



Beyond mobility : On the economics of electric vehicle's multiple roles in an energy transition framework.

Icaro Silvestre Freitas Gomes

► To cite this version:

Icaro Silvestre Freitas Gomes. Beyond mobility : On the economics of electric vehicle's multiple roles in an energy transition framework.. Economics and Finance. Université Paris-Saclay, 2021. English. NNT : 2021UPASI011 . tel-04201616

HAL Id: tel-04201616

<https://theses.hal.science/tel-04201616>

Submitted on 11 Sep 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Au-delà de la Mobilité: Economie des
Multiples Rôles du Véhicule Electrique
dans un Cadre de Transition Energétique
***Beyond Mobility: On the Economics of
Electric Vehicle's Multiple Roles in an Energy
Transition Framework***

Thèse de doctorat de l'université Paris-Saclay

École doctorale n°630 : Droit Economie Management (DEM)
Spécialité de doctorat : Sciences Économiques
Unité de recherche: Université Paris-Saclay, Réseaux Innovation Territoires et
Mondialisation, 92330, Sceaux, France
Réfèrent : Faculté de droit, économie et gestion

**Thèse présentée et soutenue à Paris-Saclay,
le 10/09/2021, par**

Icaro Silvestre FREITAS GOMES

Composition du Jury

Pascal DA COSTA

Professeur, CentraleSupélec

Président

Patrice GEOFFRON

Professeur, Université Paris-Dauphine

Rapporteur &

Examineur

Carine STAROPOLI

Professeure associée, Paris School of Economics

Rapporteur &

Examinatrice

Willet Kempton

Professeur, University of Delaware

Examineur

Ramteen Sioshansi

Professeur, The Ohio State University

Examineur

Rémy Le Boenne

Institut Vedecom

Invité

Emilia Suomalainen

Institut Vedecom

Invitée

Direction de la thèse

Yannick Perez

Professeur, CentraleSupélec

Directeur de thèse

Acknowledgements

Before anything else, I would like to thank my Ph.D. supervisor, Yannick Perez, for his immense help and guidance during all steps of the thesis. Making an analogy with football, he is the best midfielder that a team can have. Someone who have all the defensive problems taken care of and make the perfect passes to strikers so they can score. I had the chance to be one of his team's strikers during these three years. His encouragement and confidence in me were essential for overcoming the challenges.

I would also like to thank my advisors from Institut Vedecom. First and foremost, François Colet, who was responsible for the kick-off of this journey. Then, Emilia Suomalainen, who advised and supported me throughout this process almost until the end. Finally, Jaafar Berrada who assured the closure of this chapter in the best way. Further, I would like to thank Adam Abdin for introducing me to the world of optimization and equilibrium problems. I thank him for never stopping to challenge me, his enthusiasm, all the philosophical discussions, and the squash games. I would also like to thank Vincent Rious for his helpful suggestions and discussions. This work was greatly improved due to his inputs.

A huge thank you goes to the remaining committee members for accepting the invitation: Patrice Geoffron, Carine Staropoli, Pascal da Costa, Ramteen Sioshansi, Willett Kempton, and Rémy Le Boennec. I am honored to be counted among such high-level academics and to have your insights and feedback.

The path would have been much more difficult without the support of my friends and colleagues in the research laboratory. The LGI gave me the opportunity to meet distinguished and lovely people. Thank you, Gustavo, Francisco, Bassem, Emilien, Tjark, Yasmine, Eliane, Quentin, Felipe, Guilherme, Andrea, Maxime and Rémi. I also had the chance to play with some of the most excellent musicians at the university. Together we were the historical group named 'Les Gens de la Côte.' I thank François, Delphine, Flore, Mehdi, William, Naouress for being part of it. I also appreciated the time spent with my colleagues at Vedecom. The institute was full of exciting and

friendly people such as Marco, Fawaz, Félix and Zariff.

I am lucky to have a family in Brazil that is always there for me, even if they are 7,048 kilometers away. To my mother, father, and brother, I cannot thank you enough for the support, love, and encouragement over the years. Even in the most challenging times, they were the help that has sustained and lifted me. If I am not going to Brazil, Brazil comes to me somehow. I want to thank my incredible Brazilian friends that I have met on French soil. They also helped me to get over homesickness with their affection and loyalty. A huge thanks to Tiago, Pedro, Monacer, Vinícius, Bruno, Higor, Thaís T., Thaís A., Monique, Alex, Michele, Fabio, and Priscila.

Last but not least, I must reserve special mention for my Emma. *Merci pour tous les beaux moments qu'on a vécus et pour ceux qui vont venir. Merci pour ton amour, ta tendresse et ton support. Je tiens à dire que ce n'est que le début.*

Contents

Contents	i
List of Figures	vi
List of Tables	viii
Lists of Acronyms	x
1 General Introduction	1
1 Overview	1
1.1 Electric vehicle ecosystem	2
1.2 Interactions with rate design	4
2 Problem statement and purpose	5
3 Approach and methodology	6
4 Contributions of this dissertation	6
4.1 Coupling small batteries and PV generation: A review	7
4.2 Rate design with distributed energy resources and electric vehicles: A Californian case study	7
4.3 New EV rate design: An MPEC assessment	8
4.4 Further perspectives	8
5 References	9
2 Coupling small batteries and PV generation: A review	13
1 Introduction.	14
2 Technology trends	16

2.1	Photovoltaic panels	17
2.2	Batteries	18
2.3	Vehicle-to-Grid (V2G)	20
2.4	Microgrids	22
2.5	Blockchain	25
2.6	Techno-economic coupling models	29
3	Economic aspects	32
3.1	Electricity tariff impact	32
3.2	Market barriers	34
3.2.1	DER costs	34
3.2.2	EV ecosystem constraints	35
3.3	Local policies	37
3.3.1	Support instruments	37
3.3.2	Dealing with battery price floor	38
4	Societal aspects	39
4.1	User acceptance: How to assess and ensure it?	39
5	Conclusion	42
6	References	44

3 Rate design with distributed energy resources and electric vehicles:

A Californian case study	55
1 Introduction	56
2 Literature review	59
3 Model and Data	62
3.1 Methodology	62
3.1.1 DER-CAM Optimization Program	63
3.1.2 Avoided Cost Model (ACM)	66
3.2 Data	70
3.2.1 Load profiles	70
3.2.2 Electricity retail rates	71
3.2.3 DER Parameters	72

4	Results	77
4.1	Exogenous investment	77
4.1.1	Net present value	77
4.1.2	Avoided costs	80
4.1.3	Cost-shifting	84
4.1.4	Value created by electric vehicles	84
4.2	Endogenous investment	85
5	Discussion and policy implications	92
6	Conclusion	94
7	References	97
4	New EV rate design: An MPEC assessment	105
1	Introduction	106
2	Literature review	108
3	Method	109
3.1	Model overview	110
3.2	Upper-level problem formulation: the regulator	110
3.2.1	Regulator objective function	110
3.2.2	Grid capacity constraints	112
3.2.3	DSO cost-recovery constraint	113
3.3	Lower-problem formulation: the agents	113
3.3.1	Agents objective function	113
3.3.2	Agents peak power constraint	114
3.3.3	Electric vehicle capacity constraint	115
3.3.4	Battery storage investment constraints	117
3.3.5	Solar-PV investment constraints	118
3.3.6	Energy balance equation	118
4	Case study: setup and input data	120
4.1	Setup	120
4.2	Load and solar profiles	122
4.3	EV and DER data	123

4.4	Baseline electricity bill	124
4.5	Grid cost structure	126
5	Results	127
5.1	Energy profile assessment	127
5.2	Network costs impact	130
6	Discussion and policy implications	133
7	Conclusion	135
8	References	136
5	General Conclusion	141
1	Summary of contributions	142
1.1	Chapter 2	142
1.2	Chapter 3	143
1.3	Chapter 4	144
2	Transversal considerations	145
3	Future works	146
A	Appendix to Chapter 3	148
	Optimization program	148
	Exogenous investment DER sizing	152
	Charging and discharging strategies	154
	Complementary Tables	158
B	Appendix to Chapter 4	165
	The detailed mathematical model	165
	Transforming the Bi-level problem into a solvable MPEC	171
	Electric Nation Customer Trial: Insights from the pilot	178
	Complementary Tables	179
C	Research outcome	181
D	Résumé en français	184
	Chapitre 2	185

Chapitre 3	185
Chapitre 4	186

List of Figures

1.1	Breakdown of households' electricity prices. Source: European Commission (2020)	4
2.1	Conceptual framework of the technologies used in the coupling.	23
2.2	Representation of a possible future electric system.	26
2.3	Community energy system configurations	28
2.4	Synthesis of main research areas of the coupling distributed battery storage and PV	42
3.1	Methodological framework.	63
3.2	Marginal peak avoided costs profile for Forecasting Climate Zone 9 in 2020.	68
3.3	Commercial building load profiles.	71
3.4	Electricity tariff formats.	73
3.5	Electric vehicle parameters and time schedule.	76
3.6	Average EV financial flow breakdown per vehicle - Exogenous case. . .	86
3.7	Average EV financial flow breakdown per vehicle - Endogenous case (Conservative scenario).	92
4.1	Methodological framework.	111
4.2	Topology configuration of all agents.	121
4.3	Load and solar profiles.	122
4.4	Energy profiles.	126
4.5	Energy cost variation without DER investment.	128
4.6	Energy cost variation with DER investment.	129

4.7	Total network costs.	131
4.8	Network cost breakdown.	132
4.9	Total costs of Consumer/EV agent for all four scenarios.	133
A.1	Charging strategies according to different DER scenarios and tariffs during summer (September).	155
A.2	Discharging strategies according to different DER scenarios and tariffs during summer (September).	157
B.1	Electric Nation Trial data.	178

List of Tables

2.1	Solar PV technologies overview. Source: NREL (2019); Shubbak (2019); Subtil and Bergh (2016)	18
2.2	Battery technologies overview. Source: Diouf and Poda (2015); Imanishi and Yamamoto (2019); IRENA (2017b); Zubi et al. (2018)	20
2.3	Optimization method classification. Adapted from Amaran et al. (2019)	30
2.4	Techno-economic model descriptions.	30
3.1	Adopted DER costs.	75
3.2	Average percentage total electricity costs change (%).	79
3.3	Net present value by rates and technology scenarios (\$).	81
3.4	Average peak demand reduction.	81
3.5	Average avoided costs - Case 1 (\$).	83
3.6	Average cost-shifting measures by technologies and tariffs - Case 1 (\$).	89
3.7	Average DER amount in endogenous case.	89
3.8	Private financial gains - Endogenous case.	90
3.9	Average avoided costs and cost-shifting - Endogenous case. (\$)	91
4.1	Electricity bill components	125
A.1	Discharging incentives per tariff structure	156
A.2	SCE's General Services 2 electricity retail tariffs.	158
A.3	SCE's General Services 2 electricity retail tariffs time schedule.	159
A.4	Variable coincidental hours along the months.	159
A.5	Average % change in demand during system peak times for PV+BESS and PV+EV.	160

A.6	Average % change in maximum private demand for PV+BESS and PV+EV.	160
A.7	Average % change in demand for PV+EV+BESS.	161
A.8	Total building electric costs per technology scenario.	161
A.9	Average avoided costs - Case 2. (\$)	162
A.10	Average cost-shifting measures by technologies and tariffs - Case 2. (\$)	162
A.11	Average DER installed capacity - TOU-COIN Endogenous case.	163
A.12	Average avoided costs and cost-shifting - Endogenous case 2. (\$)	163
A.13	EV financial flow breakdown - Endogenous case. (\$)	163
A.14	Average EV financial flow breakdown - TOU-COIN Endogenous case. (\$)	164
B.1	Total cost and DER for different energy profiles (MILP analysis)	179
B.2	Total cost and DER for different energy profiles (PV cost = 1,500\$/kWp)	180
B.3	Total network costs for all scenarios according to grid cost structure	180

Lists of Acronyms

- AMI: advanced metering infrastructure
- CO₂: carbon dioxide
- DER: distributed energy resource
- DSO: distribution system operator
- EV: electric vehicle
- EVSE: electric vehicle supply equipment
- BESS: electric storage system
- FIT: feed-in tariff
- GHG: greenhouse gas
- ICE: internal combustion engine
- PHEV: plug-in hybrid electric vehicle
- PV: photovoltaic
- SOC: state of charge
- TOU: time-of-use
- TSO: transmission system operator
- V2G: vehicle-to-grid
- V2X: vehicle-to-everything

* * *

*“Life can only be understood backwards; but it
must be lived fowards.”*

Soren Kierkegaard

* * *

Chapter 1

General Introduction

1 Overview

The 21st century is a pivotal time for mobility. Individual mobility, in particular, has become a critical topic in environmental summits. Air pollution - to which internal combustion engines (ICE) vehicles significantly contribute - is causing severe local health impacts: in 2021, it was considered the 4th leading risk factor for early death worldwide (HEI; 2021). Furthermore, air quality and climate issues are increasingly interrelated, indicating that local air pollution is not simply a regional issue but a global challenge. CO₂ emissions from the transportation sector account for 24% of direct emissions (IEA; 2020), forcing the automobile industry to evolve and revolutionize its products. Hence, automobile electrification is pictured as an efficient and promising technological option, as it avoids a more fundamental change of individual mobility patterns. To this end, electric vehicles (EVs) need to massively substitute ICE vehicles if decarbonization goals are to be reached: between 150 and 230 million EVs are expected on the roads worldwide by 2030.

This level of energy transition brings many challenges. First of all, the uptake of electric mobility requires organizational innovation to integrate new components in the supply chain. There will be a significant demand increase for batteries, electric motors, and electronic converters that may be complex to fulfill. Then, public policies are needed to incentivize electric vehicle adoption. Direct EV purchasing subsidies and ICE banning regulations have set a global road map of electrification targets in many

countries. More than 20 countries have electrification targets or ICE bans for cars, and eight countries, plus the European Union have announced net-zero carbon emission pledges (IEA; 2021). However, the linkage with the power sector brings additional challenges since there is an undergoing decarbonization process in this sector as well.

The power sector contributes to 42% of global CO₂ emissions. Hence, reaching emissions targets compels investments in low carbon renewable energy resources such as solar PV and wind power. As a consequence of solar PV costs decreases, the ongoing decentralization of electricity generation is turning ancient consumers into active prosumers. In this context, EVs may get connected to solar PV systems behind the meter, and become valuable assets for offering flexibility to intermittent energy sources. Stationary batteries are also likely to participate as flexibility providers alongside EVs. This synergy between distributed energy resources and EVs can concomitantly bring benefits to both power and mobility sectors.

This introductory part aims at providing an overview of the EV ecosystem and its roles in this energy transition. The second part, which includes chapters 2 to 4, discusses the economics and policies that link electric vehicles and the power sector. The third part summarizes each of the three chapters of this dissertation along with a general conclusion.

1.1 Electric vehicle ecosystem

This section aims at giving a broad overview of the current electric vehicle ecosystem and the stakeholders involved. Electric vehicles comprise, by definition, all vehicles possessing a battery used for main propulsion purposes. This dissertation will focus on light-duty plug-in electric vehicles, and we will analyze the direct economic interaction with power systems.

Electric systems should power EVs without putting at risk the security of supply for customers, although, EVs may impact power grids in several ways. First, through the amount of energy (kWh) required to charge EVs. Second, through the maximum peak capacity (kW) of the electric grids. According to the French transmission system operator, its grid could integrate at least 15 million vehicles by 2035 (RTE; 2019). In terms of peak capacity (kW), a mild level of smart charging, *i.e.*, modulating the

charging power of EVs in a coordinated way, would be adequate to relieve grid congestions. This issue may also arise for distribution grids that have historically adopted the "fit and forget" approach (Burger et al.; 2019). Even with a robust operation margin, a concentration of EV charging in the medium term can cause power issues to local parts of the grid. However, EVs are not exclusively a threat to the proper functioning of power systems; they are also promising candidates to provide flexibility. As long as EVs are connected to the grid, the charge - and, if needed, discharge - could be optimally managed to support system operators while ensuring the user's driving needs.

To unlock the full potential of EVs as flexible resources, the concepts of smart charging and vehicle-to-everything (V2X) are helpful. Smart charging allows the EV to shift the charging process in time and modulate in power according to a specific strategy. This concept is mainly used to avoid high prices specified in electricity tariffs to reduce the total costs of charging. Moreover, V2X implies that vehicles have a bidirectional capability, which makes them able to deliver electricity from their battery back to the grid (Vehicle-to-Grid, V2G), home (Vehicle-to-Home, V2H), building (Vehicle-to-Building, V2B), or specific loads (Vehicle-to-Load, V2L). Kempton and Tomić (2005) first proposed this technology, raising attention to the high added value that vehicles can be to grid operators. Recent literature explored how V2G can create new value streams through power markets, direct interaction between grid operators and customers, or simply behind-the-meter (Thompson and Perez; 2020).

Hence, EVs can be considered as a distributed energy resource (DER) submitted to price-based methods for DER management. Price-based demand response is incentivized by exposing DER owners to time-varying electricity rates, so that they can adapt their consumption patterns based on adjusted economic signals (Eid et al.; 2016). However, designing rates that simultaneously incentivize demand response, avoid grid congestions and fairly recover utility costs is not obvious. The next section will give a brief overview of the challenges and solutions to the problems posed by the widespread uptake of EV and DERs. We focus mainly on the issues of existing customer charging methodology via electricity rates.

