.

3.5.2. Model validation and limitations

While the model presented in this study is primarily theoretical, several steps have been taken to validate its components and ensure the accuracy of results. Key components of the model, such as the stochastic optimization for V2G bidding and the Monte Carlo simulation for net present cost calculation, are consistent with against established methodologies in the literature and builds upon previous work by the authors.

Notably, while direct comparisons are challenging due to differences in assumptions and methodologies, the stochastic model's responses to key parameters such as demand charges, local load conditions, and capacity prices qualitatively align with another published model that has informed real-world fleet bidding strategies (Black et al., 2023; DeForest et al., 2018). The model study and pilot project, which focuses on the Los Angeles Air Force Base Electric Vehicle Demonstration project, employs a deterministic mixed integer linear program to optimize daily EV charging and regulation capacity bids. Their model, like ours, incorporates considerations for demand charges, regulation prices, and AGC utilization factors. This alignment with real-world V2G operation provides additional validation for our approach and increases confidence in the relevance of our results to real-world scenarios.

It's important to note that while these validation steps increase confidence in the model's results, the inherent complexity of the system being modeled, and the long-term nature of the projections introduce unavoidable uncertainties. The results should be interpreted as indicative of potential outcomes rather than precise predictions. As presented in 4.7, a comprehensive sensitivity analysis has been conducted to understand the model's response to variations in key parameters. Future work could further validate the model by comparing its projections with real-world data from pilot projects or early adopters of fleet electrification and V2G services.

4. Results and discussion

This section explores regulation market outcomes and operational costs, the dynamics driving them, and their influence on fleets' overall net present costs to their owners.

4.1. Regulation revenues decline with market prices and risk aversion

The annual and lifetime outcomes for fleets participating in frequency regulation market are studied as a function of different market scenarios and fleet flexibility. For each year in the NPC model, representative summer and winter months are simulated in the EV charging/bidding model and results scaled to derive revenue and net operational cost results. As is expected with diminishing regulation capacity prices, Fig. 5 shows an overall trend of annual revenue decline for the base and low regulation price cases. When regulation prices are held static, revenues generally decline to a lesser degree, if at all.

In the first year of the base case simulation (using 2022 market conditions), the 20-, 40-, and 60-vehicle fleets earn $4126, $4275, and $2650, in capacity revenue, respectively. Note that despite the 40-vehicle fleet's capacity resources exceeding that of the 20-vehicle by a factor of two, revenues are of similar order, as the 40-vehicle fleet ultimately faces the added constraint of procuring twice the energy in the same fixed period. In this regard, larger fleets carry more risk when making capacity bids rather than just charging, as they must charge within a limited window of time and be conscious large aggregate load profiles. Over the 15-year observed lifetimes, the 20-vehicle and 40-vehicle fleets earn $36,647 and $38,117 (2022$) in capacity revenue, respectively. The 40-vehicle fleet's overall revenues win out as it has more resources to provide up regulation, which is more lucrative than down regulation, upon first arriving back to the depot when prices are highest. The 60-vehicle fleet, on the other hand, earns significantly less revenue (only $2650 in the first year and $25,574 overall), despite having more grid-connected power and energy capacity to offer.

These differences arise from two factors: high demand charges for large fleet loads and cautious strategies due to uncertain regulation signals. It is also critical to recognize here, across all cases and fleet sizes, the negative synergism of electricity prices (which include demand charges) rising while regulation prices decline. If the demand charge becomes too costly relative to regulation prices, the choice to or risk of (i.e. uncertain dispatch signal) setting a new demand peak outweighs regulation revenues. In this risk-aware model, regulation becomes less attractive. The extent to which this risk-consciousness impacts the fleets' operational costs can be quantified using the expected value of perfect information (EVPI), which can be thought of as the value of having perfect foresight of uncertain variables, in this case the regulation dispatch signal. The annual EVPI in the first year is 8.7 % for the 20-vehicle fleet, 9.8 % for the 40-vehicle fleet, and 6.4 % for the 60-vehicle fleet. Indicative of the extra savings that could be attained relative to the stochastic strategy, the EVPI does *not* capture the value of avoided capacity violation and charging shortfall penalties resulting from an ill-informed deterministic strategy being subject to uncertain signals, which previous work has shown to be as much as ∼96 % of the stochastic objective value (Owens et al., 2023).

These findings highlight the importance of careful financial modeling when considering V2G investments. Fleet managers should be cautious about overly optimistic revenue projections from frequency regulation services, especially for larger fleets. The declining trend in regulation revenues suggests that frequency regulation may not be a sustainable long-term revenue stream in all markets. Policymakers should consider how changing market conditions might affect the viability of V2G services and potentially design incentives or market structures that maintain long-run attractiveness of grid-supporting services from electric vehicle fleets.

4.2. Demand charges and travel obligations diminish opportunities for large fleets

Examining further, Fig. 6 shows fleet and per-vehicle revenue outcomes as a function of different market and scenario sensitivities. Consistent with the results in Fig. 5, lifetime revenues vary greatly as a function of capacity price outcomes. Across fleet sizes, lifetime revenues are 40–45 % lower in the low regulation price case and 44–62 % higher when prices are held static. Revenues also trend to being larger for smaller fleets. The difference is most apparent when comparing revenues on a per-vehicle basis, with the 20-EV fleet vehicles generating nearly 1.9 and 4.3 times more revenue than of the 40- and 60-vehicle fleets in the base case, respectively.

This is driven in part by the demand charges and how fleet loads will influence the aggregate (fleet *and* depot) load to which they are applied. Smaller fleets do not always have to set a new aggregate peak, while larger fleets may not have a choice. In this case, the existing demand peak of the depot provides a "cushion" for the 20-vehicle fleet to operate within without consideration or risk of setting a new peak load. In base case, the load of charging 40 vehicles means the fleet is already much closer to setting a new peak and thus does not have as much flexibility in providing regulation capacity. The magnitude of this effect is measured by eliminating overnight, off-peak demand charges. Subsequent revenues increase across all fleet sizes, as there is no longer a marginal cost associated increasing aggregate load.

However, note that the impact of this change is far more substantial for the 40-vehicle fleet (a 2.3 times per-vehicle revenue increase) compared to the 20-vehicle fleet (a 1.06 times per-vehicle revenue increase) and that eliminating the demand charge does not entirely level outcomes, particularly on per vehicle basis. Similar to the influence of existing peaks or removal of demand charges, limits are imposed by the amount of charging that must be completed within the fixed 10-hour window. This is why the effect of demand charge elimination is far less substantial for the 60-vehicle fleet. The fleet operator must prioritize and account for reaching a sufficient state of charge in making capacity commitments. The same effect is observed when increasing daily vehicle

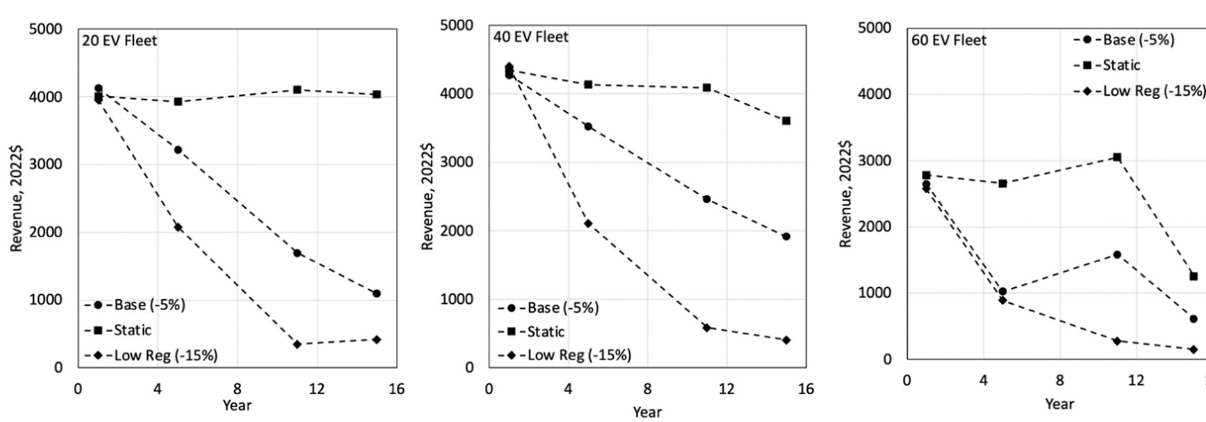

Fig. 5. : Optimal annual regulation capacity revenues under different price scenarios for a 20-, 40-, and 60-EV fleets. The base case and low regulation price cases correspond to −5 % and −15 % year-over-year capacity price changes, respectively. The small discrepancies in the year one revenues, when the capacity prices are identical, are driven by the stochastic model formulation, which in turn yields expected outcomes for both the summer and the winter seasonal simulations that determine annual revenue. With 50 scenarios samplings sufficiently characterizing the distribution and balancing well with simulation tractability, repeated simulations are not expected to be identical.