1.2 Interactions with rate design

First, it is essential to understand cost components of the electricity bill. Figure 1.1 pictures the breakdown of households' electricity prices in Europe from 2010 until 2019¹.

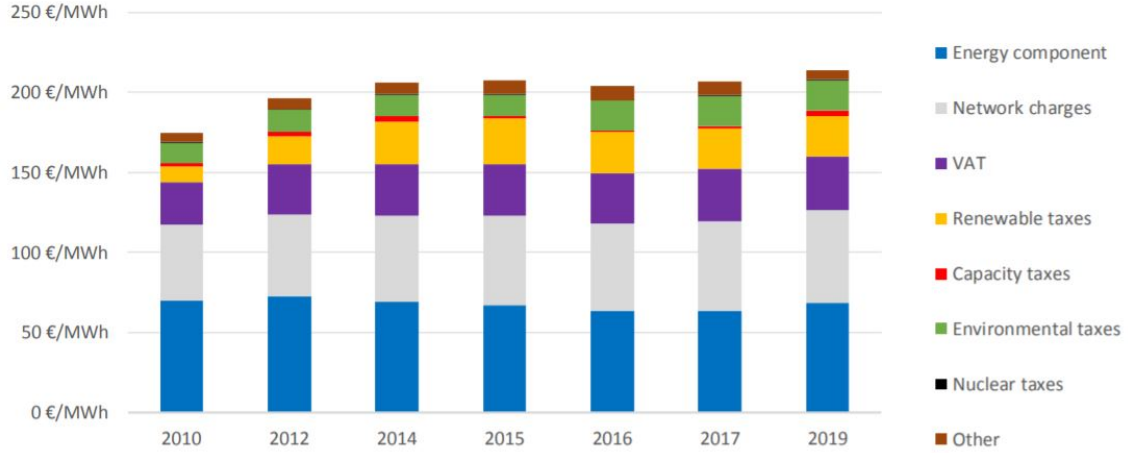


Figure 1.1: Breakdown of households' electricity prices. Source: [European Commission \(2020\)](#)

First, the share of taxes in the final price has been steadily increasing due to the growing levies for renewable energy policies. The tax allocations and possible recovery through electricity bills are up to the government, but that debate is out of this dissertation's scope. Second, energy charges reflect the wholesale market prices. The final energy price will depend on the market dynamics and on the offer proposed by the retailer, which can be time-invariant or not. Third, the last and most discussed element in the current context is network charges. Then, the question of how to recover these electricity costs components, in particular network charges, in a scenario with DERs and EVs uptake is challenging. The discussions are primarily on how it should be redesigned according to the format (energy, capacity, fixed or a combination thereof), the temporal granularity (flat or time-of-use), and locational granularity (uniform or location-specific). How should electricity tariffs be designed and which relative weights should be applied on fixed kW capacity, kW peak use, and kWhs exported/imported. There have been distributive justice concerns in some

¹The components for other sectors such as commercial and industrial remain practically the same. Only the share of each differs. For example, while taxes and levies accounted for 41% of households' electricity prices, for the industry sector it was 30-34% ([European Commission; 2020](#)).

jurisdictions about the uptake of PV in the context of kWh-based network charging and sunk grid costs (Schittekatte et al.; 2018; Simshauser; 2016). However, a similar uptake of electric vehicles might relieve these issues, by increasing the contribution of wealthy households to total network costs (Hoarau and Perez; 2019).

Modeling the impacts of PV, EVs, and distributed electrical energy storage on who bears network charges is essential and will allow the regulator to anticipate what network charging methodologies should be preferred (Pollitt; 2018). The answer for that question is likely to include volumetric charges (kWh) for imports/exports, capacity charges (kW), coincidental peak charges, and differentiated fixed charges to some extent. Pérez-Arriaga et al. (2017) provide a regulatory framework for an evolving electric system with interesting recommendations concerning rate design: a system of economic signals for electricity services that accurately reflect the marginal or incremental cost of each electricity service and the variation in these costs across both time and location. In summary, one rate seems to “not fit all” contexts since countries have different penetration levels of EV and DERs, different grid cost structures, and heterogeneous policies. Nevertheless, best practices observed from the ones that are a step ahead on the energy transition are always useful for building a solid roadmap to laggards.

2 Problem statement and purpose

The interactions between EVs and DERs can bring benefits to both mobility and power sectors. However, achieving optimal synergy requires an understanding of the underlying techno-economic aspects that drive the adoption of EVs and DERs. Rate design is identified as a critical point that influences the choice and the profitability of investments. The changes in the electricity scenario, with the uptake of innovative technologies, directly affect how utilities charge their customers a fair and cost-reflecting retail tariff. Consequently, the new and adjusted tariffs impact innovation uptake, evidencing a clear feedback loop. The purpose of this manuscript is (i) to shed light on the fundamental techno-economic relations of EVs and DER coupling and (ii) to understand better the feedback-loop between tariff design and DERs investment.

3 Approach and methodology

The methodology applied to tackle the research questions raised is the following. First, a literature review is conducted to identify the main stakeholders and elements involved in the EVs and DERs coupling. This analysis is crucial to reveal the most sensitive aspects that may influence their adoption, including rate design.

Second, to investigate how electricity rate design impacts DER and EVs adoption, a mathematical model including investment decisions concerning PV, EVs, and the stationary battery is crucial. For this purpose, we use a decision support tool that primarily serves to find optimal DER investments in the context of buildings. This tool called DER-CAM was developed by researchers at Lawrence Berkeley National Laboratory (Berkeley Lab). A sensitivity analysis with different tariff structures allows capturing the impacts of DER decision investments for various stakeholders such as buildings, utilities, and EV owners.

Third, to finally close the loop between DERs, EVs, and rate design, an equilibrium formulation to this problem is needed. We develop a game-theoretical model expressed and treated as a Mathematical Program with Equilibrium Constraints (MPEC) to capture the interaction between a National Regulatory Authority (NRA) designing these tariffs and heterogeneous agents who may possess an EV and can invest in DER. This modeling structure allows a deeper investigation of the relation between EVs and tariff design in this context. Therefore, a new EV rate design is proposed.

4 Contributions of this dissertation

This dissertation studies different aspects of the transition towards electric mobility. It contains three chapters that are linked to each other and are organized as follows: Chapter 2 explores the techno-economic aspects of the evolving electricity system where EVs and DERs become core technologies; Chapters 3 and 4 provide potential solutions for tariff design issues in the evolving electricity sector.

4.1 Coupling small batteries and PV generation: A review

This chapter provide an analytical framework identifying the main research areas dealing with PV–EV–battery relationships. The coupling between PV–EV–battery depends not only on the technological progress or economic regulations but also on the under-explored user acceptance towards the technologies. Several factors - the need to comply with climate agreements, the falling costs of PVs and battery packs, and the services battery storage can provide - further stimulate studies on the potential benefits from the synergy between those two technologies. The technical and economic issues related to EV/PV systems are well studied separately in the literature, nevertheless, a general panorama including societal aspects with EVs/PVs/batteries is lacking. Our work aims to provide an analytical framework to review the progress and hidden conditions of success for the coupling with literature support. The chapter will present the technical aspects needed to confirm the feasibility of EVs/PVs/batteries coupling - whether with well-known technologies or innovative ones. Then, an economic assessment of support mechanisms and implementation barriers is developed. Finally, we shed light on general societal goodwill and awareness towards DER adoption, user acceptance and the literature gaps warranting future research.

4.2 Rate design with distributed energy resources and electric vehicles: A Californian case study

This chapter investigates the relations between EVs and DERs (PVs and batteries) in commercial buildings under different retail tariff schemes. Regulation authorities base their tariff designs on various factors: the state of the electrical grid, consumer behavior, policy objectives, and electricity mix. In practice, fairness and cost-reflectiveness have a significant impact on the design of the network part. They depend most on the state of the grid whether grid investments still have to be made, or if costs are mostly sunk. A new rate design will be needed to prevent the increase in DER fom causing a severe deficit in the utility's final budget, changing how electricity is produced and stored. The main goal is to observe the facility's private value impact, the grid operator's financial impact quantified by cost-shifting values, and EV remuneration when

adding an EV providing vehicle-to-grid services behind the meter alongside the DER mix. We assess an optimistic DER cost scenario including EVs as an electric storage option for commercial facilities. An overview of the problem is given to explain the motivation of the research, with a literature review support. Lastly, we discuss the results and derive policy implications from them.

4.3 New EV rate design: An MPEC assessment

High penetration of electric vehicles (EVs) will deeply impact the management of electric power systems. Many utilities propose indirect load control via adapted economic signals to avoid costly grid reinforcements and the risk of load curtailment due to EV charging. Charging costs can be reduced by a domestic tariff applied only to EV charging using a dedicated measurement method of the load, while enhancing the flexibility offered by EVs. We develop a game-theoretical model expressed and treated as a Mathematical Program with Equilibrium Constraints (MPEC) to capture the interaction between a National Regulatory Authority (NRA) designing these tariffs and heterogeneous agents. First, we analyze the conditions in which EV-only tariffs can be applied for domestic slow charging sessions by comparing different energy profiles. Second, we study the impact of EV charging on different tariff structures to identify the most efficient way of recovering network costs.

4.4 Further perspectives

Our work sheds light on different rate designs for the commercial and residential sectors. Which schemes should be incentivized will depend on the local context. Heterogeneous policies, different penetration levels of DERs, EVs, and grid cost structure will influence the adjustment of tariffs. Our analysis includes an optimization program and an equilibrium framework. The optimization decision tool allows simulations using high granularity of data, resulting in reliable results for a specific case study. On the other hand, equilibrium frameworks focus on the general interactions between interrelated aspects - tariff design, DER investment and EV charging - with limited data granularity.

5 References

- Burger, S. P., Jenkins, J. D., Batlle, C. and Pérez-arriaga, I. J. (2019). Restructuring Revisited Part 1 : Competition in Electricity Distribution Systems, *The Energy Journal* . 3
- Eid, C., Codani, P., Perez, Y., Reneses, J. and Hakvoort, R. (2016). Managing electric flexibility from Distributed Energy Resources: A review of incentives for market design, *Renewable and Sustainable Energy Reviews* **64**: 237–247. 3
- European Commission (2020). Report from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Energy prices and costs in Europe. vi, 4
- HEI (2021). Impacts on your health, <https://www.stateofglobalair.org/health>. 1
- Hoarau, Q. and Perez, Y. (2019). Network tariff design with prosumers and electromobility: Who wins, who loses?, *Energy Economics* **83**: 26–39. 5
- IEA (2020). Tracking transport report. 1
- IEA (2021). Global EV Outlook 2021. 2
- Kempton, W. and Tomić, J. (2005). Vehicle-to-grid power implementation : From stabilizing the grid to supporting large-scale renewable energy, *Journal of Power Sources* **144**: 280–294. 3
- Pérez-Arriaga, I. J., Jenkins, J. D. and Batlle, C. (2017). A regulatory framework for an evolving electricity sector: Highlights of the MIT utility of the future study, *Economics of Energy and Environmental Policy* **6**(1): 71–92. 5
- Pollitt, M. G. (2018). Electricity network charging in the presence of distributed energy resources: Principles, problems and solutions, *Economics of Energy and Environmental Policy* **7**(1): 89–103. 5
- RTE (2019). Enjeux du développement de l’électromobilité pour le système électrique, *Technical report*. 2
- Schittekatte, T., Momber, I. and Meeus, L. (2018). Future-proof tariff design: Recovering sunk grid costs in a world where consumers are pushing back, *Energy Economics* **70**: 484–498. 5
- Simshauser, P. (2016). Distribution network prices and solar PV: Resolving rate instability and wealth transfers through demand tariffs, *Energy Economics* **54**: 108–122. 5
- Thompson, A. W. and Perez, Y. (2020). Vehicle-to-Everything (V2X) energy services , value streams , and regulatory policy implications, *Energy Policy* **11**(July): 111136. 3

* * *

*Para além da curva da estrada
Talvez haja um poço, e talvez um castelo,
E talvez apenas a continuação da estrada.
Não sei nem pergunto.
Enquanto vou na estrada antes da curva
Só olho para a estrada antes da curva,
Porque não posso ver senão a estrada antes da curva.
De nada me serviria estar olhando para outro lado
E para aquilo que não vejo.
Importemo-nos apenas com o lugar onde estamos.
Há beleza bastante em estar aqui e não noutra parte qualquer.
Se há alguém para além da curva da estrada,
Esses que se preocupem com o que há para além da curva da estrada.
Essa é que é a estrada para eles.
Se nós tivermos que chegar lá, quando lá chegarmos saberemos.
Por ora só sabemos que lá não estamos.
Aqui há só a estrada antes da curva, e antes da curva
Há a estrada sem curva nenhuma.*

Fernando Pessoa - *Poemas Completos de Alberto Caeiro.*

* * *

Chapter 2

Coupling small batteries and PV generation: A review

* * *

The decarbonisation of both power and mobility sectors are two main goals established during international environmental summits. Distributed battery storage, such as electric vehicles batteries and stationary ones, ranging from around a dozen to a few hundred kWh and photovoltaic (PV) systems are disruptive technologies not only because they can individually contribute to CO₂ emissions reduction but also due to the positive synergies between them. We provide an analytical framework identifying the main research areas dealing with PV–EV–battery relationships to academics, stakeholders and policymakers willing to acquire further knowledge on this topic. The coupling between PV–EV–battery depends not only on the technological progress or economic regulations, but also on the under-explored user acceptance towards the technologies. First, emerging technologies (e.g. microgrids, vehicle-to-grid and blockchain) will deeply impact PV–EV–battery synergy, forcing electricity grid operators to readjust the way how the grid is managed. Second, inappropriate economic regulations (e.g. obsolete tariff and ancillary services market designs) and outdated strategies formulated by the automotive sector could jeopardize all the potential benefits brought by the coupling. Then, user acceptance is found to be a decisive variable in whether people are willing to invest in distributed energy systems.

* * *

1 Introduction¹.

In the energy transition scenario, the need to decarbonise the power and mobility sectors are two main goals established during important international environmental meetings such as COP21 in Paris. Those two sectors contribute together with 66% of all greenhouse gas emissions on the planet with the use of fossil fuels to produce electricity in power plants accounting for 42% of the total CO₂ emissions and internal combustion engines in vehicles accounting for more 24% (International Energy Agency; 2018b). The coordination between agents in both sectors is necessary to accelerate the development and integration of recent technologies which substitute fossil fuel applications in the market (Perez-Arriaga et al.; 2017). The worldwide increase of electric vehicle (EV) units sold, crossing the threshold of one million units sold in 2017 (an increase of 54% on a year-on-year basis) (International Energy Agency; 2018a), as well as the great augmentation of photovoltaic battery systems (PVB), also known as Solar plus systems, deployed around the world are consequences of policies established to drive the deployment of these technologies to reach climate agreement targets (Shaughnessy et al.; 2018). Solar PVs accounted for only 2% of the global generation in 2017 with almost 400 GW installed, but with its massive deployment due to continuously falling cell costs, the share could reach almost 10% of worldwide generation in 2040 (European Commission; 2018).

Electric vehicles are well suitable candidates to contribute to the decarbonisation of the mobility sector worldwide since their battery used to power an electric motor will render dispensable the utilization of fossil fuels in internal combustion engines. However, if the electricity with which they are charged comes from fossil fuels power plants, all the avoided CO₂ emissions in the mobility sector could be jeopardized by the increase of emissions from the power sector, threatening the global reduction of greenhouse gas emissions. EVs charged from non-renewable energy will not improve the current situation concerning the global emissions as the Eurelectric report (2015) demonstrates Eurelectric (2015). If the country has a fossil based power sector, like

¹Published as: Freitas Gomes, I. S., Perez, Y., & Suomalainen, E. (2020). Coupling small batteries and PV generation: A review. *Renewable and Sustainable Energy Reviews*, 126(March), 109835. <https://doi.org/10.1016/j.rser.2020.109835>

Poland, the EVs will not be able to reduce effectively the average g CO₂/km towards the main goal. This is the reason why solar PV systems could benefit both sectors at once, where an intermittent power generation could match an intermittent demand from EVs with smart charging. Ideally, EVs adoption should happen concomitantly with the decarbonisation of the power sector following the pace of national policies and the renewable energy penetration levels, and considering the robustness of the transmission and distribution grid to manage the increase in peak demand and the power quality deviations in both levels.

High battery costs, including cell and pack costs, have been the greatest barrier to the massive adoption of battery storage systems in the last few years. However, since 2008, lithium-ion battery costs have been reduced by a factor of four and their costs are projected to decrease to around 100 \$/kWh by 2030 benefiting from important economies of scale driven by the growth in the electro-mobility sector ([International Energy Agency; 2018b](#)). They can be used to increase self-consumption by storing electricity surplus produced by PVs during the day to avoid curtailment ([Luthander et al.; 2015](#); [McLaren et al.; 2018](#); [Nyholm et al.; 2016](#)). Restoring energy for load peak shaving to reduce maximum demand charges ([McLaren et al.; 2018](#)) or restoring it to the external grid when constraints are identified ([Kempton and Tomi; 2005](#)) are important drivers of the technology adoption. Several other services behind and in front of the meter can be provided by battery systems and electrical vehicle fleet, such as: frequency regulation ([Borne et al.; 2018](#); [Codani et al.; 2016](#)), voltage regulation ([Mojdehi et al.; 2016](#); [Wang et al.; 2019](#)), demand response ([Xiong et al.; 2018](#)) and congestion management ([Eid et al.; 2016](#)).

There is an ongoing shift in the trend of social acceptance concerning the coupling of these technologies, where consumers are becoming more independent from the electrical grid due to the installation of their own microgeneration sources; i.e., consumers are increasingly becoming prosumers ([Sauter and Watson; 2007](#)). Furthermore, the creation of a solid market of distributed battery storage coupled with photovoltaic generation requires not only the mastery of technologies involved and its accessible costs but it also depends on the final consumer acceptance to pay for it. Willingness-to-pay (WTP) is commonly known as the maximum price range a consumer will spend

on a product or a service in a specific location. For the case of distributed energy resources, this variable is suitable to frame how ready people are to invest in batteries, EVs or renewable generation in a specific period, so policymakers could better know how to guide the development of those technologies comparing the WTP with the market prices (Claudy et al.; 2020).

The need to comply with climate agreements, the falling costs of both PVs and battery packs and the services battery storage can provide, all those facts stimulate further studies on the potential benefits from the synergy between those two technologies. The technical and economic issues related to EV/PV systems are well studied separately in the literature (Hoarau and Perez; 2018), nevertheless, a general panorama including societal aspects with EVs/PVs/batteries is lacking. Our work aims to provide an analytical framework to review the progress and hidden conditions of success for the coupling with literature support.

The chapter will be presented as follows: In section 2, the technical aspects are presented aiming to confirm the feasibility of the coupling involving both well-known technologies and innovative ones. In section 3, the economic assessment of support mechanisms and barriers to the implementation of a system with these distributed resources is done. In section 4, we shed light on aspects related to general societal goodwill and awareness towards distributed energy resources (DERs) adoption: user acceptance. Finally, we present the literature gaps warranting future research.

2 Technology trends

The core energy resources to be studied in this chapter are batteries and photovoltaic panels; nevertheless, these are not the only technologies involved to enable an efficient coupling providing benefits for those who install it and for the society. Innovative technology trends, e.g., microgrids, vehicle-to-grid and blockchain can contribute to the reduction of energy loss and profit maximization, thus enhancing economic gains.

2.1 Photovoltaic panels

The main carbon-free distributed generation technology easily installed in residential and rural areas is solar PV. It is a noiseless, renewable, environmentally friendly and reliable source that converts solar light into electricity, but with a relatively high initial cost (Luz et al.; 2013). According to Shubbak (2019) and Subtil and Bergh (2016), there are three generations of photovoltaic technology: the first is crystalline silicon based on silicon wafers; the second is the thin film technology and the third refers mostly to disruptive changes in the way the technology works, in this case, organic cells, advanced inorganic thin films and multijunction cells are used.

The silicon-based wafer technology accounted for about 95% of the total production of PV technology in 2017, while the 5% left consisted of the thin film technology production (Fraunhofer ISE; 2019.). Silicon cells have excellent conversion efficiency ranging from 22.3% for multicrystalline cells to 27.6% for single crystal cell. The researches on thin-cells were able to lower costs and reduce the required material to fabrication compared to crystalline silicon cells which use 99% more material to absorb the same amount of sunlight (Gonçalves et al.; 2017). Thin film panels are easy to install, flexible, durable (25 years of lifetime) and have an efficiency from 14% for the newest amorphous silicon cell to 23.3% for copper, indium and gallium-selenide (CIGS) cells (NREL; 2019).

The last emerging generation of PV technology stands mostly for organic photovoltaic cells aiming at massive applications on future power generation field and multijunction cells aiming space power applications. The motivation for organic cells research relies on the use of low cost and abundant materials like organic polymers and the less expensive manufacturing processes. The technology has been in continuous progress since 2005 when the efficiency was five times lower (Benanti and Venkataraman; 2006) resulting in a maximum efficiency nowadays of 17.4% and 28% for organic tandem cells². On the other hand, the main objective of researches on multijunction cells is to increase its conversion efficiency using multiple materials to absorb a large

²The main difference between organic and inorganic cells lies in how the charge carriers, electrons and holes responsible for the photovoltaic effect, are generated and their spatial distribution in the cell (Gregg and Hanna; 2003).

range of wavelengths coming from the sunlight. A maximum efficiency of 47.1% was achieved for a four-junction cell with concentrated systems that focus the irradiation on a smaller surface using special mirrors and lenses. The Table 1 summarizes the information about the PV generations and provides some additional information on each technology presented.

Table 2.1: Solar PV technologies overview. Source: NREL (2019); Shubbak (2019); Subtil and Bergh (2016)

PV Generation	1st		2nd			3rd	
Solar cell technology	Monocrystalline (mc-Si)	Multicrystalline (pc-Si)	Amorphous Silicon (a-Si)	Copper, Indium and gallium-selenite (CIGs)	Cadmium telluride (CdTe)	Organic PV (OPV)	Four-junction
Efficiency (%)	26.1 - 27.6	22.8	14	23.3 - 23.4	22.1	17.4 - 28	39.2 - 47.7
Lifetime (years)	25 - 30	25 - 30	25 - 30	25 - 30	25 - 30	5	25+
Cost (US\$/Wp)	0.26 - 0.45	0.21 - 0.29	0.5 - 1.5	1 - 1.5	1 - 1.5	0.55	300+
Market Share (%)	24	69	3	2	2	Under Research	<1
Application	Civil ^a	Civil	Civil	Civil	Civil	Civil	Spatial

^aResidential, commercial, and power plants.

2.2 Batteries

When coupled with PV, batteries can perform many different services behind-the-meter and in front-of-the-meter in the form of ancillary services. The most used technologies for stationary battery applications are lead acid batteries and Li-ion batteries. As for electric vehicles applications, the NiCd and NiMh batteries were initially used, but due to their limited energy density and low autonomy, they have been substituted by Li-ion batteries since 2009 (Armand and Tarascon; 2008; Yang and Tarascon; 2012).

Lead acid batteries are in use since late 1800s, being the oldest technology among the others referred to in this section. Obviously, many improvements have been made since the first use; however, since the first appearance of sealed batteries, known as valve regulated lead-acid (VRLA) batteries, in 1957 the technology did not have as much evolution as expected (Exide Technologies; 2003). This type of battery has some limitations, such as: an usable capacity between 30-50% of the nominal capacity to avoid excessive battery degradation; a very low lifetime of 3-5 years if compared to the PV average lifetime of 25 years; a limited number of cycles during lifetime between 300-500 with a 80% depth-of-discharge; a high sensitivity to Peukert's loss meaning that when the power output required is higher than the one specified by the manufacturer, the delivered capacity is lower than expected (Diouf and Podge; 2015). Regardless

of its limitations, VRLA batteries still dominate the market for photovoltaic off-grid applications due to their affordable costs for large installed capacities, but they are the overall weakness of the system and tend to be substituted by more promising technologies like Li-ion batteries (Diouf and Avis; 2019).

Li-ion batteries are nowadays the major technology applied in electrical vehicle main battery and a very good candidate to stationary applications. They can be use with a depth-of-discharge up to 80% of their total capacity, with great number of cycles varying between 2000 and 5000 according to some manufacturers and greater efficiency with great loads as their power inverters have almost no Peukert's loss (Diouf and Pode; 2015). In terms of chemistry, four different cathode cell technology can be highlighted: Lithium Nickle-Cobalt-Aluminum (NCA), Lithium Iron Phosphate (LFP), Lithium Nickle-Manganese-Cobalt (NMC) and Lithium Manganese Oxide + Nickle Manganese Cobalt (LMO-NMC). Due to the great prevalence of carbon-based anode materials in Li-ion batteries, all the cell technologies normally omit the names of the anode material and just mention which cathode material is being used.

NCA presents the superior behavior concerning calendar life, the highest specific capacity vs cell potential ratio and its degradation due to changes in temperature and state of charge (SOC) results in the least amount of capacity fade (Gyan, P.; 2015). However, it comes with the highest cost to manage the temperature rise to be operated without problems. LFP degradation is more temperature-driven than SOC-driven causing a pronounced power loss and capacity fade at high temperatures. LFP does not require high investments to manage its operating temperature because the technology is the safest concerning possible thermal runaways; however, this comes with a trade-off of reducing specific energy and specific capacity vs cell potential ratio (Thompson; 2018). The predominant characteristics of NMC and LMO-NMC come from the NMC technology, while the addition of LMO is done to improve safety and increase specific capacity vs cell potential ratio in the overall system. They show similar behaviors in capacity loss degradation and power loss being highly affected by high SOC's and high temperatures (above 50 °C), although the influence of the SOC tends to be less present in the pure NCM technology. Comparing with NCA and LFP, the NMC and LMO-NMC have the second-best specific capacity vs cell potential ratio

and the second worst thermal characteristics, in other words, they are the technology right between the other two regarding these technical aspects (Krieger et al.; 2013). EV manufacturers are investing a lot in thermal management battery systems to maintain cell temperature at an acceptable level enabling the use of the technology with the highest specific energy and lowest degradation ratio (Dubarry et al.; 2018).

The promising metal-air battery technology started to raise attention especially from the automotive sector due to the high energy density and the facility to obtain oxygen from air responsible for the reduction reaction in the cathode electrode. Among all the candidate metals to compose the battery anode, lithium as it is the lightest metal, holds the highest theoretical capacity and energy density (several times higher than that of all lithium-ion batteries) being the most suitable one for electric vehicle application (Tan et al.; 2017). Nevertheless, several barriers like poor cycling life, low peak power and low practical capacity still need to be overcome with further researches in this field (Adams et al.; 2013). Finally, Table 2 summarizes the information about the battery technologies presented.

Table 2.2: Battery technologies overview. Source: Diouf and Pode (2015); Imanishi and Yamamoto (2019); IRENA (2017b); Zubi et al. (2018)

Specifications	Lead-acid	Lithium-ion			Lithium-Air
		NCA	LFP	NCM	
Specific energy/capacity(Wh/kg)	30-50	200-250	90-140	140-200	3500
Cycle life	300-500	1000-1500	2000	1000-2000	10-300
Charge/discharge efficiency (%)	50-95	80-90	80-90	80-90	60-90
Installation Cost (US\$/kWh)	200	350	580	420	Under research
Nominal cell voltage (V)	2	3.6	3.3	3.8	2.96
Maintenance	3-6 Months	Not required	Not required	Not required	Under research
Thermal protection complexity	Thermally Stable	Very High	Low	High	High
First appearance in	Late 1800s	1999	1999	2006	1996
Applications	Power Grid	EVs and power grid	EVs and power grid	EVs, electronic devices and power grid	EVs, electronic devices and power grid

2.3 Vehicle-to-Grid (V2G)

The main purpose of electrical vehicles is to fulfill mobility needs of their owners by providing a reliable, efficient and convenient mean of transportation. As both battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) have a battery inside them and at some point, they need to be connected to the grid, they could also return the stored energy back to it. The ability to restore electricity to the grid by plug-

in vehicles is referred in the literature as vehicle-to-grid (V2G). This concept was first introduced in 1997 (Kempton; 1997); however, it was just ten years later, in 2007, that the first experiment using V2G-equipped electrical vehicle took place (Markel et al.; n.d.), starting a new development for the technology with many project demonstrations since then. There are currently around 50 V2G projects going on around the world with half of them in Europe (Everoze; 2018). Turning an ordinary EV into a V2G capable EV is a relatively simple task for research laboratories; however, to have them ready to participate in the ancillary services market is not a simple task due to the high technical complexity of the ecosystem and the number of agents involved.

First, the EV must have a bidirectional charger located either in the vehicle (on-board) or in the charging station (off-board) to enable the bidirectional power flow between the battery and the grid (Yilmaz and Krein; 2013). The rated power of the charger varies according to the available charging infrastructure, for example, slow charging is commonly called Level 1, typically using low power levels from 1 kW to 2 kW located at home. Level 2 charging ranges from 4 kW to 20 kW that is mostly found in commercial buildings and workplaces. The last level 3, known as fast charge, occurs with power rates above 20 kW such as: 50 kW, 150 kW and even 350 kW that can make the charging as fast as filling up at a gas station (Electrek; 2018).

Then, the communication between the EV, charging station and aggregators must be assured by different protocols so that the aggregator which is a commercial entity responsible for grouping distributed energy resources like EVs to provide grid services as an intermediary between the system operator and EV owners. The protocols dealing with the communication between the vehicle and the electric vehicle supply equipment (EVSE) have as main objective assuring the interoperability between cars and EVSEs so that the whole infrastructure can be shared by the users. The SAE J2847 and CHAdeMO are currently being used in V2G projects (Schmutzler; 2013), while the European ISO 15118 is a partially published standard which is still under development ISO (2013). The Open Charge Point Protocol (OCPP) and ISO 61850 complete the communication network linking the EVSE and aggregator.

EVs can provide a good number of services in front-of-the-meter to both transmission and distribution grids increasing the opportunity of economic gains for the

user. As pointed out in [Eid et al. \(2016\)](#) concerning the short-term market, EVs can provide frequency containment reserves (FCR) and secondary reserves according to the market rules at the transmission level. Additionally, they can also participate in congestion management, voltage regulation and network investment deferral at the distribution grid level. Behind-the-meter services could also be profitable depending on the market and tariffs applied. Vehicle-to-everything (V2X) applications are exhaustively reviewed in [Pearre \(2019\)](#); however, the economic gains will be discussed in details in section 3. Besides the participation in those markets, the vehicle-grid integration is a promising concept for the easier integration of intermittent renewable generation like wind power ([Lund and Kempton; 2008](#)) and solar PV ([Alirezaei et al.; 2016](#)) whereas vehicles stay parked almost 95% of their lifetime thus potentially connected to the grid ([Barter; 2013](#)).

The majority of V2G pilots are using plug-in based connections to the grid; however, the wireless charging concept also appears in several V2G prototypes ([Member et al.; 2010](#)). The wireless charging introduces more complexities than the plug-in charges due to lack of actualized standards and relatively low efficiency caused by the great air gap and misalignments between the primary and secondary magnetic coils. Introducing a bidirectional wireless charger would add up the difficulties of V2G implementation with induction power transfer constraints. Nevertheless, the opportunities to reduce installed battery capacity once the battery would be continuously charging in the case of dynamic wireless charging, thus reducing EV costs, and the massive adoption of driverless autonomous vehicles are clearly in concordance with the development of this technology ([Machura and Li; 2019](#)). The Figure 2.1 describes a conceptual framework of the technologies presented using a bottom-up approach, from a local to a broader territorial point of view.

2.4 Microgrids

The advances of the technologies discussed until now (PVs, batteries and V2G) opened the path to the development of microgrids. A microgrid is not just characterized by a combination of DERs and interconnected loads, it is a necessary condition, yet it is not a sufficient one. Several technical requirements must be met to qualify a cluster

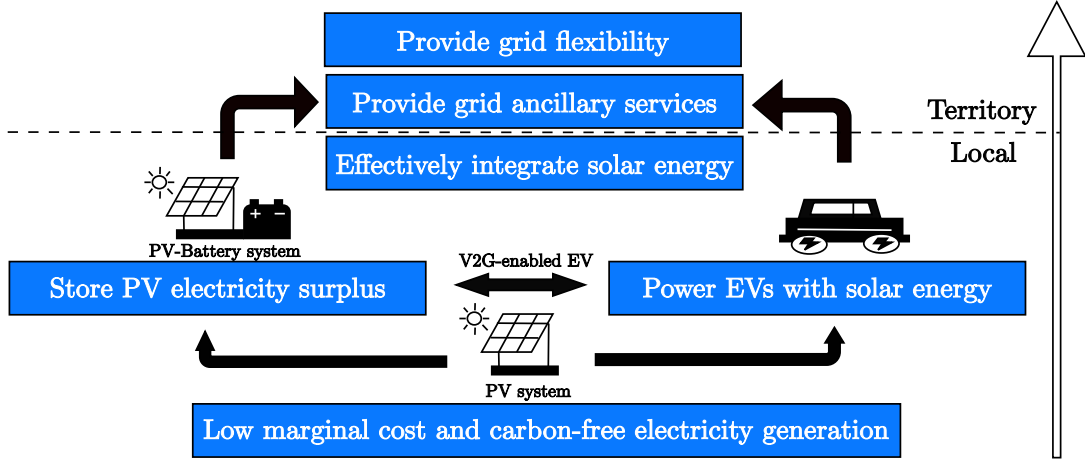


Figure 2.1: Conceptual framework of the technologies used in the coupling.

of interconnected loads and DERs as a microgrid, such as: the capacity to operate in grid-connected mode and islanded mode, the ability to ensure a smooth transition between them, reliable protection against unexpected events and great power quality (Stadler et al.; 2016). Microgrids can be classified according to the power type (AC or DC), supervisory control (centralized or decentralized), operational mode (islanded or grid-connected), phase (single phase or three phase) and the application (residential, industrial; utility, etc).