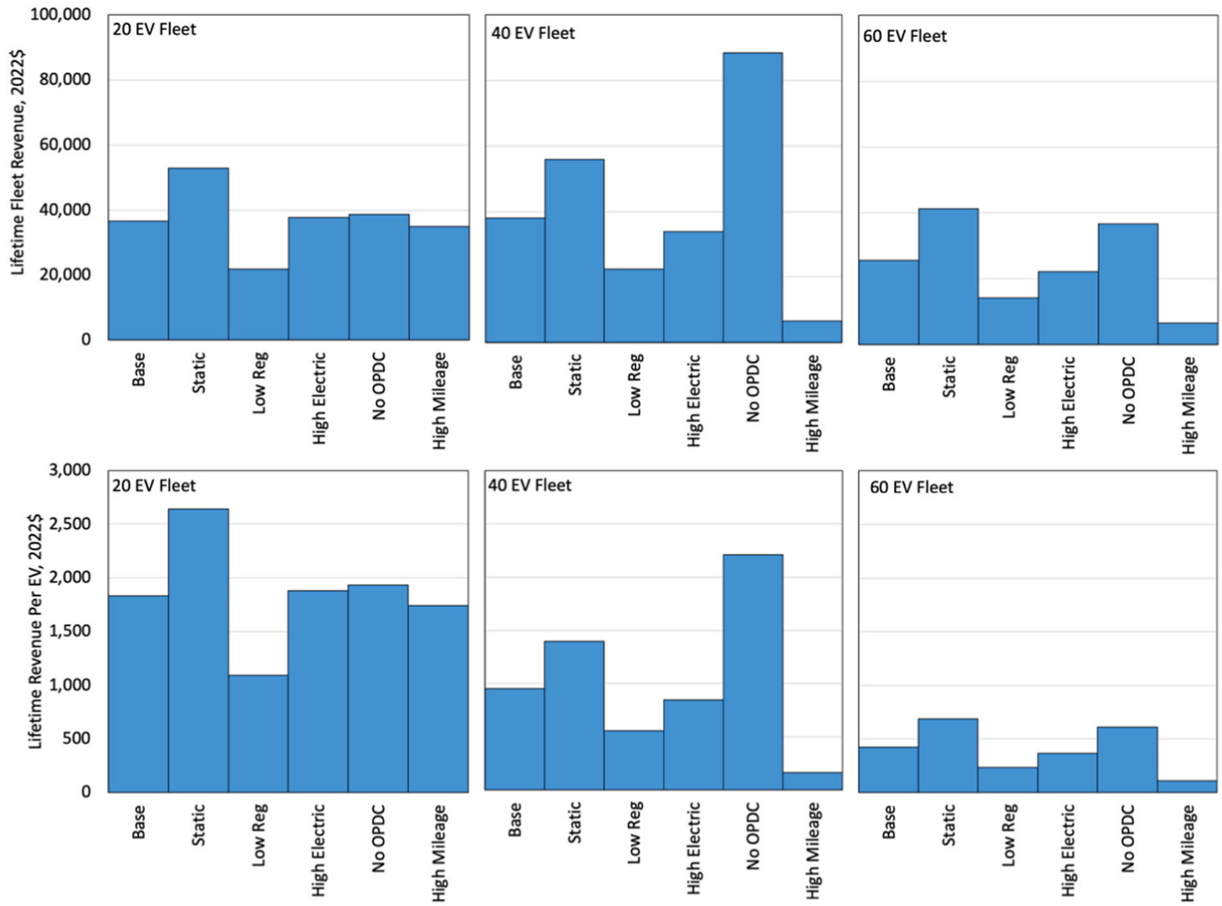

Fig. 6. **:** Lifetime, fleet-wide **(top row)** and per-vehicle (**bottom row)**. regulation capacity revenues as a function of market prices and scenarios.

mileage from 60 to 90 miles. The 40-vehicle fleet is far less flexible when it must procure 1.5 times the amount of energy than in the base case. Due to demand charge limitations and charging requirements, the marginal benefit of V2G decreases as fleet size and required charging increase. Though at a different scale, this trend of diminishing returns is consistent with what is observed at the systems level for V2G (Owens et al., 2022). Lastly, all else equal, higher electricity prices do not independently diminish revenue outcomes to a substantial degree for any fleet size.

Fleet managers, especially those overseeing larger fleets, should carefully evaluate the impact of demand charges on their potential V2G revenues. For many, smart charging strategies focused on minimizing demand charges may prove more beneficial than pursuing V2G revenues. Policymakers and utilities should reassess demand charge structures, as discussed in the previous publication, potentially implementing time-of-use or critical peak pricing models that better align with grid needs and enable fleet participation in grid services without prohibitive costs.

4.3. Seasonal downsides of california markets

Simulation outcomes also yield valuable insights into seasonal variations and related modeling approaches. For this study of California, nearly half of annual revenues are earned during the four summer months (June-September), when capacity on prices are on-average 30.6 % and 35.8 % higher than winter prices for down and up regulation, respectively (Fig. 7). Month-to-month performance is highly uncertain for a number of reasons (e.g. weather effects on system load, renewable utilization, other market participants, etc.) and low revenues during just one of these months can compromise revenues for an entire year. This disproportionate reliance on returns for 1/3 of the year poses an additional layer of uncertainty and risk to fleet owners assessing V2G market opportunities in this particular instance, for which they may wish to consider other options. The result also underscores the importance of capturing key temporal and seasonal variations in modeling and assessing regulation opportunities. Instead, several works opt to use average, annual prices(Noel and McCormack, 2014; Shirazi et al., 2015). Here, for instance, using the average hourly price for down regulation

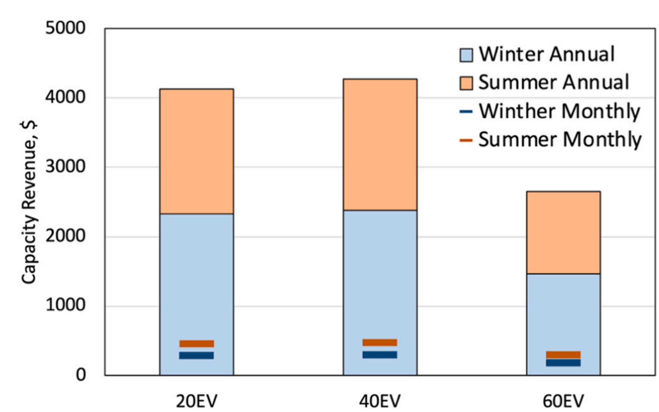

Fig. 7. **:** Monthly and seasonal breakdown of regulation revenues for different sized fleets in their first year of market participation. Monthly capacity revenues are $291, $297, and $183 (winter) and $450, $475, and $297 (summer) for the 20-, 40-, and 60-EV fleets, respectively. This corresponds to annual seasonal revenues of $2328, $2376, and $1462 (winter) and $1798, $1899, and $1189 (summer).

capacity during winter months is, on average, 18.7 % more than median prices during the overnight hours being modeled here. Similarly, the annual median price is 25.8 % higher.