Starting with the power type classification, AC power has dominated the appliances of electrical network since the 19th century due to its long-distance high voltages transmission capabilities with easy protection scheme, the ability to power rotating machines in factories and the facility to change the voltage level with transformers. With the development of power electronic converters, the connexion of small DC loads to the AC main grid was possible; nowadays, DC loads like stationary batteries, EVs and photovoltaic DC generators are getting greater in number and capacity, reviving the debate about the efficacy of AC versus DC power network. DC microgrid can avoid multiple power electronic interfaces, using a single stage with easier design, control and reduce energy conversion losses (John et al.; 2013). For example, inverters present in photovoltaic panels systems, batteries systems and in V2G-capable charging stations must operate first with the DC-DC stage and then DC-AC to be compatible with the grid; in DC microgrids, the second stage would disappear, reducing losses and costs for

these DERs. According to Weiss et al. (2015) 50% of energy losses and 70% of volume necessary for the rectifier (AC-DC) of a small DC load would be avoided in the case of a DC grid connection. For higher DC loads and with onsite generation literature suggests an overall energy savings up to 15% depending on the microgrid configuration, converters efficiency and the building distribution system configuration (Vossos et al.; 2018). DC microgrids are applied to offices, data centres and residential areas, although they deserve more research efforts in standardization, bus selection, islanding control techniques (Planas et al.; 2015) and economic evaluations using not only PV and batteries (Vossos et al.; 2018), but electric vehicles equipped with bidirectional-chargers as well.

The energy management of a microgrid is done basically by a joint operation of the central controller (CC) and local controllers (LC) to increase energy efficiency, reduce energy consumption, increase reliability and avoid energy losses Fahad et al. (2018). In a centralized control strategy, all the requirements and resources available of each prosumer or consumer composing the microgrid are sent from the LCs to the CC, so the latter can determine the optimal energy schedule for the microgrid. On the other hand, in the decentralized control strategy, there is a real-time negotiation between LC and CC to optimize the schedule according to local and the microgrid global objectives.

Regarding the operating mode, it is worth clarifying the concept of islanded mode, for example, a microgrid which can stay indefinitely in this mode can be considered an off-grid microgrid. Usually, self-sufficiency will lead to an overinvestment in DERs to fulfil all the load needs of the microgrid, whereas using the grid as a support for the periods with low power generation could be an economically sensible decision (Quoilin et al.; 2016). The maximum amount of time a microgrid can stay islanded will be defined by the quantity of local generators and storage available to maintain the supply, correct frequency and voltage level in the microgrid. Finally, the microgrid framework can evolve into energy community systems and storage community systems where houses, commercial buildings, factories can all manage their own microgrid together and communicate with the external world as one virtual power plant (VPP), being able to sell and buy electricity from the main grid available or from other

community systems (Prasad et al.; 2018).

2.5 Blockchain

A flexible option to enable electric vehicle integration in short term and peer-to-peer (P2P) microgrids in a long-term involves a blockchain based platform (Brilliantova and Thurner; 2019). The technology itself dates from approximately 2008, but the different applications are disruptive and fit in many different sectors. It mainly works as a distributed ledger that can securely store digital transactions using a consensus algorithm to avoid using a central point of authority or validation. The most famous one is the Proof of Work (PoW) used by Bitcoin where validators, also called miners, solves a cryptographical puzzle by computational brute force to add a block in the existing chain (Roschin et al.; 2018). Researches state different algorithms to reach this consensus in different and more efficient ways, without wasting great amount of energy and achieving scalability (Andoni et al.; 2019). Andoni et al. (2019) built a map of potential applications derived from a review of more than 140 blockchain research projects, ranging from billing, sales, trading to automation, smartgrid applications and grid management. Most of these applications are Ethereum based, which allow users to create smart contracts and their own transaction-based applications. Although there are many experiments using this new technology coupled with DERs and electric vehicles, there is still a need to fill the gap between the technical application and the economic, social and environmental dimensions to facilitate the interoperability between conventional and forthcoming energy systems (Ahl et al.; 2019).

The technologies discussed in the previous sections are changing the way the electricity system is functioning around the world in different spatial configurations. The rising amount of DERs connected to the distribution grid is changing the passive management historically done by DSOs in several ways. Differently from TSOs which are frequently experiencing and responding to congestion problems, the DSOs have had limited operational tools to deal with issues in real-time, maintaining a robust operating margin. In a few years, distribution network infrastructures may not be adapted to meet peak power injection in high PV penetration areas or withdrawal, if many EVs are charging at the same time, in this case, coordinated DER dispatch

and demand control can be used as operational instruments to comply with the grid constraints (Burger et al.; 2019). An efficient coupling between EVs/PVs/Batteries could minimize emergency PV curtailments, provide flexibility to both transmission and distribution grids, avoid network reinforcements and prevent blackouts. As a result, a part of the future electricity system could be represented by Figure 2.2 with the main changes from the actual system being the bidirectional power flow active management at the distribution level, the P2P ethereum-based energy trading between buildings and the V2G-enabled vehicles participating in electricity markets.

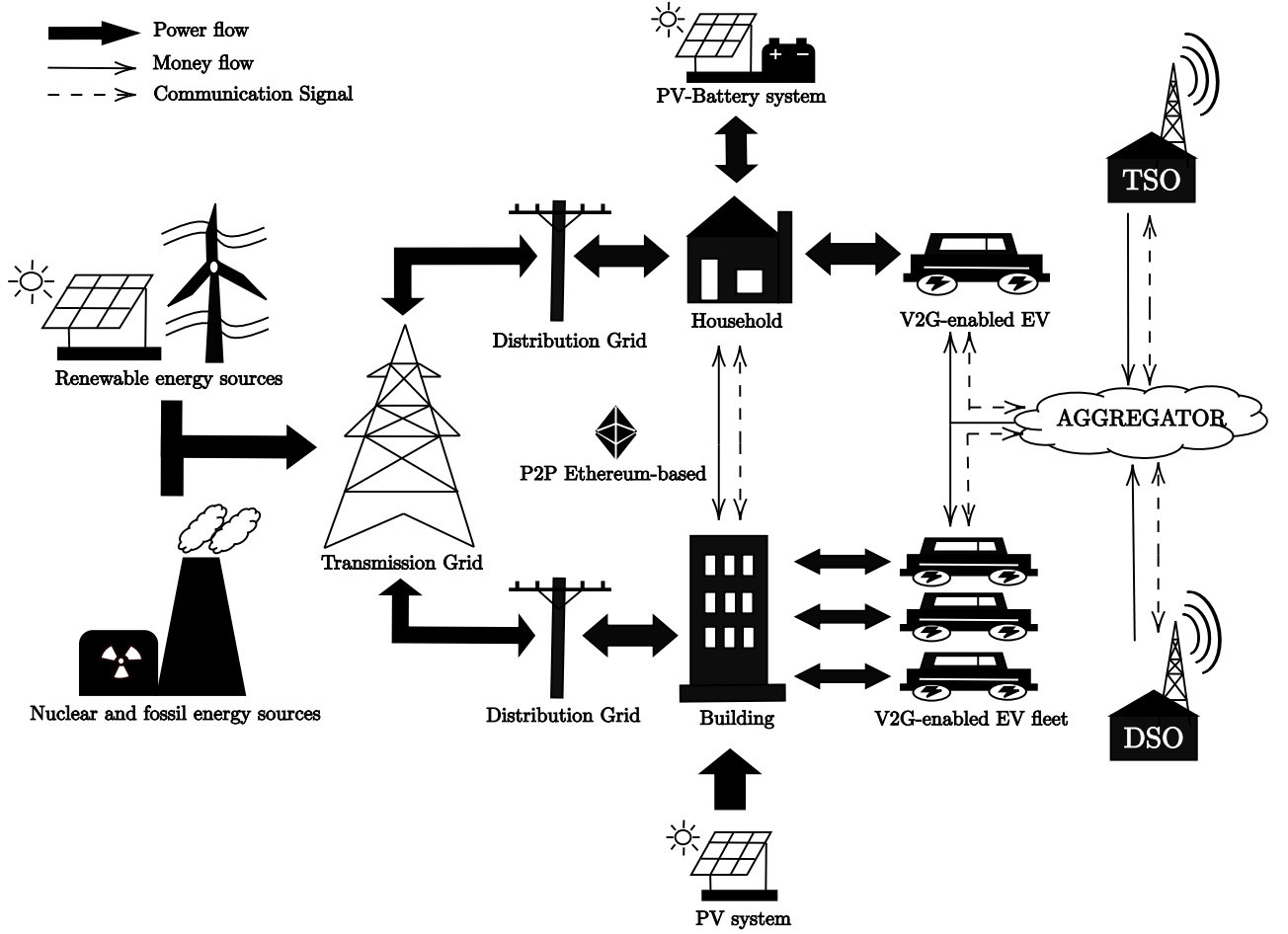


Figure 2.2: Representation of a possible future electric system.

Once some of the explored DERs are present, the fundamental spatial unit is formed by individual dwellings, which may be aggregated in residential or commercial buildings, so all of them together can constitute a single community. The socio-technical implementation complexity increases with the number of units involved. In

the single dwelling case, the household get all the benefits obtained from the DERs on its property. In the collective self-consumption case, multiple households share a centralized solar PV, battery and EV charging stations. The community energy systems and community energy storage are found to be a promising socio-technical trend in the field of DERs. The objective of these communities is to group different households together to invest in renewable generation, storage or electric vehicles to supply their own needs for electricity as a heterogenous community and to become an example to be followed (Koirala et al.; 2018). An aggregation of communities is often called an integrated community energy system (ICES) in the literature and defined by Mendes et al. (2011) as a “multi-faceted approach for supplying a local community with its energy requirements from high-efficiency cogeneration or trigeneration energy sources and from renewable energy technologies coupled with innovative energy storage solutions including the EV and energy efficiency demand-side measures”. The contribution from these communities is twofold: firstly, they make a great contribution to the direct decarbonisation of electricity once investments in distributed renewable generation have been made to avoid buying electricity generated from fossil fuels. Secondly, they also play an important role as flexibility providers, allowing higher penetration of intermittent energies in the electricity mix. They can also be a very good platform for regulators and policymakers to test, on a small-scale, new policies for local electricity markets and to analyze different social behaviors among communities.

The barriers to ICES development are of different nature due to its high socio-technical complexity. Firstly, the purpose of the community will define how many different actors are involved and its complexity (Prasad et al.; 2018). Shared residential energy resources are often DERs installed behind-the-meter of a household for its own needs and those of the community. Shared local energy resources owned by the community are installed in front of the meter and behind the transformer to supply local needs and be shared with the outsider distribution grid. Finally, shared virtual energy are aggregated resources located in different communities able to share energy on a national or international level depending on market design. The number of actors increases as we go from shared residential to virtual shared energy where the

figure of the aggregator clearly appears alongside international regulators. Germany is a pioneer country regarding the development of energy community systems³, an example of local shared energy is the Feldheim energy community where 10 MW of Li-ion batteries were jointly constructed with 2.25 MWp of solar PV and other kinds of renewables NEFF (2019). A second example also in Germany⁴ SonnenCommunity (2019), but of virtual energy community, is the project sonnenCommunity where the surplus of solar energy which is not stored in the sonnenBattery is fed into a virtual energy pool to serve other members. Figure 2.3 shows the difference between the three main configurations of community energy systems. Nonetheless, if the ICES development is completely uncoordinated, the system might end up centralized again with the aggregation of many communities, quickly saturating the market. The control of the electricity production and flexibility could get partially, if not fully, transferred to private aggregators rather than system operators which local governments would have less power over, risking societal welfare.

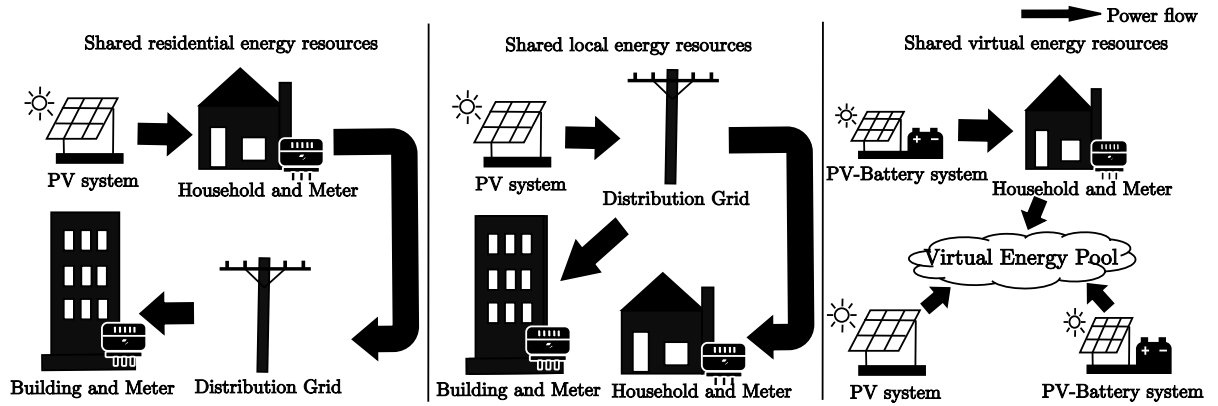


Figure 2.3: Community energy system configurations

³The great political support for renewables with ambitious targets (60% of final energy consumption by 2050 coming from renewables), financial incentives, availability of loan capital for projects, a high sensitivity to environmental problems and a great local energy activism contributed to the development of ICES (Romero-rubio et al.; 2015).

⁴Other European country such as the UK also see the CES as a possibility to reduce energy poverty for households and help with a more sustainable electricity production despite the high complex regulations for generation and trade found there (Brummer; 2018).

2.6 Techno-economic coupling models

Techno-economic models are often used to assess the financial and environmental gains of different DERs in residential, commercial or industrial sites and optimize them compared to the base scenario without any DER installed. These models are well explored in the literature, however, due to the high number of parameters included, their complexity and the different optimization methods, a lot of different models are proposed with their own particularity. We focus mainly on models with distributed battery resources and photovoltaic power generation, nevertheless, those which occasionally add other distributed resources such as heat pumps, hydrogen storage or cogeneration can also be considered in this section if they show interesting results and optimization methods. These models can be exogenous, where the amounts of installed DER is already fixed before simulation. Here the model results in the optimized battery charging and discharging strategies to reduce electricity costs, CO₂ emissions or increase self-consumption according to the input load profile, the electricity tariffs proposed by the utility, the cost of each DER unit and externalities like insolation degree. In all these exogenous cases, the models are used to simulate the home energy management system (EMS). On the other hand, if the model is endogenous, it will decide both the optimal amount of DERs installed and battery charging and discharging decisions having the same objectives as the exogenous models plus the possibility to achieve self-sufficiency. The models containing distributed battery resources and PVs can get very complex depending on physical detailing adopted, the method used to optimize it and the number of decision variables selected which can easily go up to millions of variables tested during the simulation. The literature explores a great variety of mathematical methods used to model and find an optimal solution to those problems. Table 1 classifies the techniques that can be used according to each problem specificity whereas Table 2 describes several models in the literature according to: the DERs adopted; the main objective to be achieved; number of user load profiles used; the load profile itself that can be real (R), synthetic (S) or unknown (?) according to the measured step in minutes; the model type if it is exogenous or endogenous and the mathematical modelling approach.

Table 2.3: Optimization method classification. Adapted from [Amaran et al. \(2019\)](#)

	Algebraic model	Unknown/complex problem structure
Deterministic	Traditional math programming (linear, integer, MILP, nonlinear)	Derivative-free optimization (direct search algorithms, metaheuristics, etc)
Uncertainty present	Stochastic programming, robust optimization	Simulation optimization (Grid and random search, state machines, genetic algorithm, system dynamics, etc)

Table 2.4: Techno-economic model descriptions.

Author	PV	BESS	EV/V2G	Objective	User profile	Load profile	Model type	Modelling
Schopfer et al. (2018)	Yes	Yes	No/No	Profitability	4190	R30	Endogenous	Stochastic Programming
Doroudchi et al. (2018)	Yes	Yes	Yes/Yes	Self-sufficiency	1	S60	Exogenous	MILP
Ancillotti et al. (2014)	Yes	Yes	Yes/Yes	Self-sufficiency	251	S1	Exogenous	Finite state machine
Hoppmann et al. (2014)	Yes	Yes	No/No	Profitability	1	R15	Endogenous	Grid search
Laurischkat and Jandt (2018)	Yes	Yes	Yes/No	Profitability	3	?15	Endogenous	System dynamics

[Schopfer et al. \(2018\)](#) use a Monte-Carlo optimization coupled with machine learning algorithms to predict, based on few input variables, the profitability of a PVB system. They assess the maximal net-present value for 4190 households in Zurich, Switzerland to show how the heterogeneity of load profiles among dwellings can completely change the optimal investment (if there is one) in PVs and batteries. According to them, battery costs should decrease towards the range of 250-500 €/kWh to become profitable in a residential scale.

[Doroudchi et al. \(2018\)](#) develop a mixed integer linear programming (MILP) model to approach as much as possible net zero energy housing in Finland, i.e., the summation of exported and imported energy should be minimized and the use of on-

site energy should be maximized. A PV, a stationary battery and an EV equipped with V2G functionalities are used to achieve this goal. Net zero energy buildings (NZEB) are not yet economically viable due to the large gap between annual savings and high system costs, mainly in countries where electricity is not expensive like in Finland.