Overall, when accounting for risk, reliance on summer revenues, and changing market conditions, these results demonstrate that regulation revenue potentials in this use case are not as lucrative as described in other works offering economic analysis of fleets. Over the lifetime of the 20-vehicle fleet, regulation revenues come out to just $14 per vehicle per month. This pales in comparison to the result one would expect if using the "product of average hourly price, capacity, and hours plugged in" approximations employed in other works, which neglect the risks and constraints imposed by demand charges and next-day charging requirements(Noel and McCormack, 2014; Shirazi et al., 2015). For example, using the average up/down regulation capacity price for CAISO in 2022 ($5.51/MW-h) and assuming 10 hours of grid connection with a 30-kW charger, vehicles will earn $51 per month if prices hold and an average of $37 per month if they decline 5 % year-over-year – over 3.5 times (72 % less) and 2.5 times (62 % less) what is reported here, respectively.

Of course, these outcomes will vary among specific use cases and may be more lucrative for others outside the delivery fleet context (e.g. a school bus parked for 20 hours per day). In any case, the present work demonstrates that several estimation methods of revenue in the literature are likely overstating the value of frequency regulation.

Given the significant seasonal variations in regulation revenues, fleet managers in California (and perhaps elsewhere) should develop flexible operational strategies. This might include focusing V2G efforts during summer months and prioritizing other cost-saving measures during winter. Additionally, fleet operators should consider diversifying their grid service offerings to mitigate the risk associated with seasonal market fluctuations. Policymakers might explore mechanisms to stabilize revenues across seasons, ensuring consistent grid support and more predictable income for fleet operators.

4.4. Analysis of net operating costs

This section examines the regulation revenues in the context of net operating costs across scenarios. Fig. 8 shows the per-vehicle, net annual operating cost of the 40-vehicle fleet under different charging strategies.

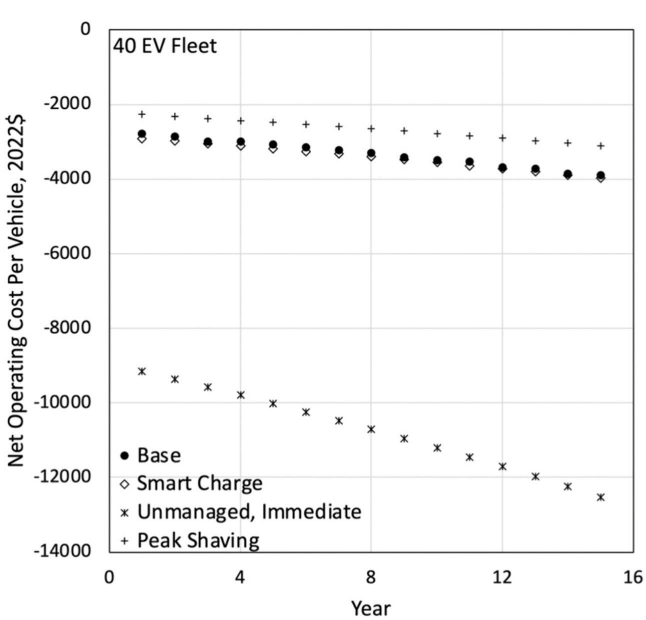

Fig. 8. : Annual, per-vehicle net operating costs as a function of different strategies for a 40-vehicle EV fleet. Other sensitivity cases are omitted for clarity.

In the base case, frequency regulation offers only marginal benefits compared to traditional smart charging, approximately 2.5 % operational savings over each of the 15 years. However, managed charging is still critical, as the strategy of immediate, maximum rate charging drives up the demand charge such that operational costs are nearly three times greater. It is also found that the potential for V2B price arbitrage (i.e. no peak shaving) in this use case is relatively limited due to (1) the short time span, and (2) the time-of-use cost profile being relatively flat. Still, local price arbitrage via V2B delivers an average of 5.2 % annual savings compared to smart charging alone. Savings increase dramatically when the fleet is present to reduce the depot's peak load (peak shaving sensitivity) and accompanying demand charge. For the 40-vehicle fleet, peak load is reduced by 13.3 %, which corresponds to a net operational savings of 22 %. Outcomes are similar for the 20- and 40-vehicle fleets.

Fig. 9 shows the lifetime operating cost per-vehicle relative to regulation capacity revenues and V2B savings. There is limited impact of V2G regulation capacity revenues (green) in this use case when compared to the net cost of simple managed charging (dashed black line). Lifetime (15-year) capacity revenues are on the order of $1000–2000 per vehicle. These underwhelming outcomes of long-run regulation opportunities, especially when considered against simple smart charging, again highlight the utility and importance of the risk-based modeling approach. If one were to assume the $37 per month per vehicle using the assumptions and simplifications discussed above, the average lifetime earnings of each vehicle would be inflated to $6660. This would lead one to incorrectly assume that net costs being as much as ~13 % lower than smart charging in this use case, as is indicated by the dashed blue line.

Rather, V2B peak shaving enables the lowest net operation cost across all fleet sizes by far, driven primarily by peak demand charge reduction. There are also differences in the relative impact of V2B for different sizes, with the 20-vehicle fleet realizing far more benefit (29.8 % savings relative to managed charging) than the 60-vehicle fleet (5.9 % savings relative to managed charging). While regulation uncertainty is no longer a factor, large fleets still face (1) next-day charging requirements that must be satisfied, and (2) the possibility of new, unavoidable peak demands. Thus, the charging requirements of the 60-vehicle fleet mean that it cannot as substantially reduce peak load via V2B discharge.

These results underscore the critical importance of intelligent charging management for fleet electrification economics. Fleet managers should prioritize implementing smart charging systems as a baseline strategy. While V2G for frequency regulation offers limited benefits in this scenario, V2B peak shaving presents a significant opportunity, especially for smaller fleets. Operators should conduct site-specific analyses to determine the potential for peak shaving based on their depot's load profile and local tariff structures. Policymakers and utilities should consider incentive structures that reward behind-the-meter services like peak shaving, which can provide localized grid benefits.

4.5. Net present costs of vehicles and fleets across scenarios

As detailed in the framework description, operational cost outcomes inform the NPC model alongside Monte Carlo sampling of other model variables. Fig. 10 shows the distribution of the total fleet NPC for select cases (for clarity) for 20-, 40-, and 60-vehicle fleets: the business as usual Internal Combustion Engine (ICE) vehicles, EVs providing regulation, EVs equipped with smart charging, EVs with uncontrolled charging (immediate upon plug in), and EVs providing peak shaving services. In addition to most likely costs, note that the simulated distributions also differ in their variability. For the 40-vehicle fleet, the standard deviation of the distribution is $389,300 for ICEV and spans $179,500 to $197,300 for the EV cases. This difference is an artifact of electricity price outcomes being set manually (for model tractability, as mentioned above) rather than sampled from a continuous distribution for the EV fleets. For