Ancillotti et al. (2014) study plug-in EV integration to NZEBs using their mobility model and building load models. In the first scenario where PEVs are the only energy storage resource, self-sustainability is not guaranteed due to the mobility needs; however, it can avoid 40% of energy import over the year with a 75% of battery capacity available for discharging. When a stationary battery is added it can contribute with more than 5% to 18% of energy import reduction depending on the size of PV installed.

Hoppmann et al. (2014) use a techno-economic model to investigate the conditions in which battery storage will be economically viable in residential PV systems in Germany under eight different electricity price scenarios from 2013 to 2022. They found PVB systems to be already profitable in 2013 for small households, showing an optimal system size rising at a point that they become net electricity producers over time in a context that electricity retail prices tend to increase whereas wholesale prices and initial DERs investment costs tend to decrease.

Laurischkat and Jandt (2018) develop a model based on system dynamics to evaluate which scenarios containing PV, battery and EV or ICE vehicle are financially attractive depending on the electricity price and mobility needs. In the German market, it is found that EV will be economically viable for customers who hardly ever take highways and own a PV. On the other hand, financially speaking, those drivers with a annual mileage higher than 29.200 km should keep the ICE even if the oil prices are likely to rise. In specific cases, the use of an EV, needs a larger PV and a stationary storage to enhance self-consumption, thus improve savings. This finding contradicts a part of the literature which states a lower total cost of ownership (TCO) with high annual mileages for EVs. The TCO difference between EV and ICE is reduced significantly to a point where it become negative (International Energy Agency; 2018a).

3 Economic aspects

The following section is dedicated to the economic impacts and constraints linked to DERs implementation. First, the impact on electricity tariffs is explored aiming to uncover issues that arise for electricity providers when distributed photovoltaic power generation and batteries are present, as well as possible solutions. Then, the barriers to the implementation of the coupling between DERs are pointed out considering the great but not enough price decreases in all technologies discussed. Ultimately, a socio-economic analysis of the most important local actions and policy examples taken worldwide to promote the development of these technologies alone or concomitant with the coupling itself is conducted.

3.1 Electricity tariff impact

The electric power system has been under an important transformation since the past few years due to the strong development of renewable energy sources (RES) which are becoming more affordable and cost-competitive with the traditional ways of producing electricity from fossil fuels, for example. The generation part of the system is undergoing a bottom-up transformation since a growing number of consumers are becoming prosumers, i.e. they are producing their own electricity and are not highly dependent on electricity from the grid like before (Perez-Arriaga et al.; 2017). The current energy-based network tariffs, however, are not adapted to recover all distribution systems operator costs in a scenario with a high penetration of photovoltaic systems and decentralized electricity production for self-consumption (Schittekatte et al.; 2018). Furthermore, the addition of battery storage systems would increase the self-consumption rate, avoiding curtailment of the photovoltaic systems and saving even more money than before (Hoppmann et al.; 2014). In fact, this is likely to happen due to the rapid cost decrease of battery packs, cells and battery managements systems. The “spiral of death” is a problem inflicted on the network operator by the penetration of photovoltaic battery systems (Costello and Hemphill; 2014). When prosumers are consuming less electricity than before, the energy volume sold in kWh by the utility decreases and so does its revenue, making a full cost recovery unlikely.

Consequently, the tariff increases, giving even more incentive to install photovoltaic panels and become less dependent on the power grid. To illustrate this effect with a real case, [Gautier, Axel \(2018\)](#) studied the impacts of tariff increase on the adoption of PVs in the region of Wallonia in Belgium, they founded that for each eurocent per kWh of tariff increase leads to, all else equal, an increase of around 5% of new PV installations. This is a case in which those who do not have PV panels will end up subsidizing those who have, raising an equity issue between consumers and an efficacy issue linked to the high electricity prices if more panels are installed. Researchers have suggested different tariff designs to break the spiral using a capacity-based tariff ([Simshauser; 2016](#)); however, this type of tariff also has issues if badly formulated as it could overstate the value of the facility peak load and give even more the incentive for battery storage ([Boampong and Brown; 2020](#)).

In addition to their environmental contribution, electric vehicles could also play an important role in providing even more services to the electric power grid if equipped with a bidirectional charger. They can also attenuate the negative effect of increasing tariffs caused by PVs, as the general electricity consumption would increase to fulfill mobility needs, the utility could recover its fixed and variable costs more easily and the tariff would tend to decrease for all customers ([Küfeoğlu and Pollitt; 2019](#)); however, knowing the quantity of vehicles needed to counterbalance the tariff increase caused by PV generation in the case of sunk grid costs is very important and not obvious to determine. [Hoarau and Perez \(2019\)](#) show that EVs and DERs may be conflicting under the main tariff based on volumetric and capacity schemes by inducing negative spillovers on each other through the recovery of grid costs. A change of regulation would make winners and losers, so regulators should be careful about which kind of technology they want to promote. This question is still open to discussion among researchers, network operators and regulators willing to know the most effective, from the system point of view, and fair, from the consumers perspective, tariff structure under different DERs like batteries, EVs, PVs or heat pumps.

3.2 Market barriers

In this section, the barriers to the massive adoption of the DERs are discussed, precising the first and most evident barrier is the cost of the technology along with EV ecosystem constraints.

3.2.1 DER costs

Starting with PV panels, according to one benchmark study done by [Fu et al. \(2017\)](#), from 2010 to 2017 the price of the kW installed in residential PV dropped 61%, from 7240 \$/kW to 2800 \$/kW. The fast decrease in price is explained by several reasons: the increase in fabrication efficiency, such as decrease in raw silicon material use, reduced by almost 25% the cost of PV modules from 1980 to 2012; private and public R&D, economies of scale and learning effects also played an important role ([Kavlak et al.; 2018](#)). [Pillai \(2015\)](#) adds that from 2005 till 2012 the most important factors leading price reduction of solar panels were also the increasing market penetration of lower costs firms in China and increases in industry investments; however, economies of scale and learning effect are insignificant when fabrication efficiency is considered, suggesting that policies should be aligned with technological advancement incentives more than direct subsidies. The projection made by [IRENA \(2017a\)](#) is that PV systems will cost around 1000 \$/kW already in 2022.

The high cost of batteries is not only a barrier to the worldwide adoption of PVB systems but also to electric vehicles sales increase. The prices of lithium-ion batteries have decreased 73% from 2010 till 2016, achieving the mark of 273 \$/kWh ([BNEF; 2017](#)). In a so-called realistic prediction of 2030 prices, they are expected to be around 124 \$/kWh ([Hsieh et al.; 2019](#)), that could be economically viable for PVB systems adoption ([Hassan et al.; 2017](#)) but not for EVs compared to internal combustion engines vehicles if no subsidy is given for the purchase. The same factors discussed for the PV technology cost reduction also had an important effect in the battery case, however, the prices of lithium and cobalt are likely to reach a price floor due to the scarcity of active materials in the future, which can lead to a cost increase of the materials over time and outperform the gains due to efficiency increase,

economies of scale and learning effect. In a medium-term horizon, five years from now, there are no risks concerning the scarcity of those two raw materials due to the limited investments and slow battery certification process in the electric vehicles industry which slows the demand for the materials. However, in a long-term run, ten years from now, their security of supply may face a serious threat due to limited viable large-scale supply options, especially for cobalt, where the most important reserves are in regions with serious geopolitical issues ([Benchmark Mineral Intelligence; 2018](#)). That is the reason why many important companies in this field are investing more in cobalt-free technologies like LFP and LMO or simply to reduce the amount of this mineral in the higher energy density technologies NCM and NCA cited in section 2.

3.2.2 EV ecosystem constraints

EVs adoption would be enhanced if a solid and widespread charging infrastructure with different power levels according to user's needs was in place. There is always the question of who is supposed to invest first in infrastructure to unlock all other investments; some automakers delegate this task to the public administration and electricity companies, so they can manufacture cars. The electricity providers tend to think that automakers with public support should first fabricate electric cars that will increase the need for infrastructure planning and development.

To find an adapted policy to push more EVs on the streets, Springel [Springel \(2019\)](#) uses data from the Norwegian automotive market between 2010 and 2015 to verify if EV purchases were more affected by station subsidies or consumer price subsidies. It was found that every dollar spent on public charging station subsidies resulted in more than two times additional EVs purchases compared with one dollar spent in price subsidies, but the relation inverts as spending increases. At the beginning of EVs development, more subsidies on infrastructure means more EVs on the market, consequently, more possibilities to provide V2G services, which can help to increase once more EV sold numbers. The “chicken and egg” dilemma of which should come first, infrastructure or vehicles, to encourage investments in the other is still an issue warranting further investigation.

Besides a solid EV charging infrastructure, knowing that V2G will add value to

certain EVs by providing remunerated services behind and in front of the meter, policies and adapted market rules to V2G services will directly enhance EV adoption as well. If those services are provided, mainly the frequency containment reserve (FCR) which has the higher revenue potential among them (Borne et al.; 2018) and energy arbitrage by delaying the charge when electricity prices are low and discharging when the spread high, they could reduce the total cost of ownership of an electric vehicle (Noel and McCormack; 2014). Many experiments show that V2G technology is ready from a technical point of view; however, the barriers for large-scale implementation are mostly market-based rules in many countries. The current rules and a new market design to allow EVs participation in France are discussed in Borne et al. (2019), highlighting the importance of increasing the temporal granularity of products from one week long to four hours long and decreasing at least the bid increment if it is not technically possible to enhance volume granularity. Regarding the services provided for the distribution grid, due to the great heterogeneity of distribution systems and the diversity of regulatory frameworks, policies should be recommended almost individually and carefully following one roadmap, as discussed and proposed in Marinelli et al. (2017). EVs are almost all the time connected to the distribution grid system that has its own limitations and it can be highly constrained at some point of the day; that is why an optimal coordination between and TSO and DSO is required to avoid undesirable congestion possibly caused by EV charging or discharging in the grid. Several mechanisms for optimal DSO-TSO coordination are reviewed in Hadush and Meeus (2018) for different scenarios.

Christensen et al. (2018) summarize the actual barriers for large scale V2G projects based on a real experiment as well as possible solutions. Metering is still a current issue due to the specific technical requirements needed to provide FCR services, the equipment high cost can jeopardize all the revenue obtained from those services, meaning that an agreement between parties regarding the standardization of which meter to use should be reached. The last identified barrier is the different performances of the system parts: battery management system, EVSE and aggregator. The effectiveness of the final service provided could be measured using key performance indicators (KPI) for each part of the system to know exactly where the performance

was the lowest to correct it later. For example, if the aggregator is not complying with some requirements agreed between the parties, the related key performance indicator would be low indicating that this part of the system needs to be improved.

3.3 Local policies

The following section is dedicated to the exploitation of solutions discussed around the world to overcome the DER high prices. First, we discuss the main support mechanisms for DER implementation in general. Then, alternatives to avoid the case of battery price floor are presented.

3.3.1 Support instruments

The main support instruments to promote RES are feed-in tariffs (FiTs), bidding and exchangeable quotas (Finon and Perez; 2006). FiTs are a supporting scheme used to accelerate the development of renewable energy production, notably solar PVs and wind power, by offering a remuneration, either valued at retail price or higher, for each kWh of energy produced from a green source and exported to the grid. Using FiTs, countries like Spain and Germany experienced successful PV development since 2008. The United States, mainly in California, and Australia also presented a boom in PV installations after FiT implementation. However, the high penetration of PVs has led to the duck curve problem, as in the Californian case, in electrical system, raising doubts about the continuation of FiT tariffs and starting the debate about the methods that should be used to deal with this problem (Denholm et al.; 2015). This curve appears when an important amount of the electricity in the system is generated by solar PV. Two main problems can be identified: Firstly, the energy produced during sun-hours can sometimes be excessive and lead to curtailment of PVs which will reduce its economical and environmental gains; secondly, when the production goes down at the beginning of the evening the need to quickly ramp energy production can be very costly to the system generators.

Moreover, Nelson et al. (2011) alert about the regressive form of taxation almost three times higher for low income households that could appear under some FiT

schemes in Australia. [Gao et al. \(2015\)](#) evaluate many FiT schemes over the world and propose solutions to countries which experienced a PV proliferation under these conditions. They propose a FiT based in tendering schemes which would allow competition, controlling booms and contributing even more to the development of the technology. Net-metering could also be combined with FiT to balance the development in adoption of PVs according to [Ramírez et al. \(2017\)](#), the systems being more or less profitable depending on the location, the kind of system and level of tariffs. Although FiT for storage systems is also discussed as a possible solution to improve storage in coupled PVB systems in [Krajac et al. \(2011\)](#), the continuity of the strategy is still under debate depending on the location and PV penetration. The focus now should be on how to elaborate innovative strategies to stimulate storage to increase self-consumption and offer flexibility to the grid using the generated electricity. While FiTs are considered a price instrument, bidding auctions and exchangeable quotas like green certificates are more a quantity instrument ([Finon and Perez; 2006](#)). The bidding process chooses by auctions the best renewable energy projects and obliges distributors to buy electricity from them whereas the quotas are targets for suppliers to have a defined amount of green electricity provided to customers. As the main groups concerned by the coupling between small batteries and PVs are very specific like farmers, private households, commercial and industrial sites, a price instrument based on FiT scheme is more adapted to them although it also has some drawbacks.

3.3.2 Dealing with battery price floor

As discussed in section 3.2, regardless of price decreases in the future, Li-ion batteries will face a minimum price limit caused by the scarcity of available cobalt and lithium. The reutilization of batteries is an option to lower their price floor, where those coming from EVs can be reused as stationary batteries when they still have 80% of their initial capacity, providing power support to fast EV chargers for over 30 years, self-consumption and grid-oriented services for 6 years ([Casals et al.; 2019](#)). Nevertheless, a study about markets dynamics of second-life electric vehicle batteries done by [Sun et al. \(2018\)](#), shows that the need for recycling is not much diminished by reutilization because there may be a saturation of the second-life battery market

and they still need to be recycled at the end of their second life. The recycling of Li-ion batteries is important to avoid pollution caused by the disposal of the metals inside and to reuse directly or indirectly the remaining materials in the manufacturing process of new batteries, lowering their price. To date, the existing recycling methods require sophisticated techniques and costly materials to recover components from a Li-ion battery due to the great variety of materials inside (Huang; 2018). The example of lead-acid battery recycling in United States shows that even if one day those techniques become economic favourable, a regulatory drive may be required. Today, nearly 100% of lead-acid batteries are recycled after the prohibition of their disposal in landfills and required recycling in the late 1980s (SmithBucklin Statistic Group; 2014). Policies to standardize the recycling processes and implement a design for recycling concept according to the battery composition could also be a solution. The absence of environmental regulations and information on economics of recycling makes even more difficult the recycling of end-of-life Li-ion batteries (Mayyas et al.; 2018).

4 Societal aspects

In this section, variables like WTP used to financially assess how ready people are to invest in DERs are discussed along with mechanisms such as bundled solutions to ensure the user acceptance towards the adoption of the technologies present in the coupling.

4.1 User acceptance: How to assess and ensure it?

The emerging social aspects are found to be decisive variables in whether people are receptive and willing to invest in distributed energy systems. Willingness-to-pay is a treatment of data coming from surveys used to quantify, in a monetary way, how much people in a determined geographical area are ready to pay for green energy coming from PVs, electric vehicles or participation in V2G services. Nevertheless, different valuation methods, knowledge of technologies, households' characteristics, income and education might result in biased results of WTP (Sundt and Rehdanz; 2015). Although the quantitative results among researchers vary a lot, a qualitative

analysis between countries can be used to frame which factors are decisive in a higher WTP. In Germany, Denmark and Japan the WTP for green energy tends to be higher due to massive information campaigns about renewable energy sources [Lee and Heo \(2016\)](#). Countries with high electricity consumption and low prices like the United States and Finland also have a high WTP per household, but low per kilo-watt hour ([Sundt and Rehdanz; 2015](#)). This kind of study helps policymakers to get an idea of the direction to follow to help developing DERs in their cities, states and countries. For example, regarding solar electricity specifically, in 2010 British people were willing to pay £2831 ([Scarpa and Willis; 2010](#)) and Irish people 6207€ for PVB systems ([Claudy et al.; 2011](#)). At that time, the market price was much higher than the WTP, but today with supporting policies to enhance WTP and with decreases in technology costs, they may reach parity soon, meaning that people are ready to install PVs.

Regarding electric mobility, variables like income level, mobility patterns, environmental concerns and attitude towards technology are found to be decisive in the WTP for EVs ([Ramos-Real et al.; 2018](#)). Regarding participation in V2G services, people are becoming less worried about remuneration and mainly seeing it as a service provided to the community via the electricity power grid [Geske and Schumann \(2018\)](#). This last finding could be applied to the viability of the whole coupling; information campaigns and commitment to achieve energy transition towards renewable energies (e.g. solar PVs) could work very well in many countries around the world.