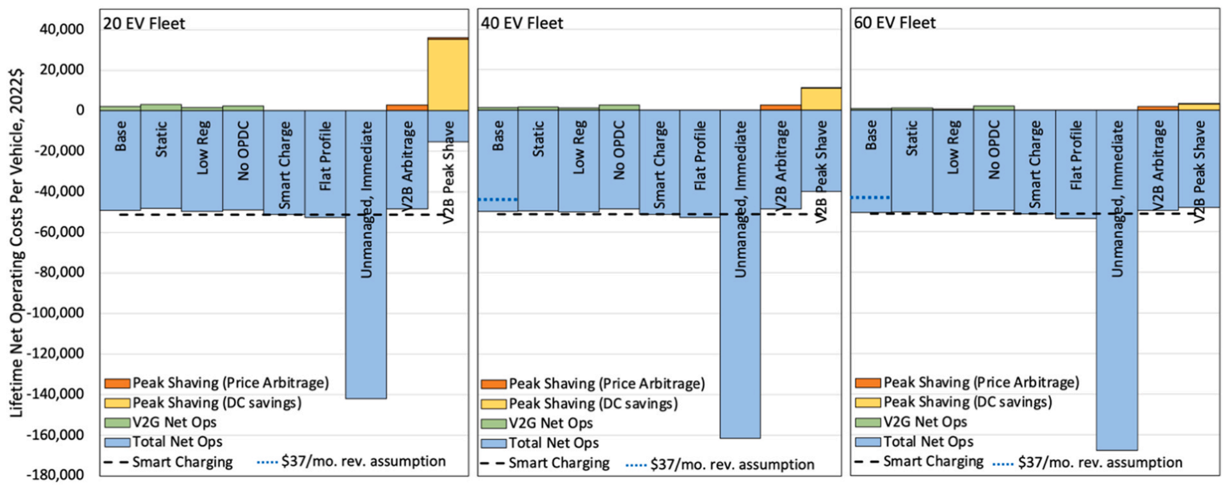

Fig. 9. : Lifetime, per-vehicle net operating cost components as a function of different strategies for 20-, 40-, and 60-vehicle EV fleets. Outcomes from the smart charging "Base" case (dashed black line) and simplified model, with no uncertainty or changing markets (dashed blue line), are overlaid for comparison.

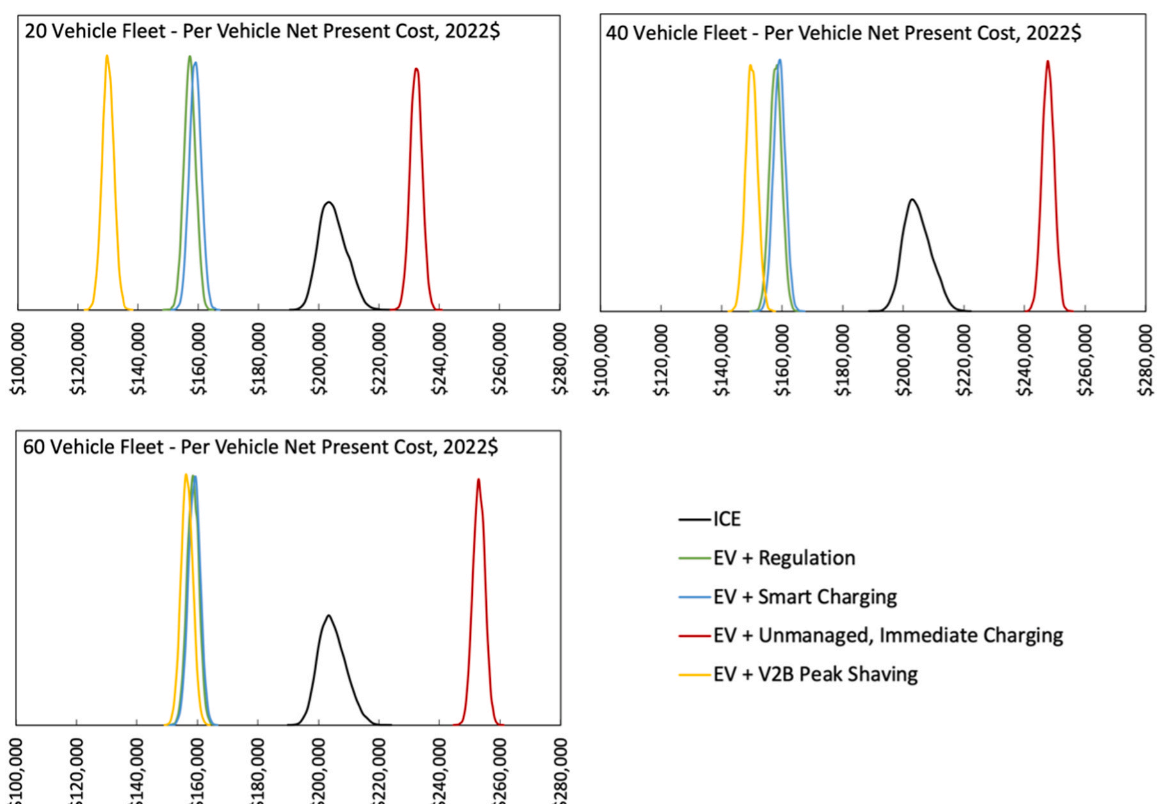

Fig. 10. : Monte Carlo distribution of normalized, per-vehicle net present cost for 20-, 40-, and 60-vehicle EV fleets and under different strategies.

ICEV fleets, fuel price outcomes are sampled over a range of price inflation values. Operation and maintenance costs make up the majority cost for both ICEVs and EVs, and so the modeling difference is evident in the final distributions.

For all fleet sizes, most EV options are significantly lower cost compared to ICEV, on the order of 22 % for regulation and smart charging options in the base case. The exception is in a potential case of uncontrolled charging, for which all vehicles charging simultaneously incurs significant demand charges by setting new peak loads. Hence, a sound charge management strategy is critical to achieving full cost savings for EVs. Seeing as V2G capabilities require only a small increase in infrastructure and maintenance costs (~$500/vehicle) over a smart charging set-up, the similar net operation costs carry over to the total NPC, with regulation revenues demonstrating only a marginal cost benefit over the lifetime of the vehicle. When peak shaving is possible, V2B can unlock even more savings, with total NPCs as much as 27–36 % less than ICEV incumbents.

Simulated costs are further segmented into capital, fuel/operation, maintenance, and emissions components, normalized to a per vehicle basis. Fig. 11 breaks down cost outcomes for 20-, 40-, and 60-vehicle fleets. Across all of the cases and fleet sizes, operation and maintenance combined make up the majority of costs. In the immediate charging case, new peak demand charges account for over 68 % of the net operating costs. In contrast, peak shaving can significantly lower

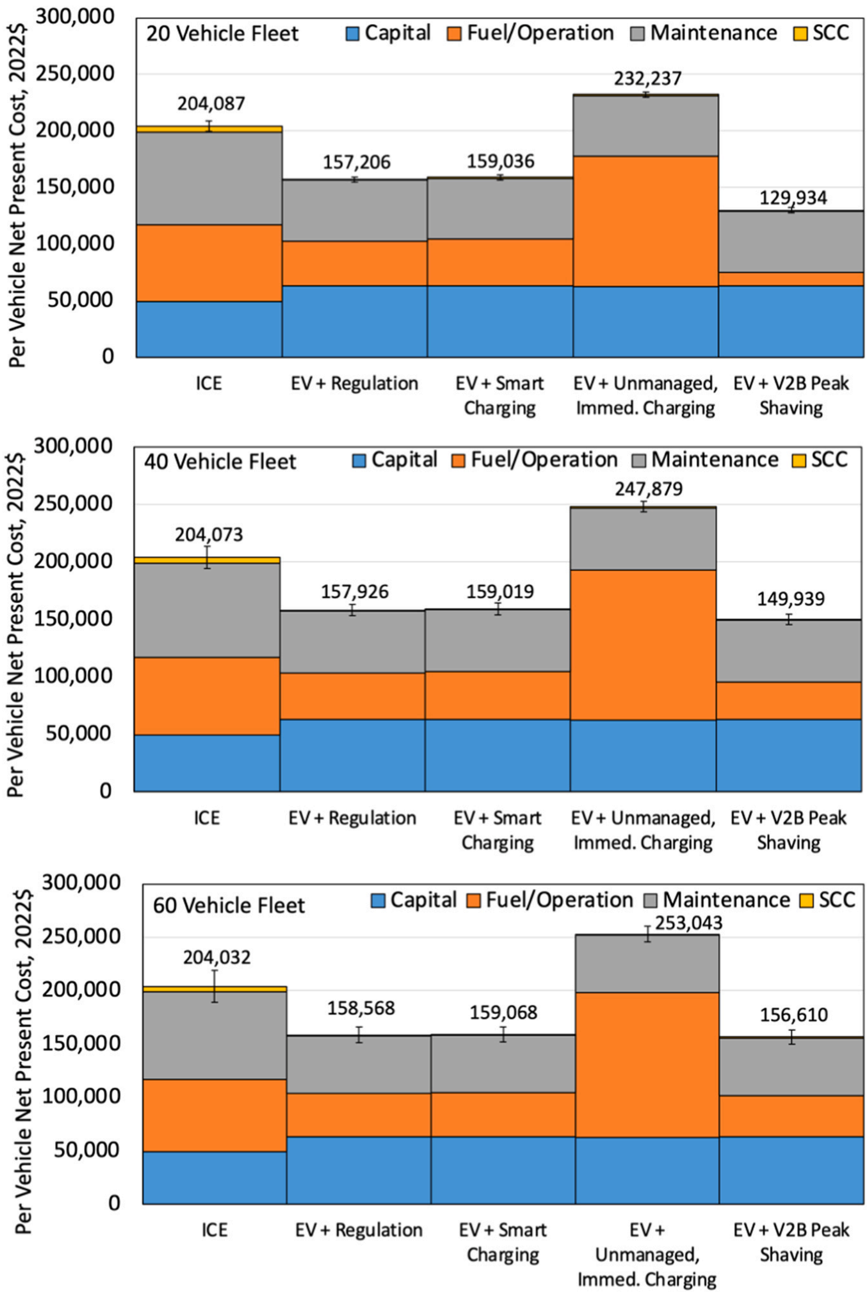

Fig. 11. Normalized, per-vehicles net present cost components for across strategies for 20-, 40-, and 60-vehicle fleets. Error bars represent one standard deviation from median expected outcomes.

operational costs compared to smart charging when it is possible. Further EV cost savings are also possible as capital costs, approximately one-third of the total in the base case, go down with economies of scale and cheaper batteries. Lastly, and though relatively small in contribution, the embodied on-road carbon emissions and associated costs are nearly 6.5 times greater for the ICEVs than the EVs charging during overnight hours.

Overall, per vehicle EV costs are comparable across regulation and smart charging scenarios, with smaller fleet sizes showing very slight advantage as a function of relatively fleet flexibility. Differences in flexibility are most apparent in evaluating immediate charging and V2B peak shaving scenarios. As a result of the large peak demand charges incurred from maximum and immediate charging, per vehicles cost increases span $73,201 and $93,975 between the 20- and 60-EV fleets, respectively. With more vehicles charging at once, the aggregate load profile scales with fleet size. Likewise, V2B benefits are most pronounced for the smaller fleets, as vehicles can dispatch energy to shave building loads and charge at later hours without significant increase to peak load.

The substantial cost advantages of EVs over ICEVs in most scenarios provide a strong economic case for fleet electrification. However, fleet managers must ensure proper charging management to realize these benefits. The marginal additional benefit of V2G capabilities suggests that fleet operators should carefully weigh the added complexity against potential returns. For policymakers, these results support the case for incentivizing fleet electrification, but also highlight the need for programs that assist with upfront costs and charging infrastructure to accelerate adoption.

4.6. Parity analysis of fleet investments

Results also indicate that while the upfront investment and infrastructure costs of EVs are higher than those of ICEVs, it is the lower operating cost of EVs that overcome the difference in the long run. However, there may also be instances in which ICE powertrains are already owned outright and fleet owners may be evaluating the relative payoff of investing in EVs vs simply continuing with ICEVs. To evaluate this, a parity analysis is conducted for different fleet and service configurations. Fig. 12 plots per-vehicle net present cost as a function of time, with the solid black and gray lines corresponding to ICEVs *total* and *operational only* (fuel, maintenance, emissions), respectively. Since the cost outcomes for smart charging, regulation, and peak shaving services (across fleet sizes) all fall within the bounds of the 20-EV fleet providing peak shaving and the 60-EV fleet smart charging, they are omitted from the figure for clarity.

On the basis of total investment and ownership cost, EVs quickly achieve cost parity with ICEVs within 2–3 years, with the exception of the immediate charging cases. EV investment costs become more comparable when ICEVs are already owned ("ICE Ops Only"). Still, nearly all EV configurations surpass or achieve parity within the 15-year model horizon.

Fleet managers can use this parity analysis as a framework for phased electrification planning. For fleets with existing ICEVs, the rapid achievement of cost parity supports a case for gradual replacement with EVs as old vehicles are retired. However, the specific timeline will depend on individual fleet characteristics and local market conditions. Policymakers could use this information to design targeted incentives that address the initial cost barrier, potentially accelerating the payback period and encouraging faster fleet transitions.

4.7. Analysis of scenario and model sensitivities

The following sensitivity analysis reveals that the economic viability of fleet electrification and V2G services is influenced by a complex interplay of factors, with varying degrees of impact across different fleet sizes and operational strategies. These sensitivities are examined through two complementary approaches: scenario analysis (Fig. 13) and parameter sensitivity analysis (Fig. 14), while also considering the impact of our model assumptions and specifications.

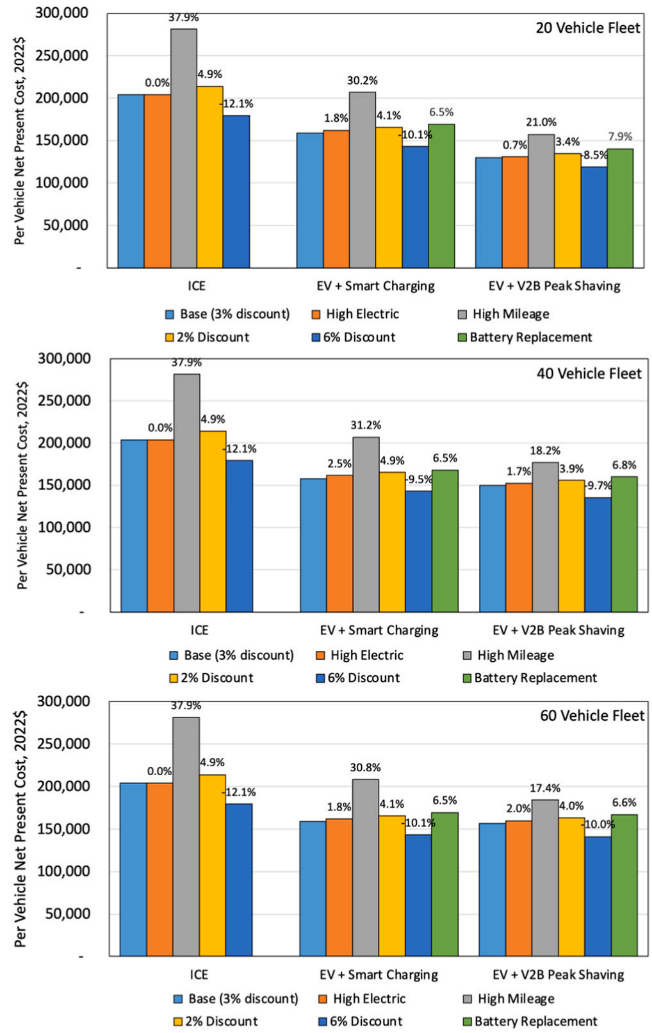

Fig. 13. Key sensitivities of normalized, per-vehicle net present cost across strategies for 20-, 40-, and 60-vehicle fleets.