Solutions that aggregate more than one DER to promote their adoption can be a shortcut to increase customer acceptance. If PVB systems were proposed as a “package”, customers might understand faster the benefits of the coupling, which might increase their willingness to pay for both resources rather than for separated PV and battery systems which both have their own benefits, constraints and costs. [Oberst and Madlener \(2015\)](#) found that the motivation of German households to become prosumers by investing in PVB systems is mostly driven by a high level of self-sufficiency. The bundled solution, regardless if it is a highly profitable investment or not, increases their willingness to adopt renewable energy once it enhances their self-supply of electricity. In [Alfons and Nina \(2020\)](#) EVs are also included in a bundled solution alongside PVB systems in an Austrian experiment to investigate the effect on pur-

chase willingness. The majority of potential EV drivers, around 77.4%, would have a preference to buy it in this specific bundle than a standalone EV. Nevertheless, in this case the purchase price is the most important attribute for the purchase decision while power self-sufficiency comes in the fourth place. The same bundling framework could be applied to the automotive industry regarding EVs sales and infrastructure. Automakers might sell a “package” of EV plus charging infrastructure, due to the intrinsic relation between them. Car industries could thus expand their business models exploring the gains from EVSEs, and consequently, from EV sales in the way Tesla is actually doing with the development of a Supercharger network. The V2G capability could also be a part of the package; however, the relationships between the car manufacturers, charging point operators and aggregators should be simplified to potential clients.

As a summary of our findings we propose a graphical representation (Figure 2.4) of our different layers of analysis. Points at the intersection between layers naturally appeared during the review process, revealing the importance to analyse the impacts over both fields that they belong. The most important information in each area was highlighted with the support of literature on each aspect studied as well as the relations between them. This allows the identification of the impacts and feedbacks that one field has over the others and the literature gaps that warrant further investigation.

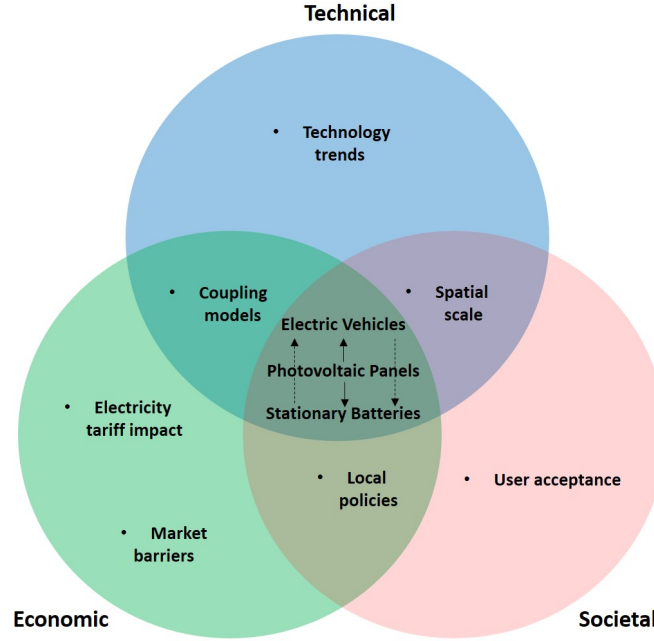


Figure 2.4: Synthesis of main research areas of the coupling distributed battery storage and PV

5 Conclusion

In this chapter, the technological trends were discussed along with economic issues and societal impacts of the DER coupling adoption. The synergies of the coupling between distributed battery resources and photovoltaic power generation will help to decarbonise the electric power and mobility sectors while profitable, if well managed, to most agents involved: system operators, regulators, ordinary consumers, etc. To frame the most important aspects involving the coupling itself, we proposed an analytical framework with three layers of research: Technical, economic and societal.

We showed that technological progress regarding PVs, batteries and EVs has often been a step ahead of policies and regulations, causing actors' strategies to be outdated and imposing barriers to extraction of the maximum benefit from each resource, like in the uncoordinated PV boom caused by unadapted FiT schemes and V2G limited market participation. Policy innovation considering user acceptance towards the technologies could assure that the other way around is true, with policies that are usually ahead of the technical progress, creating an adapted ecosystem for its development. It can prepare the field to accommodate DERs and accelerate their

adoption based on the results from the techno-economic models and socio-technical analysis.

Our analysis identified the gaps warranting further investigation and we propose a timeline for research purposes. In the short-term, the focus should be on how to adjust policies and regulations to extract the maximum benefit of the coupling. More tariff design studies showing the effects of EVs coupled with PVs and stationary batteries could help policymakers to find an adapted rate for the synergy. Regarding policies, no joint policy for the couple EV/PV, to the best of our knowledge, was object of study in the literature, this could be important to establish a correlation and accelerate together both DERs. Moving towards the technology trends, the economic assessment of DC microgrids connected with only DC generators (PV) and DC loads (EV and stationary batteries) compared to AC microgrids is lacking. In medium and long-term, the battery technological change will be decisive to the continuation of the EV and battery industries. Researchers should focus on cobalt-free and less-lithium technologies to avoid all the geopolitical and material scarcity issues. We limited our analysis to three different layers, e.g. technical, economic and societal; however, an environmental layer could also be added to the framework to explore in depth the impacts of the coupling development on the environment.

6 References

- Adams, J., Karulkar, M. and Anandan, V. (2013). Evaluation and electrochemical analyses of cathodes for lithium-air batteries, *Journal of Power Sources* **239**: 132–143. 20
- Ahl, A., Yarime, M., Tanaka, K. and Sagawa, D. (2019). Review of blockchain-based distributed energy : Implications for institutional development, *Renewable and Sustainable Energy Reviews* **107**(March): 200–211. 25
- Alfons, P. and Nina, H. (2020). Can product bundling increase the joint adoption of electric vehicles , solar panels and battery storage ? Explorative evidence from a choice-based conjoint study in Austria, *Ecological Economics* **167**(March 2019). 40
- Alirezaei, M., Noori, M. and Tatari, O. (2016). Getting to net zero energy building: Investigating the role of vehicle to home technology, *Energy and Buildings* **130**: 465–476. 22
- Amaran, S., Sahinidis, N. V., Sharda, B. and Bury, S. J. (2019). Simulation optimization : a review of algorithms and applications, *Annals of Operations Research* **240**(1): 351–380. viii, 30
- Ancillotti, E., Bruno, R., Crisostomi, E. and Tucci, M. (2014). Using electric vehicles to improve building energy sustainability, *Electric Vehicle Conference (IEVC), 2014 IEEE International* pp. 1–7. 30, 31
- Andoni, M., Robu, V., Flynn, D., Abram, S., Geach, D., Jenkins, D., Mccallum, P. and Peacock, A. (2019). Blockchain technology in the energy sector : A systematic review of challenges and opportunities, *Renewable and Sustainable Energy Reviews* **100**(February 2018): 143–174. 25
- Armand, M. and Tarascon, J. (2008). Building better batteries, *Nature* **451**(February): 2–7. 18
- Barter, P. A. (2013). Reinventing park.
URL: <https://www.reinventingparking.org/2013/02/cars-are-parked-95-of-time-lets-check.html>.
Accessed in 25 March 2019 22
- Benanti, T. L. and Venkataraman, D. (2006). Organic solar cells : An overview focusing on active layer morphology, *Photosynthesis Research* pp. 73–81. 17
- Benchmark Mineral Intelligence (2018). Mine to battery cell: risks to the speed of adoption of electric vehicles. 35
- BNEF (2017). Lithium-ion battery costs and market.: Squeezed margins seek technology improvements & new business models. 34
- Boampong, R. and Brown, D. P. (2020). On the Network Value of Behind-the-Meter Solar PV plus Energy Storage : The Importance of Retail Rate Design, *Energy Economics* . 33

- Borne, O., Korte, K., Perez, Y., Petit, M. and Purkus, A. (2018). Barriers to entry in frequency-regulation services markets: Review of the status quo and options for improvements, *Renewable and Sustainable Energy Reviews* **81**(July 2016): 605–614. 15, 36
- Borne, O., Perez, Y. and Petit, M. (2019). Market integration or bids granularity to enhance flexibility provision by batteries of electric vehicles, *Energy Policy* **119**(March): 140–148. 36
- Brilliantova, V. and Thurner, T. W. (2019). Technology in Society Blockchain and the future of energy, *Technology in Society* **57**(July 2018): 38–45. 25
- Brummer, V. (2018). Community energy – benefits and barriers : A comparative literature review of Community Energy in the UK , Germany and the USA , the benefits it provides for society and the barriers it faces, *Renewable and Sustainable Energy Reviews* **94**(November 2017): 187–196. 28
- Burger, S. P., Jenkins, J. D., Batlle, C. and Pérez-arriaga, I. J. (2019). Restructuring Revisited Part 1 : Competition in Electricity Distribution Systems, *The Energy Journal* **40**. 26
- Casals, L. C., García, B. A. and Canal, C. (2019). Second life batteries lifespan : Rest of useful life and environmental analysis, *Journal of Environmental Management* **232**(November 2018): 354–363. 38
- Christensen, B., Trahand, M., Andersen, P. B., Olesen, O. J. and Thingvad, A. (2018). Project report Integration of new technology in the ancillary service markets, (March): 1–17. 36
- Claudy, M. C., Michelsen, C. and Driscoll, A. O. (2011). The diffusion of microgeneration technologies – assessing the influence of perceived product characteristics on home owners ’ willingness to pay, *Energy Policy* **39**(3): 1459–1469. 40
- Claudy, M. C., Michelsen, C., Driscoll, A. O. and Mullen, M. R. (2020). Consumer awareness in the adoption of microgeneration technologies An empirical investigation in the Republic of Ireland, *Renewable and Sustainable Energy Reviews* **14**(2010): 2154–2160. 16
- Codani, P., Perez, Y. and Petit, M. (2016). Financial shortfall for electric vehicles: Economic impacts of Transmission System Operators market designs, *Energy* **113**: 422–431. 15
- Costello, K. and Hemphill, R. (2014). “electric utilities’ ‘death spiral’: Hyperbole or reality?”, *The Electricity Journal* **27**: 10. 32
- Denholm, P., Connell, M. O., Brinkman, G., Jorgenson, J., Denholm, P., Connell, M. O., Brinkman, G. and Jorgenson, J. (2015). Overgeneration from Solar Energy in California : A Field Guide to the Duck Chart Overgeneration from Solar Energy in California : A Field Guide to the Duck Chart, (November). 37

- Diouf, B. and Avis, C. (2019). The potential of Li-ion batteries in ECOWAS solar home systems, *Journal of Energy Storage* **22**(January): 295–301. 19
- Diouf, B. and Podo, R. (2015). Potential of lithium-ion batteries in renewable energy, *Renewable Energy* **76**: 375–380. viii, 18, 19, 20
- Doroudchi, E., Alanne, K., Okur, Ö., Kyyrä, J. and Lehtonen, M. (2018). Approaching net zero energy housing through integrated EV, *Sustainable Cities and Society* **38**(August 2017): 534–542. 30
- Dubarry, M., Qin, N. and Brooker, P. (2018). Calendar aging of commercial Li-ion cells of different chemistries – A review, *Current Opinion in Electrochemistry* **9**: 106–113. 20
- Eid, C., Codani, P., Perez, Y., Reneses, J. and Hakvoort, R. (2016). Managing electric flexibility from Distributed Energy Resources: A review of incentives for market design, *Renewable and Sustainable Energy Reviews* **64**: 237–247. 15, 22
- Electrek (2018). Vw’s first 350kw ultra-fast charger, (December).
URL: <https://electrek.co/2018/12/06/electrify-america-first-350kw-charger-california/> Accessed 25 March 2019 21
- Eurelectric (2015). Smart charging : Steering the charge , driving the change, (March). 14
- European Comission (2018). *PV Status Report*. 14
- Everoze (2018). V2g global roadtrip: Around the world in 50 projects., (October). 21
- Exide Technologies (2003). Handbook for gel-vrla-batteries part 1 : Basic principles , design , features, (December): 1–22. 18
- Fahad, M., Elbouchikhi, E. and Benbouzid, M. (2018). Microgrids energy management systems : A critical review on methods , solutions , and prospects, *Applied Energy* **222**(March): 1033–1055. 24
- Finon, D. and Perez, Y. (2006). The social efficiency of instruments of promotion of renewable energies : A transaction-cost perspective, *Ecological Economics* **2**. 37, 38
- Fraunhofer ISE (2019.). Photovoltaics report. 17
- Fu, R., Feldman, D., Margolis, R. and Woodhouse, M. (2017). U . s solar photovoltaic system cost. 34
- Gao, A. M.-z., Fan, C.-t., Kai, J.-j. and Liao, C.-n. (2015). Sustainable photovoltaic technology development : step-by-step guidance for countries facing PV proliferation turmoil under the feed-in tariff scheme, *Renewable and Sustainable Energy Reviews* **43**: 156–163. 38

CHAPTER 2. COUPLING SMALL BATTERIES AND PV GENERATION: A REVIEW

- Gautier, Axel (2018). PV adoption in Wallonia : The role of distribution tariffs under net metering
*. 33
- Geske, J. and Schumann, D. (2018). Willing to participate in vehicle-to-grid (V2G)? Why not!,
Energy Policy **120**(July 2017): 392–401. 40
- Gonçalves, P., Sampaio, V., Orestes, M. and González, A. (2017). Photovoltaic solar energy : Con-
ceptual framework, *Renewable and Sustainable Energy Reviews* **74**(June 2016): 590–601. 17
- Gregg, B. A. and Hanna, M. C. (2003). Comparing organic to inorganic photovoltaic cells : Theory
, experiment , and simulation and simulation, *Journal of Applied Physics* **3605**(March). 17
- Gyan, P. (2015). Calendar ageing modeling of lithium-ion batteries, (Mat4Bat Summer Sch., La
Rochelle, France): 1–49. 19
- Hadush, S. Y. and Meeus, L. (2018). DSO-TSO cooperation issues and solutions for distribution grid
congestion management, *Energy Policy* **120**(April): 610–621. 36
- Hassan, A., Cipcigan, L. and Jenkins, N. (2017). Optimal battery storage operation for PV systems
with tariff incentives, *Applied Energy* **203**: 422–441. 34
- Hoarau, Q. and Perez, Y. (2018). Interactions between electric mobility and photovoltaic generation:
A review, *Renewable and Sustainable Energy Reviews* **94**(October): 510–522. 16
- Hoarau, Q. and Perez, Y. (2019). Network tariff design with prosumers and electromobility : Who
wins , who loses ?, *Energy Economics* **83**: 26–39. 33
- Hoppmann, J., Volland, J., Schmidt, T. S. and Hoffmann, V. H. (2014). The economic viability
of battery storage for residential solar photovoltaic systems - A review and a simulation model,
Renewable and Sustainable Energy Reviews **39**: 1101–1118. 30, 31, 32
- Hsieh, I.-y. L., Pan, M. S., Chiang, Y.-m. and Green, W. H. (2019). Learning only buys you so much
: Practical limits on battery price reduction, *Applied Energy* **239**(January): 218–224. 34
- Huang, B. (2018). Recycling of lithium-ion batteries : Recent advances and perspectives, *Journal of*
Power Sources **399**(June): 274–286. 39
- Imanishi, N. and Yamamoto, O. (2019). Perspectives and challenges of rechargeable lithium e air
batteries, *Materials Today Advances* **4**: 100031. viii, 20
- International Energy Agency (2018a). Global ev outlook: towards cross-modal electrification, *France,*
Paris . 14, 31
- International Energy Agency (2018b). World energy outlook, *France, Paris* . 14, 15

- IRENA (2017a). Boosting solar pv markets: The role of quality. 34
- IRENA (2017b). *Electricity Storage and Renewables: Costs and Markets to 2030*, number October. viii, 20
- ISO (2013). Iso 15118-1:2013—road vehicles—vehicle to grid communication interface—part 1: general information and use-case definition, **2**(3): 65. 21
- John, J., Mwasilu, F., Lee, J. and Jung, J.-w. (2013). AC-microgrids versus DC-microgrids with distributed energy resources : A review, *Renewable and Sustainable Energy Reviews* **24**: 387–405. 23
- Kavлак, G., Mcnerney, J. and Trancik, J. E. (2018). Evaluating the causes of cost reduction in photovoltaic modules, *Energy Policy* **123**(October): 700–710. 34
- Kempton, W. (1997). Electric vehicles as a new power source for electric utilities, *Transportation Research Part D: Transport and Environment* **2**(3): 157–175. 21
- Kempton, W. and Tomi, J. (2005). Vehicle-to-grid power implementation : From stabilizing the grid to supporting large-scale renewable energy, *Journal of Power Sources* **144**: 280–294. 15
- Koirala, B. P., van Oost, E. and van der Windt, H. (2018). Community energy storage: A responsible innovation towards a sustainable energy system?, *Applied Energy* **231**(June): 570–585. 27
- Krajac, G., Duic, N., Tsikalakis, A., Zoulias, M., Caralis, G., Panteri, E. and Grac, M. (2011). Feed-in tariffs for promotion of energy storage technologies ~ ic, *Energy Policy* **39**: 1410–1425. 38
- Krieger, E. M., Cannarella, J. and Arnold, C. B. (2013). A comparison of lead-acid and lithium-based battery behavior and capacity fade in off-grid renewable charging applications, *Energy* **60**: 492–500. 20
- Küfeoğlu, S. and Pollitt, M. G. (2019). The impact of PVs and EVs on domestic electricity network charges : A case study from Great Britain, *Energy Policy* **127**(August 2018): 412–424. 33
- Laurischkat, K. and Jandt, D. (2018). Techno-economic analysis of sustainable mobility and energy solutions consisting of electric vehicles , photovoltaic systems and battery storages, *Journal of Cleaner Production* **179**: 642–661. 30, 31
- Lee, C.-y. and Heo, H. (2016). Estimating willingness to pay for renewable energy in South Korea using the contingent valuation method, *Energy Policy* **94**: 150–156. 40
- Lund, H. and Kempton, W. (2008). Integration of renewable energy into the transport and electricity sectors through V2G, *Energy Policy* **36**(2008): 3578–3587. 22