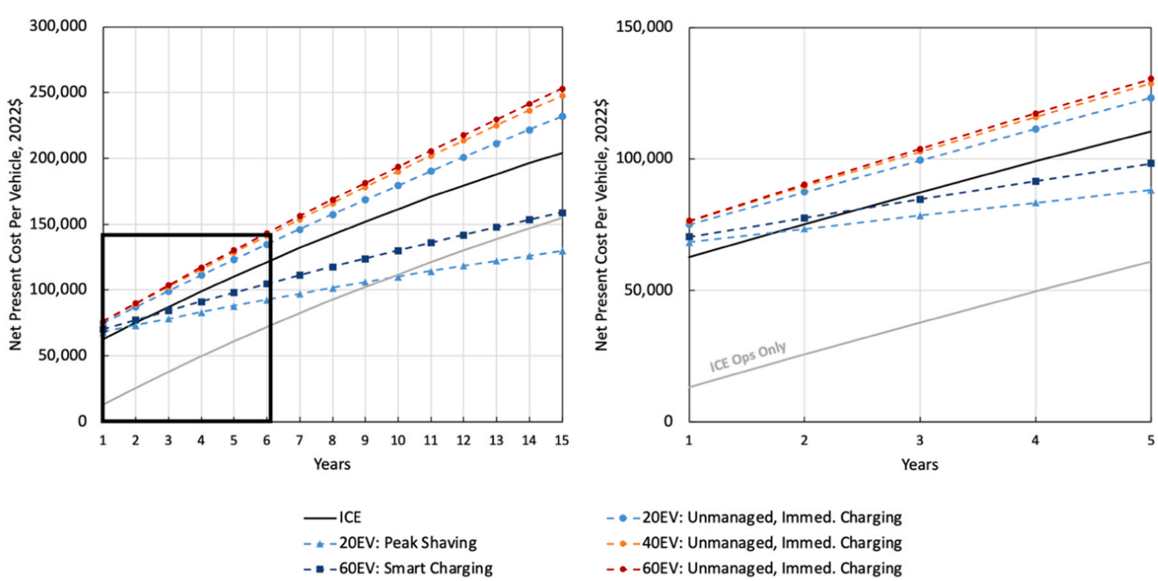

Fig. 12. Parity analysis of EV net present costs relative to ICEV, normalized per vehicle. Year 1 corresponds to initial purchase and the first full year of operation.

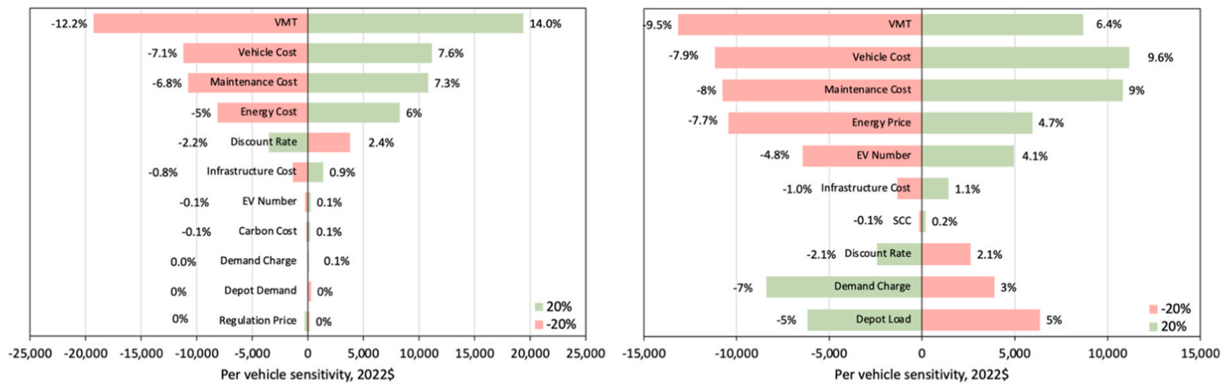

Fig. 14. Per-vehicle cost model sensitivity analysis relative to the base case for 40-EV fleet providing regulation service **(left)** and per-vehicle cost model sensitivity analysis relative to the base case for 20 EV fleet providing peak shaving service (**right**).

4.7.1. Scenario analysis

First, the impacts of the discount rate, electricity price, fuel costs, and mileage scenarios detailed in 3.4 are examined. Fig. 13 illustrates the per-vehicle net present cost across different scenarios for 20-, 40-, and 60-vehicle fleets. Across all fleet sizes, EVs with smart charging or V2B peak shaving capabilities consistently show lower net present costs compared to ICE vehicles, even under challenging scenarios such as high electricity prices or increased mileage. This robustness supports the overall economic case for fleet electrification. However, the magnitude of these benefits varies with fleet size and operational strategy.

The high mileage scenario has the most significant impact on costs across all fleet types and sizes, increasing net present costs by 30–38 %. This underscores the critical importance of accurate travel demand forecasting in fleet electrification planning. Interestingly, the relative cost increase for high mileage is slightly lower for EV fleets with V2B peak shaving compared to other scenarios, indicating that this strategy provides some mitigation against increased operational demands. However, it's important to note that this study assumes a fixed charging window. Day-to-day, high-mileage fleets might require more flexible charging opportunities, which could alter the relative benefits of different charging strategies.

It is also observed that the higher mileage has a more pronounced relative effect on the 40-EV fleet than the 20- and 60-EV fleets in the simple smart charging scenario. This is because for the 40-EV fleet, there is a step change in cost associated with the mileage forcing a new aggregate peak demand exceeding that of the depot base load, whereas the 20-EV fleet avoids doing so and the 60-EV fleet already does so in the base case. This nuanced interaction between fleet size, mileage, and demand charges underscores the complexity of fleet electrification economics and suggests that optimal strategies may vary significantly based on specific fleet characteristics.

Higher electricity prices have a noticeable but less dramatic impact on EV fleet costs, increasing net present costs by 0.7–2.5 % depending on fleet size and strategy, suggesting some resilience to energy price fluctuations. For V2B peak shaving specifically, both higher electricity costs and increased mileage effects are further curbed. Through a combination of price arbitrage and reducing demand charges, the increased energy demands do not hold a one-to-one equivalency with charging/operating costs. However, the exact realization of these benefits depends on factors not fully captured in the case study model, such as the specific load profile of the depot and the flexibility of vehicle availability for V2B services.

This sensitivity also reveals that EVs remain competitive with ICEVs when a one-time battery replacement is imposed. The impact of battery replacement varies across fleet sizes and strategies but generally increases costs by 6.6–7.9 %. Overall, the net present costs of EV fleets with a battery replacement is still ~17 % and ~18 %-31 % lower than ICEVs across fleet sizes for the smart charging and peak shaving cases, respectively. This robustness to battery replacement costs is encouraging for the long-term economics of fleet electrification. However, it's worth noting that our model assumes a single battery replacement at a fixed cost. Battery degradation and replacement needs could vary based on usage patterns, potentially altering this conclusion for fleets with particularly intensive use profiles.

Finally, varying discount rate of future years when calculating NPC, the effect is more pronounced for ICEVs than EVs, responding approximately 20 % more. This is because, in the base case, ICEV fleets spend more on fuel and maintenance costs relative to all EV scenarios tested. This difference in sensitivity to discount rates suggests that the economic advantage of EVs over ICEVs could be even more pronounced in scenarios with higher discount rates, potentially strengthening the case for fleet electrification.

4.7.2. Parameter sensitivity analysis

A full-model parameter sensitivity analysis is performed for the net present cost over the 15-year period. Beginning with the 40 EV fleet regulation case as the basis, key parameters are varied both positively and negatively by 20 % and results are given in Fig. 14. This analysis provides a more granular view of how individual parameters affect the per-vehicle cost for a 40-EV fleet providing regulation services and a 20-EV fleet engaged in peak shaving.

Consistent with the analysis of key cost components, the greatest sensitivity is to vehicle miles traveled (VMT), which ultimately influences both the amount of energy required to be purchased, maintenance costs incurred, and the flexibility the fleet has in providing V2G and V2B services. A 20 % increase in VMT leads to a 6.4–14 % increase in per-vehicle net present cost. Also significant are vehicle, maintenance, and energy costs, with 20 % variations in these parameters resulting in 5–10 % changes in net present cost. This highlights the need for fleet managers to carefully consider both upfront investment and long-term operating costs in their decision-making process. The heightened sensitivity to mileage underscores the critical importance of accurate travel demand and schedule forecasting in fleet electrification planning, while the sensitivity to maintenance costs suggests that realizing the full economic benefits of electrification depends on achieving the projected maintenance savings.