CHAPTER 2. COUPLING SMALL BATTERIES AND PV GENERATION: A REVIEW

- Luthander, R., Widén, J., Nilsson, D. and Palm, J. (2015). Photovoltaic self-consumption in buildings : A review, *Applied Energy* **142**: 80–94. 15
- Luz, J., Eduardo, C. and Queiroz, W. D. (2013). The need of subsidy for the implementation of photovoltaic solar energy as supporting of decentralized electrical power generation in Brazil, *Renewable and Sustainable Energy Reviews* **20**: 133–141. 17
- Machura, P. and Li, Q. (2019). A critical review on wireless charging for electric vehicles , *Renewable and Sustainable Energy Reviews* **104**(January): 209–234. 22
- Marinelli, M., Zecchino, A. and Andersen, P. B. (2017). Supporting involvement of electric vehicles in distribution grids : Lowering the barriers for a proactive integration, *Energy* **134**: 458–468. 36
- Markel, T., Meintz, A., Hardy, K., Chen, B., Bohn, T., Smart, J., Scofield, D., Hovsapien, R., Saxena, S., Macdonald, J. and Kiliccote, S. (n.d.). Multi-Lab EV Smart Grid Integration Requirements Study Providing Guidance on Technology Development and Demonstration Multi-Lab EV Smart Grid Integration Requirements Study Providing Guidance on Technology Development and Demonstration, (May 2015). 21
- Mayyas, A., Steward, D. and Mann, M. (2018). The case for recycling : Overview and challenges in the material supply chain for automotive li-ion batteries, *Sustainable Materials and Technologies* **17**: e00087. 39
- Mclaren, J., Anderson, K., Laws, N., Gagnon, P., Diorio, N. and Li, X. (2018). Identifying Critical Factors in the cost effectiveness of solar and battery storage in commercial buildings in Commercial Buildings, *National Renewable Energy Laboratory. NREL PR-6A20-70813* (February). 15
- Member, D. J. T., Madawala, U. K., Member, S. and Shi, Y. (2010). Design of a Bi-Directional Inverter for a Wireless V2G System, *2010 IEEE International Conference on Sustainable Energy Technologies (ICSET)* pp. 1–5. 22
- Mendes, G., Ioakimidis, C. and Ferrao, P. (2011). On the planning and analysis of Integrated Community Energy Systems : A review and survey of available tools Gonc, *Renewable and Sustainable Energy Reviews* **15**: 4836–4854. 27
- Mojdehi, M. N., Fardad, M. and Ghosh, P. (2016). Technical and economical evaluation of reactive power service from aggregated EVs, *Electric Power Systems Research* **133**: 132–141. 15
- NEFF (2019). New energies forum feldheim.
URL: <https://nef-feldheim.info/the-energy-self-sufficient-village/?lang=en>. Accessed March 31, 2019 28

- Nelson, T., Simshauser, P. and Kelley, S. (2011). Australian Residential Solar Feed-in Tariffs : Industry Stimulus or Regressive form of Taxation ?, *Economic Analysis and Policy* **41**(2): 113–129. [37](#)
- Noel, L. and McCormack, R. (2014). A cost benefit analysis of a V2G-capable electric school bus compared to a traditional diesel school bus, *Applied Energy* **126**: 246–255. [36](#)
- NREL (2019). Best research-cell efficiency chart, **54**.
URL: <https://www.nrel.gov/pv/cell-efficiency.html>, Accessed in 18 March 2019 [viii](#), [17](#), [18](#)
- Nyholm, E., Goop, J., Odenberger, M. and Johnsson, F. (2016). Solar photovoltaic-battery systems in Swedish households – Self- consumption and self-sufficiency, *Applied Energy* **183**: 148–159. [15](#)
- Oberst, C. A. and Madlener, R. (2015). Prosumer Preferences Regarding the Adoption of Micro-Generation Technologies : Empirical Evidence for German Homeowners Christian A . Oberst and Reinhard Madlener December 2014 Revised September 2015 Institute for Future Energy Consumer Needs and Behavior (FCN), (22). [40](#)
- Pearre, N. S. (2019). Review of research on V2X technologies , strategies , and operations, *Renewable and Sustainable Energy Reviews* **105**(April 2018): 61–70. [22](#)
- Perez-Arriaga, I. J., Jenkins, J. D. and Batlle, C. (2017). A regulatory framework for an evolving electricity sector: Highlights of the MIT utility of the future study, *Economics of Energy & Environmental Policy* **6**(1): 71–92. [14](#), [32](#)
- Pillai, U. (2015). Drivers of cost reduction in solar photovoltaics , *Energy Economics* **50**: 286–293. [34](#)
- Planas, E., Andreu, J., Gárate, J. I., Alegría, I. M. D. and Ibarra, E. (2015). AC and DC technology in microgrids : A review, *Renewable and Sustainable Energy Reviews* **43**: 726–749. [24](#)
- Prasad, B., Araghi, Y., Kroesen, M. and Ghorbani, A. (2018). Energy Research & Social Science Trust , awareness , and independence : Insights from a socio-psychological factor analysis of citizen knowledge and participation in community energy systems, *Energy Research & Social Science* **38**(December 2016): 33–40. [25](#), [27](#)
- Quoilin, S., Kavvadias, K., Mercier, A., Pappone, I. and Zucker, A. (2016). Quantifying self-consumption linked to solar home battery systems : Statistical analysis and economic assessment q, *Applied Energy* **182**: 58–67. [24](#)
- Ramírez, F. J., Honrubia-Escribano, A., Gómez-Lázaro, E. and Pham, D. T. (2017). Combining feed-in tariffs and net-metering schemes to balance development in adoption of photovoltaic energy:

- Comparative economic assessment and policy implications for European countries, *Energy Policy* **102**(September 2016): 440–452. 38
- Ramos-Real, F. J., Ramírez-Díaz, A., Marrero, G. A. and Perez, Y. (2018). Willingness to pay for electric vehicles in island regions: The case of Tenerife (Canary Islands), *Renewable and Sustainable Energy Reviews* **98**(November 2017): 140–149. 40
- Romero-rubio, C., Ramón, J. and Díaz, D. A. (2015). Sustainable energy communities : a study contrasting Spain and Germany, *Energy Policy* **85**: 397–409. 28
- Roschin, P., Efanov, D. and Efanov, D. (2018). ScienceDirect All-Pervasiveness of the Inspired Blockchain 8th Annual The The of the Blockchain Technology 1 the Blockchain The of The of the Blockchain Technology The All-Pervasiveness of the Blockchain Technology The of Blockchain 1 Technology, *Procedia Computer Science* **123**: 116–121. 25
- Sauter, R. and Watson, J. (2007). Strategies for the deployment of micro-generation : Implications for social acceptance, *Energy Policy* **35**: 2770–2779. 15
- Scarpa, R. and Willis, K. (2010). Willingness-to-pay for renewable energy : Primary and discretionary choice of British households ' for micro-generation technologies, *Energy Economics* **32**(1): 129–136. 40
- Schittekatte, T., Momber, I. and Meeus, L. (2018). Future-proof tariff design: Recovering sunk grid costs in a world where consumers are pushing back, *Energy Economics* **70**: 484–498. 32
- Schmutzler, J., A. C. A. . W. C. (2013). Evaluation of ocpp and iec 61850 for smart charging electric vehicles. 21
- Schopfer, S., Tiefenbeck, V. and Staake, T. (2018). Economic assessment of photovoltaic battery systems based on household load pro fi les, *Applied Energy* **223**(November 2017): 229–248. 29, 30
- Shaughnessy, E. O., Cutler, D., Ardani, K. and Margolis, R. (2018). Solar plus : A review of the end-user economics of solar PV integration with storage and load control in residential buildings, *Applied Energy* **228**(April): 2165–2175. 14
- Shubbak, M. H. (2019). Advances in solar photovoltaics : Technology review and patent trends, *Renewable and Sustainable Energy Reviews* **115**(June 2018): 109383. viii, 17, 18
- Simshauser, P. (2016). Distribution network prices and solar PV: Resolving rate instability and wealth transfers through demand tariffs, *Energy Economics* **54**: 108–122. 33
- SmithBucklin Statistic Group (2014). National recycling rate study. battery council international. 39

SonnenCommunity (2019). Sonnen community.

URL: <https://sonnengroup.com/sonnencommunity>. Accessed March 31, 2019 28

Springel, K. (2019). Network Externality and Subsidy Structure in Two-Sided Markets : Evidence from Electric Vehicle Incentives Network Externality and Subsidy Structure in Two-Sided Markets : Evidence from Electric Vehicle Incentives *. 35

Stadler, M., Cardoso, G., Mashayekh, S., Forget, T., DeForest, N., Agarwal, A. and Schönbein, A. (2016). Value streams in microgrids: A literature review, *Applied Energy* **162**: 980–989. 23

Subtil, J. and Bergh, J. C. J. M. V. D. (2016). Diversity in solar photovoltaic energy : Implications for innovation and policy, *Renewable and Sustainable Energy Reviews* **54**: 331–340. viii, 17, 18

Sun, S. I., Chipperfield, A. J., Kiaee, M. and Wills, R. G. (2018). Effects of market dynamics on the time-evolving price of second-life electric vehicle batteries, *Journal of Energy Storage* **19**(May): 41–51. 38

Sundt, S. and Rehdanz, K. (2015). Consumers ’ willingness to pay for green electricity : A meta-analysis of the literature, *Energy Economics* **51**: 1–8. 39, 40

Tan, P., Jiang, H. R., Zhu, X. B., An, L., Jung, C. Y., Wu, M. C., Shi, L., Shyy, W. and Zhao, T. S. (2017). Advances and challenges in lithium-air batteries, *Applied Energy* **204**: 780–806. 20

Thompson, A. W. (2018). Economic implications of lithium ion battery degradation for Vehicle-to-Grid (V2X) services, *Journal of Power Sources* **396**(April): 691–709. 19

Vossos, V., Gerber, D., Bennani, Y., Brown, R. and Marnay, C. (2018). Techno-economic analysis of DC power distribution in commercial buildings, *Applied Energy* **230**(May): 663–678. 24

Wang, Y., John, T. and Xiong, B. (2019). A two-level coordinated voltage control scheme of electric vehicle chargers in low-voltage distribution networks, *Electric Power Systems Research* **168**(December 2018): 218–227. 15

Weiss, R., Ott, L. and Boeke, U. (2015). Energy Efficient Low-Voltage DC-Grids for Commercial Buildings. 24

Xiong, Y., Wang, B., Chu, C.-c. and Gadh, R. (2018). Vehicle grid integration for demand response with mixture user model and decentralized optimization, *Applied Energy* **231**(August): 481–493. 15

Yang, P. and Tarascon, J.-m. (2012). Towards systems materials engineering, *Nature Materials* **11**(7): 560–563. 18

CHAPTER 2. COUPLING SMALL BATTERIES AND PV GENERATION: A REVIEW

Yilmaz, M. and Krein, P. T. (2013). Review of Battery Charger Topologies , Charging Power Levels , and Infrastructure for Plug-In Electric and Hybrid Vehicles, *IEEE Transactions on Power Electronics* **28**(5): 2151–2169. 21

Zubi, G., Dufo-lópez, R., Carvalho, M. and Pasaoglu, G. (2018). The lithium-ion battery : State of the art and future perspectives, *Renewable and Sustainable Energy Reviews* **89**(March): 292–308. viii, 20

* * *

mf cresc. f

From: Johann Sebastian Bach, *H.514 - Violin and Piano Sonata in C minor*.

* * *

Chapter 3

Rate design with distributed energy resources and electric vehicles: A Californian case study

* * *

The high penetration of distributed energy resources and electric vehicles is changing the way the electricity system is managed. In turn, the way utilities have been recovering their expenditures through tariffs needs reformulation. We investigate the impact of different retail tariff designs from a Californian scenario on private investment incentives and cost-shifting using solar PVs, stationary batteries, and electric vehicles. The private commercial facilities studied do not own the vehicles, and the vehicle owners are remunerated for energy services provided; this remuneration strongly depends on the connection hours of the vehicles and the type of tariff applied. EV net income varies annually from \$57 to \$218 per vehicle, reaching the highest values when stationary batteries are present and significant demand charges are applied. We found that an energy-based tariff incentivizes the adoption of solar PVs, bringing high private gains, but often with high cost-shifting. A shift towards coincident peak tariffs in the short term and capacity-based tariffs in the long run, if the cost of DERs continues to fall quickly, can alleviate cost-shifting caused by strong DER penetration.

* * *

1 Introduction¹

The world's electricity demand is expected to grow by 60% between 2017 and 2040 to reach 35,500 TWh. However, the amount of CO₂ emitted must not be allowed to increase in pace with this demand but instead fall to half of today's level to follow the sustainability scenario of limiting temperature rise to 1.7 - 1.8 (IEA; 2018). The power sector is currently undergoing a bottom-up transformation caused by the continuous introduction of distributed energy resources at the consumer end. A system that was once almost purely centralized is nowadays becoming more decentralized as more distributed generation and storage are being installed (Perez-Arriaga et al.; 2017). The increase in solar photovoltaics and stationary battery system adopters is mainly due to the decrease in overall costs and the development of a more substantial societal acceptance of the benefits of these renewable energy resources (Lee and Heo; 2016; Schumacher et al.; 2019). Solar photovoltaics in both residential and commercial sectors have seen their costs fall by a factor of three since 2010 (Fu et al.; 2018) and they are predicted to achieve around 1,200 \$/kW and 1,000 \$/kW for utility-scale PV by 2025 (NREL; 2020). At the same time, the average costs of lithium-ion battery packs also fell threefold from 2007 to 2014, down to 300 \$/kWh (Nykqvist and Nilsson; 2015), and are expected to reach 100 \$/kWh by 2030, as a result of economies of scale from massive investments in research and development in the electric vehicle industry (IEA; 2018). More optimistic previsions foresee the achievement of this price level in 2024 (BloombergNEF; 2019) or even in 2023 (IHS-Markit; 2020). The need to decarbonize the mobility sector, which has a large share of the total worldwide CO₂ emissions, 24% in 2018, has been driving the penetration of electric vehicles (EVs) in recent years. The global number of EVs exceeded 7.1 million in 2019, up by 2.1 million since 2018 and 5 million since 2016 (IEA; 2020). However, EVs can be more than a mere transportation mode and can be considered a distributed energy resource (DER) if smart charging and vehicle-to-grid (V2G) capabilities are enabled.

¹This chapter was published as a working paper in Florence School of Regulation Energy Publications 2021 and at the Chair European Electricity Markets Working paper series 2021 from the University Paris-Dauphine. Currently, the manuscript was accepted for publication in Energy Economics after a decision taken on 4th August 2021. The work was done in collaboration with Yannick Perez and Emilia Suomalainen.

All these changes in the electricity scenario, with the uptake of innovative technologies, directly affect how utilities charge their customers a fair and cost-reflecting retail tariff. Consequently, the new and adjusted tariffs impact innovation uptake, evidencing a clear feedback loop. The tariff² structure is divided into energy charges³, network charges⁴ (transmission and distribution) and taxes and levies⁵. Of these three tariff parts, the one including the distribution network has been the subject of growing debates among national regulatory authorities and academics over the last few years (Brown and Sappington; 2018; Brown and Faruqui; 2014; Pollitt; 2018). The discussions are primarily on how it should be redesigned according to the format (energy, capacity, fixed or a combination thereof), the temporal granularity (flat or time-of-use), and locational granularity (uniform or location-specific). The regulation authorities around the world design tariffs considering specific aspects, such as a combination of the state of the electrical grid, consumer behavior, policy objectives, and electricity mix. Schittekatte and Meeus (2020) argues that, in practice, fairness and cost-reflectiveness have a significant impact on the design of the network part. The results depend more on the state of the grid, if grid investments still have to be made or if costs are mostly sunk. To prevent a severe deficit in the utility's final budget caused by an increase in installed DERs, changing how electricity is produced and stored, a new rate design will be needed⁶.

This paper investigates the relations between EVs and DERs (PVs and batteries) in commercial buildings under different retail tariff schemes using a method similar to that proposed by Boampong and Brown (2019). The main goal is to observe (i) the facility private value impact, (ii) the grid operator financial impact quantified by cost-shifting values, and (iii) EV remuneration when adding an EV providing vehicle-to-grid services behind the meter alongside the DER mix. To the best of our knowledge, no

²For simplicity, the term tariff and rate will refer to the retail tariff when used alone in the text.

³The energy part reflects the wholesale electricity market where retailers buy electricity at a set price to honor contracts with their customers.

⁴The network part reflects the costs of transmitting and distributing the electricity from the generation sites to end-customers. It should include the costs inflicted on the network by the user's load profiles.

⁵Finally, the taxes and levies applied are decided by the national governments.