Interestingly, EV number, demand charges, depot load, and regulation prices all have minimal impact on lifetime NPC in the base case for the 40-EV fleet providing regulation services. This is consistent with the small share of lifetime regulation revenues relative to other operating costs. Further, it is not necessarily prices driving underwhelming revenues, but rather practical limitations related to scheduling and risk-averse bidding. This finding challenges the assumption that V2G revenues are highly dependent on favorable regulation prices and suggests that operational constraints may be more limiting than market conditions in some cases. However, the relative sensitivities to each parameter are highly dependent on "where" they are being probed in the model space. For instance, in the case of a 20 EV fleet providing V2B peak shaving, the NPC is similarly sensitive to mileage, maintenance, energy, and vehicle costs, but much more responsive to utility demand charges and size of the depot load (3–7 %). This is because the net operating cost of the fleet is a function of aggregate, depot plus fleet load savings. Thus, the marginal utility of fleet peak shaving varies inversely with both peak demand charges and the size of the depot load.

This difference in sensitivity profiles between the regulation and peak shaving scenarios underscores the importance of considering the specific grid services a fleet intends to provide when evaluating the impact of various cost components. It suggests that the economic case for V2B peak shaving might be stronger in scenarios with high demand charges or for fleets associated with facilities that have significant peak loads. Likewise, the fleet size is also more impactful in the peak shaving scenario, indicating that it is one of the binding constraints influencing the amount of service the fleet can provide and derive savings from. This suggests that the optimal fleet size for maximizing V2B benefits might differ from that for regulation services, potentially leading to different electrification strategies depending on the primary grid service being considered.

4.7.3. Impact and limitations of model and assumptions

These varying sensitivities highlight that conclusions about the relative benefits of different charging strategies (e.g., smart charging vs. V2G vs. V2B) could shift based on specific fleet and market characteristics. For example, in scenarios with high demand charges and suitable depot loads, V2B peak shaving might prove more beneficial than the base case analysis suggests. Conversely, for fleets with very high mileage or in areas with low demand charges, the benefits of V2G services might be less pronounced than in the primary results. Likewise, it's crucial to consider how other underlying assumptions and model specifications might alter conclusions drawn from this work.

First, the study assumes a fixed 10-hour charging window (8 PM to 6 AM) for a homogeneous fleet. In reality, charging opportunities may be more flexible or constrained, which could significantly impact the benefits of V2G services. Likewise, fleet heterogeneity, whether in schedule or duty cycle, could impact the aggregate flexibility and economics of V2G services. A more flexible window could enhance these benefits by allowing better alignment with grid needs and electricity prices, potentially making V2G strategies more attractive than our current results suggest. Conversely, a more constrained window might reduce V2G benefits and increase overall costs, possibly making smart charging more favorable compared to V2G in some scenarios.

Additionally, the model assumes uniform daily operations without distinguishing between weekdays and weekends. While many e-commerce and last-mile delivery services now operate with relatively consistent patterns throughout the week, some fleets may experience reduced travel demands on weekends. This could potentially increase V2G revenue opportunities. The effect of lower weekend mileage is partially captured in the sensitivity analysis of reduced daily vehicle miles traveled (VMT), which demonstrates improved flexibility for grid services. However, explicitly modeling weekday/weekend variations could reveal more nuanced optimization strategies for fleets with distinct weekend operations. For instance, these fleets might be able to offer more extensive V2G services during lower-demand periods, potentially offsetting reduced operational revenues with increased grid service income.

The model also assumes optimal market participation when profitable and historical regulation dispatch patterns. In practice, forecast errors, operational constraints, and changes of regulation signal characteristics (e.g. volatility with increasing renewable penetration) could reduce V2G revenues and increase costs. This might furthering narrow the gap between smart charging and V2G strategies. In certain cases (e.g. large fleets with demand charge limitations, like the 60-EV base case), the additional complexity and risk associated with V2G might not be justified by the reduced economic benefits.

Similarly, the depot load profile significantly impacts V2B opportunities. Different load shapes could substantially change the value proposition of V2B services. For instance, a load profile with higher coincidence between peak demand and EV availability could increase V2B benefits, potentially making this strategy even more attractive than our current results suggest. Conversely, a flatter load profile could reduce the benefits of V2B, possibly making it less advantageous compared to smart charging in some cases.

Finally, the case study uses two specific electricity rate structures (PG&E baseline and no OPDC). Different structures, particularly those with more dynamic pricing or different demand charge mechanisms, could significantly alter the relative benefits of different charging strategies. In regions with higher demand charges, for example, the benefits of V2B peak shaving could be even more pronounced than our results indicate. Alternatively, in areas with flatter rate structures, the economic case for complex V2G strategies might be weaker.

It's important to note that while these factors might alter the magnitude of benefits or the relative attractiveness of different strategies, they are unlikely to fundamentally change the core finding that EV fleets offer economic advantages over ICE fleets across a wide range of scenarios. The robustness of this conclusion is supported by the significant cost advantages observed even in "worst-case" scenarios. However, the specific ranking of strategies (e.g., smart charging vs. V2G vs. V2B) and the magnitude of their benefits could shift based on these factors. For example, under less favorable assumptions about fleet travel obligations and market participation, smart charging might emerge as the most attractive strategy in more scenarios than our current results suggest. Alternatively, with more flexible charging windows and favorable rate structures, V2G services might prove even more beneficial than our analysis indicates.

In all, these considerations underscore the importance of tailored analysis for individual fleet circumstances and highlight areas where future research could provide more nuanced insights. Real-world pilot studies that capture these complex interactions would be particularly valuable in refining our understanding of fleet electrification economics under diverse conditions.

5. Conclusions

The goal of this work is to obtain a more accurate assessment of the economic viability of fleet electrification and vehicle-to-grid (V2G) strategies, particularly accounting for future uncertainties in electricity markets and regulatory environments. Key research questions were: (1) What are the effects of demand charges and operational uncertainties on financial V2G benefits? (2) How do potential long-term risks (i.e. market saturation) impact fleet electrification and V2G economics? (3) How do adaptive charging and bidding behaviors evolve with changing market conditions? This section summarizes key findings and takeaways.

5.1. Summary of case study findings

This study introduces a risk-informed Monte Carlo modeling framework to evaluate electrification costs and vehicle-to-grid (V2G) benefits, accounting for operational uncertainties and changing market conditions. The framework integrates stochastic optimization to inform fleet decisions, revenues, and operating costs across seasons and years, providing more realistic outcomes than deterministic models or simplified assumptions used in previous works.

Applied to a commercial delivery fleet in California over a 15-year investment horizon with a 3 % discount rate, the study reveals that frequency regulation revenues are less lucrative than previously suggested. V2G participation provides only marginal benefits over smart charging in some cases, with lifetime capacity revenues per vehicle of \$1832, \$952, and \$426 for 20-, 40-, and 60-vehicle fleets, respectively. These figures are relatively small compared to the lifetime operating costs of about $51,200 incurred via smart charging. Vehicle-to-building (V2B) services show more promise, with net operational savings via pure arbitrage around 5 % relative to smart charging, and peak shaving savings up to 29.8 % for the 20-vehicle fleet. Sensitivity analysis identifies mileage, energy and vehicle prices, and maintenance costs as the most influential factors affecting lifetime net present cost. The relative influence of parameters like demand charges and depot load scale varies depending on the service provided by the fleet. Notably, the effects of higher electricity costs and increased mileage are mitigated when peak shaving is available.

Overall, electric vehicle (EV) fleets generally demonstrate favorable economics compared to internal combustion engine vehicles (ICEVs), with 30–40 % lower net present costs in most scenarios. However, uncontrolled charging can lead to high demand charges due to new peak loads, offsetting these benefits. The results highlight that demand charges and charging window constraints significantly impact regulation revenues, particularly for larger fleets. Seasonal variations are crucial, with nearly half of annual revenues earned during the four summer months in California.

While this study focuses on a California-based delivery fleet, the framework methodology and qualitative conclusions are applicable and generalizable to other locations and fleet types. First, the fundamental economic trade-offs identified, such as balancing upfront costs with long-term savings and comparing different charging strategies, are applicable across various electricity markets and regulatory environments. Second, the finding that V2G frequency regulation revenues are less lucrative than previously suggested is likely to hold in other markets due to universal challenges of signal uncertainty and risk-averse bidding. Third, the importance of managed charging and the potential benefits of V2B services, particularly peak shaving, are principles that apply broadly, especially where commercial rates include demand charges. While the specific magnitudes of costs and benefits will vary based on local conditions, the relationships and trends identified offer valuable insights for stakeholders worldwide. Future research can further refine how these principles manifest under varied conditions, enhancing the broad applicability of this approach.

5.2. Implications across stakeholder groups

These findings have significant implications for fleet managers, policymakers, and utilities considering fleet electrification and V2G services. For fleet managers, results underscore the importance of conducting detailed, context-specific analyses using frameworks like the one presented in this study. Such analyses are crucial for informing electrification strategies that consider both upfront investments and long-term operating costs. Sensitivity analysis reveals that vehicle miles traveled (VMT), vehicle costs, maintenance costs, and energy prices are the most influential factors affecting lifetime costs. Fleet managers should pay particular attention to accurately forecasting these parameters when evaluating electrification options. Additionally, the study shows that the benefits of V2G services can vary significantly based on fleet size and local market conditions. Smaller fleets, for instance, demonstrated greater flexibility in providing V2G services and realizing associated benefits. Therefore, fleet managers should carefully assess their specific operational patterns, local electricity rate structures, and potential for providing grid services when developing their electrification strategies.

Policymakers need to design flexible frameworks that can adapt to diverse fleet characteristics and evolving market dynamics. Analysis shows that the economic viability of fleet electrification and V2G services is robust across various scenarios, but the magnitude of benefits can vary significantly. This variability calls for policies that are adaptable and can provide targeted support where it's most needed. Policymakers should consider supporting initial capital investment in EVs and charging infrastructure, particularly for smaller fleets that may face higher barriers to entry. Encouraging the development of V2G and V2B capabilities through incentives or grants for bidirectional charging equipment is also crucial. Facilitating fair compensation for grid services provided by EVs, potentially through revised market rules that recognize the unique characteristics of fleet-based V2G services, is another important policy area. Addressing regulatory barriers to EV participation in electricity markets, such as minimum size requirements that may exclude individual fleets, is also necessary. Additionally, developing policies that align the interests of fleet operators, utilities, and grid operators can help maximize the system-wide benefits of fleet electrification. Sensitivity analysis also highlights the significant impact of demand charges on fleet economics, especially for larger fleets. Policymakers should work with utilities to review and potentially reform demand charge structures to ensure they do not unduly penalize EV fleets while still reflecting true system costs.

Utilities also play a crucial role in realizing the potential benefits of fleet electrification and V2G services. Based on study findings, utilities should consider developing rate structures that incentivize beneficial EV charging and discharging behaviors. This could include time-of-use rates that encourage off-peak charging and demand charge structures that don't penalize occasional high-power charging events. Investing in infrastructure to support V2G and V2B services, including grid upgrades to accommodate bidirectional power flows and communication systems to enable real-time coordination with EV fleets, is also important. Collaborating with fleet operators to pilot and scale V2G programs is crucial, as our results show that V2B peak shaving, in particular, can offer significant benefits. Utilities could partner with fleet operators to demonstrate these benefits and develop best practices for implementation. Exploring innovative tariff designs that reflect the true value of grid services provided by EV fleets is another area for utility focus. Analysis of the "No OPDC" (no off-peak demand charge) scenario showed increased V2G participation and cost savings, suggesting that more nuanced demand charge structures could unlock additional value. Finally, utilities need to consider the long-term impacts of widespread EV adoption on grid operations and planning. While this study focused on individual fleets, utilities must prepare for scenarios where a significant portion of their load comes from EVs. By taking these steps, fleet managers, policymakers, and utilities can work together to maximize the benefits of fleet electrification and V2G services, supporting the transition to a more sustainable and resilient energy system while also realizing economic benefits for fleet operators.

5.3. Regulatory landscape, technical challenges, and future trends

While the case study focuses on the California market, it's crucial to consider the broader regulatory landscape and future trends for V2G technology. In the United States, while there is no comprehensive federal regulation specifically for V2G, the Federal Energy Regulatory Commission (FERC) has issued orders that impact V2G implementation. State-level initiatives vary, with California leading through its Rule 21, while other states are developing their own V2G pilot programs and regulations. Internationally, the European Union is working on standardizing V2G technologies and regulations across member states, the United Kingdom is actively promoting V2G through various pilot projects and regulatory sandboxes, and Japan has supportive regulations in place and widely adopts the CHAdeMO charging standard, which supports bidirectional charging. As more renewable energy sources are integrated into the grid, the value of flexible resources like V2G is likely to increase. However, this may be counterbalanced by increased competition from stationary storage systems. Future regulations will need to address standardization of V2G technologies and communication protocols, fair compensation mechanisms for V2G services, integration of V2G into broader grid management strategies, and consumer protection and data privacy concerns.

The impact of these factors could vary significantly across regions. For instance, areas with less developed V2G regulations may face higher barriers to entry, potentially reducing the economic benefits observed in our study. Conversely, regions with more supportive policies might see enhanced benefits. Electricity market structures also play a crucial role; markets with different pricing mechanisms could significantly alter the value proposition of smart charging and V2G services. Grid reliability and renewable penetration levels in different regions may impact the value of ancillary services, potentially increasing V2G revenues beyond what this study observed in California. Results highlighted the significant impact of demand charges on fleet economics; in markets without demand charges or with different structures, the relative benefits of V2B peak shaving and smart charging strategies could shift considerably. Additionally, regions offering generous incentives for fleet electrification or V2G services could see more favorable economics than those presented in this California-based study. The level of competition in V2G markets and local climate considerations could further influence the outcomes. These factors underscore the importance of conducting location-specific analyses when applying our framework to different markets. While the general methodology and many of the qualitative insights from this study are broadly applicable, the quantitative results may vary significantly based on local conditions.

Several technical challenges also need to be addressed for widespread implementation of V2G services. These include the development and deployment of cost-effective, efficient bidirectional chargers, addressing concerns about battery degradation due to V2G services, establishing robust and standardized communication protocols between vehicles, charging stations, and grid operators, and ensuring grid stability and power quality as EV adoption increases. Improving predictive analytics for EV availability, grid demand, and renewable energy generation will also be crucial for optimizing V2G services.

5.4. Limitations and future research directions

While this study provides valuable insights, it is important to acknowledge its limitations and areas for future research. Discussion across Sections 3.5.2 and 4.7.3 above capture specific limitations of the model and specific case study assumptions. More broadly, the analysis focuses on a specific case study of delivery vehicles in California, and future studies should examine a broader range of geographical locations with different electricity market structures and regulatory environments to enhance the generalizability of the findings. Expanding to other fleet types, such as public transit or long-haul trucking, could provide insights into how different operational patterns affect V2G potential. Future work could also incorporate more sophisticated market models to project long-term V2G value and consider the impact of increasing EV penetration on electricity markets at a macro level.

Likewise, a more comprehensive life-cycle assessment of the environmental impacts of fleet electrification and V2G services would be valuable, as would studies incorporating behavioral factors that might influence fleet operators' decisions regarding EV adoption and V2G participation. As the field evolves, the risk-informed modeling framework developed here can be adapted and expanded to address these limitations and explore new research questions.

In conclusion, this study contributes to the growing body of knowledge on fleet electrification and V2G services by providing a more realistic assessment of their economic potential. The findings can inform decision-making for fleet managers, policymakers, and utilities, highlighting the importance of tailored strategies and careful consideration of local market conditions. As the transportation and energy sectors continue to transform, further research building on these findings will be crucial in realizing the full potential of EVs as flexible grid assets and in supporting the transition to a more sustainable and resilient energy system.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Claude AI to edit and revise discussion of results. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Emre Gençer: Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **James Owens:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

Data will be made available on request.

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