⁶This problem inflicted on the network by the presence of DERs is called the "death spiral of utilities" (Costello and Hemphill; 2014).

study has assessed these aspects concomitantly, observing the impacts of rate designs on them. For instance, we complement the work of [Boampong and Brown \(2019\)](#) by assessing an extra optimistic DER cost scenario and including EVs as an electric storage option for commercial facilities. In addition, while in the prior work the major part of commercial load profiles has a valley around midday and a peak rising late afternoon, in our case, we adopted bell-shaped load curves typically present in commercial offices, warehouses, and medium-sized malls. We find that energy tariffs increase private economic gains and incentivize PV adoption, whereas capacity tariffs reduce cost-shifting under all combinations of DERs for the commercial buildings studied. This mainly happens when DER prices are low. However, the lowest cost-shifting with conservative DER prices is observed under coincident peak tariffs. Looking specifically at EV net income, we show that it varies annually from \$57 to \$218 per vehicle, reaching the highest values when batteries are present and demand charges are applied.

The Californian case is well suited to this study for several reasons. First, the state of California has one of the world’s most aggressive targets concerning EVs, with 5 million vehicles on the road by 2030 ([IEA; 2020](#)). In addition, California government issued an Executive Order to phase out the selling of combustion engine vehicles by 2035. The Order states that all new cars and passenger trucks sold in California must be zero-emission vehicles by 2035 ([CA.GOV; 2020](#)). Renewable energy should provide 50% of the state’s energy production by 2030 with a considerable amount of solar PV encouraged via rebate programs of the order of 6 billion dollars until 2016 ([CEC; 2019](#)). Although there are no more state rebates for solar installations, the focus now is to push storage with the Self-Generation Incentive Program, which can give an incentive as high as 400 \$/kWh for battery systems ([CPUC; 2019](#)). Secondly, the electricity tariffs applied are highly diversified among the utilities in the state. It is possible to find buildings under time-of-use energy or capacity-based rates with different attributed on-peak periods and high-value variability within the state ([SCE; 2019b](#)). The various rate designs, the relatively low cost of DERs, and the high penetration of EVs enable us to study different scenarios combining them.

The structure of our paper is as follows. First, an overview of the problem is given to explain the motivation of the research, with a literature review support. The data

used are then presented, along with the method proposed. In section 4, the results are presented according to two types of investments. In section 5, we discuss the results and derive policy implications. Finally, the last section comprises the conclusion.

2 Literature review

In this section, we analyze three main strands of the literature. The first concerns the interaction between EVs, solar PVs, and distributed battery storage, which has received much attention recently due to its potential help in decarbonizing both power and mobility sectors at the same time. The second looks at the impacts of diversified tariff schemes when grid users install DERs. Finally, the third domain is the EV remuneration when energy services are provided to the grid.

The way that the synergy between PVs, EVs, and distributed stationary batteries can help to decarbonize the power and mobility sector is to effectively integrate solar energy while lending the grid more flexibility using battery storage. Solar PVs produce carbon-free low marginal cost electricity that can be used to enhance private self-consumption and power electric mobility with green energy for batteries and EVs, respectively. Charging EVs with PVs on a small microgrid scale can significantly decrease demand peaks and defer network reinforcement investments (Kam and Sark; 2015). Kuang et al. (2017) show that this synergy can be more relevant for certain categories of buildings, e.g. offices, restaurants, and warehouses, where a smart control strategy of EV/PV energy building systems can reduce costs by up to 18%. Moreover, low-cost batteries can support EV charging by synchronizing the intermittent PV generation with EV demand (Kaschub et al.; 2016). We contribute to this field by analyzing the private investment impact of different DER combinations under modern tariff schemes. Although the benefits of the coupling between these DERs are clear, they are deeply impacted by the economic environment and inappropriate regulations. Obsolete tariffs and obsolete ancillary service market designs could jeopardize all the potential benefits brought by the coupling (Freitas Gomes et al.; 2020).

The high penetration of DERs in the electricity system will not only demand changes in the way utilities technically manage their grid but also require reformula-

tion of the tariffs applied to end-customers (Burger et al.; 2019). Classic formulations using energy-based tariffs with net-metering are not efficient in recovering network costs, leading to cross-subsidy issues, mainly when high shares of solar PVs are installed (Schittekatte et al.; 2018; Simshauser; 2016; Sioshansi; 2016). In this case, the electricity savings of prosumers that invest in DERs would be higher than the avoided costs of the utility, threatening the financial equilibrium of the utility. As a consequence, utilities would need to raise their tariffs to recover their costs, and non-prosumer customers could see their bills increase due to the increase in the tariff for all network users. This would initiate the death spiral of utilities (Costello and Hemphill; 2014) in which low-income customers are usually the most severely affected by this tariff rise. According to Burger et al. (2020), network cost recovery can be enabled using differentiated fixed charges while preserving marginal costs signals. They demonstrate that fixed charges designed using customer demand profiles or geography can provide efficient bill protection. Several studies propose a solution to these issues based on demand charges (or capacity tariffs). For instance, Simshauser (2016) argues that a capacity-based demand tariff is a more efficient structure that improves stability, cost-effectiveness, and fairness in allocating network sunk costs between prosumers and ordinary consumers. Sioshansi (2016) proposes a two-part tariff based on a time-invariant energy charge as its first part, the second part being a capacity charge based on the cost of the peaking capacity, which will have cost-allocation benefits in the face of DERs. In the same line of thought, Dameto et al. (2020) propose a two-part tariff with a peak-coincident and a fixed charge in a current context. They argue that this rate configuration promotes efficient network usage as well as an equitable share of the costs for all the network users.

There is no consensus in the literature on capacity-based demand tariffs as the means to balance efficiency and equity. Borenstein (2016) states that fixed charges reflecting customer service levels and time-varying pricing are more effective than demand charges in kW⁷. Another problem with this type of rate is that it can (over)incentivize storage adoption and create similar efficiency and fairness issues in network cost allo-

⁷These tariffs are especially wasteful, from a societal point of view when the customer's peak demand does not coincide with the system's peak. The coincident peak demand tariff could send the right signal but may create another coincident peak period in another period.

cations to those of pure energy charges if low-cost batteries are available (Schittekatte et al.; 2018). Besides considering solar PVs and stationary batteries like previous studies, other studies also included EVs in their tariff design analysis (Hoarau and Perez; 2019; Küfeoğlu and Pollitt; 2019). Küfeoğlu and Pollitt (2019) show the counterbalancing effect of EVs over the tariff increase caused by PVs under the current energy-based rate in Great Britain. If batteries are added to the DER mix, Hoarau and Perez (2019) show that EVs and DERs may conflict under the main tariffs based on energy-based and capacity-based schemes by inducing negative spillovers on each other through the recovery of grid costs. A change of regulation would make winners and losers, so regulators should be careful about which kind of technology they want to promote⁸. Our paper goes a step further to study the impact on avoided costs from a utility perspective and the cost-shifting to find what DER mix and tariff would be fairest assuming that when there is cost-shifting these costs may be passed on to consumers who do not install a DER system⁹.

EVs can provide a good number of front-of-the-meter services to both transmission and distribution grids, increasing the opportunity of economic gains for the user. As pointed out in Eid et al. (2016) concerning the short-term market, EVs can provide frequency containment reserves and secondary reserves according to the market rules at the transmission level which involve more actors in the electricity system¹⁰. Additionally, they can participate in congestion management, voltage regulation, and network investment deferral at the distribution grid level (Pearre; 2019). Behind-the-meter services could also be profitable depending on the market and tariffs applied, varying from pure energy arbitrage or demand charge reduction. However, not all of them have the same economic value: for instance, Thompson and Perez (2020) list the annual value stream ranges of these services; they found that bill management, which

⁸This question is still open to discussion among researchers, network operators and regulators seeking to determine the tariff structure that is the most effective from the system point of view, and fairest, from the consumers' perspective, under different DERs such as batteries, EVs, PVs or heat pumps.

⁹In line with Boampong and Brown (2019), our proxy for fairness is the average cost-shifting caused by the private facilities. Contrary to Simshauser (2016) and Schittekatte et al. (2018) the cost-allocation analysis among prosumers and ordinary consumers is not in the scope of this study.

¹⁰Besides the TSO and DSO or the ISO and Utilities in our Californian scenario, we also have the aggregator, a commercial entity responsible for grouping distributed energy resources such as EVs, to provide grid services as an intermediary between the system operator and EV owners.

is mainly time-of-use management and demand charge reduction, could bring the highest remuneration. Since that research was done using different markets from various utilities, the conditions in which those revenues arise are heterogeneous, including the tariffs used by each utility. Therefore, it is essential to know under what types of electricity tariff it is possible to have discussed revenues, especially behind-the-meter services. Finally, we contribute to the literature on EV energy services by assessing the maximum remuneration vehicle-to-grid enabled EVs can obtain connected to commercial buildings by providing services to the facility according to the DER mix and tariff schemes applied.

3 Model and Data

This section describes the model used to pursue the main goals of this research and presents the data used as parameters to feed the model.

3.1 Methodology

The method used to obtain the results is based on that used in [Boampong and Brown \(2019\)](#), relying on two complementary tools, as shown in Figure 3.1. First, we use the Distributed Energy Resources Customer Adoption Model (DER-CAM) developed by Lawrence Berkeley National Laboratory to simulate private investments using DERs, in our case PVs, stationary batteries, and EVs. We couple it with the Avoided Cost Model (ACM) developed by [E3 \(2018\)](#), which accounts for the costs avoided by the electricity supply-side when one kWh is returned to the grid or is no longer consumed by the private facility.

Two different types of investments are considered in this study: exogenous and endogenous. For the exogenous part, we consider three possible DER combination (PVs plus battery, PVs plus electric vehicles, and PVs plus battery and electric vehicles) in which the amount of DERs installed is fixed so that it is possible to isolate the impact of changes in tariffs, leaving the model only the task of finding the optimal charge and discharge strategies. As we go towards the endogenous investment, the model chooses the optimal charge and discharge strategies concomitantly with the amount of DERs

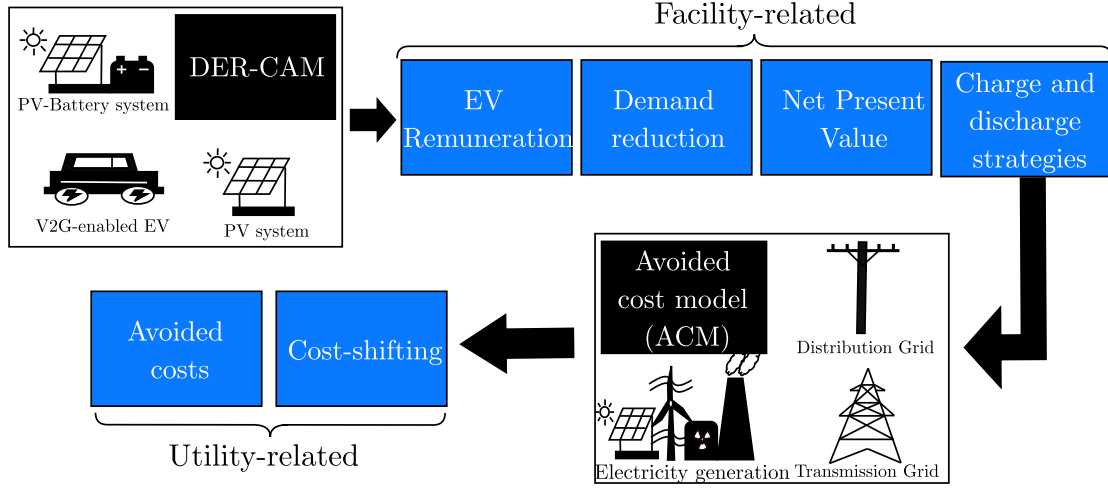


Figure 3.1: Methodological framework.

to minimize private costs. The latter option is more likely once investors act rationally to find the highest possible net present value. Nevertheless, the study of the exogenous case can shed light on many hidden relationships between DERs according to the retail scheme applied.

We then compute the NPV, taking into account the electricity savings minus the capital and operation expenditures of all the investments to check whether they are profitable. The main input is the annualized cash flow, which is given by the difference between the base case scenario annualized energy costs without DER and the scenario annualized energy costs with a DER. We considered a nominal discount rate of 8%, a maximum payback period of 20 years (the lifetime of solar PVs), and an inflation rate of 1.5%¹¹. The costs of DERs and the base case electricity value (the cost of electricity when there are no DERs installed for a specific facility) will be decisive as to whether the value is positive.

3.1.1 DER-CAM Optimization Program

DER-CAM models the optimization problem to minimize the annual costs of facilities investing in DERs according to the tariff structure applied as a Mixed-Integer Linear Program (MILP). The adapted total cost function of the fully endogenous model is

¹¹For a yearly time period i , the net present value is calculated by :

$$\sum_{i=1}^{20} \frac{\text{Annualized cash flow} \cdot (1 + \text{inflation})^i}{(1 + \text{nominal discount rate})^i}$$

divided into electricity costs, DER costs, EV costs, and export revenues:

$$\text{Min } c_{total} = c_{elec} + c_{DER} + c_{EV} - \sum ExportsRev \quad (3.1)$$

We implement compound retail rates such as time-varying three-part tariffs taking into account diversified fixed, energy (in kWh), and demand charges (on-peak, mid-peak, coincidental or non-coincidental) so that the variable electric costs reflect the tariff components summed over the year. The DER costs include capital and operating expenditures over a specified duration for energy resource installed by the private facility. We can compute the Net Present Value (NPV), considering the electricity savings minus the capital and operation expenditures of all the investments to check whether they are profitable. The main input is the annualized cash flow, which is given by the difference between the annualized energy costs of the base case scenario without DERs and the annualized energy costs with DERs. The costs of DERs and the base case electricity cost (the cost of electricity when there are no DERs installed for a specific facility) will be decisive as to whether the value is positive.

The EV costs then account for the additional expenditures linked to EV ownership; for instance, unlike PVs and a stationary battery, only the charging station is owned by the private facility. By contrast, the EV itself is not, meaning that costs such as battery degradation caused by private facility strategies and the electricity used coming from home charging should be refunded¹². Since the vehicle starts home charging in the evening, the charging event is under the off-peak period, making the discharge to the grid of the facility virtually profitable¹³. Although discharging EV battery into the facility grid can bring high financial gains, in the case of PV generation excess, charging these vehicles can also become profitable. The model allows the EV owner to pay the facility back if the net energy exchanged between the vehicle and the facility's grid becomes negative (see the first part of equation A.4), that is, if the charging events using electricity generated in the facility outweigh the discharging events into the facility's grid. There are, therefore, financial flows between these two

¹²The full equations and constraint formulations are presented in B based on Cardoso et al. (2017); Momber et al. (2010); Stadler et al. (2013).

¹³A study from Idaho National Laboratory show that around 85% of EV charging in the United States is done at home (INL; 2016).

players: the private facility and EV owner. These financial flows will depend on the electricity costs during home charging, battery degradation caused by the grid usage of the facility, and electricity bill reduction due to energy services provided by the EV¹⁴. If the sum of the first two factors is positive, in this case, the first flow will be from the facility towards EV owners; if it is negative, the flow will go in the opposite direction (see Equation A.4). This first flow is mainly a financial compensation: in the former case, compensation for the electricity used to charge EVs at their owners' homes under a specific EV tariff and the battery degradation caused by V2G services provided to the facility grid. Then, there is a second flow corresponding to the value created using EVs. This flow captures the spread between home charging (or local solar PV charging) and the discharging to arbitrage energy and offset demand at the local facility. We focus on the most valuable service provided in California by EVs, which is bill management (maximum demand reduction stacked with energy arbitrage), according to Thompson and Perez (2020) to verify the effects of electricity tariffs on this type of service. As this kind of service does not directly involve any third parties such as aggregators, distribution system operators, or transmission system operators, the sharing of value is defined between facility and EV owners, and our goal is to assess the maximum amount of revenue to be split between them. There are several ways to define vehicle owners' net income based on the total amount to be split. In our case, we assume that both parties have the same bargaining power so that a fifty-fifty strategy will be adopted and the total value created by EVs will be equally shared between EV owners and the commercial facility¹⁵. Finally, the additional export revenue can represent the financial contribution of any incentive program, like solar or storage feed-in-tariff or even net-metering schemes, to the final total cost.

The constraints applied to the program require it to meet several conditions so that the facility DERs can work properly together. First, the energy balance equation matching supply and local demand links all the generation coming from the PVs, grid purchases, and storage discharge with the charging episodes and the load of the facility.

¹⁴The value is the actual net income and is calculated by the difference between the total energy costs in the scenario without EVs and the one with the EV providing energy services to the facility.

¹⁵Chapter 4 of Borne (2019) describes more complex negotiations in the V2G ecosystem where actors have different bargaining power.

The solar PV maximum output is then limited by its maximum peak efficiency, solar radiation conversion efficiency, and solar insolation. Finally, storage maximum and minimum state of charge, together with the charging input and discharge output power, are considered separately to prevent them from occurring simultaneously. General constraints are also present to define boundaries for the DER operations, defining an arbitrarily large number \mathbf{M} to avoid unexpected outcomes such as buying and selling (exporting) electricity at the same time, as stated in Equations A.11 and A.12. Also, the annuity factors and the payback constraint in which all investments must be repaid in a period shorter than the payback period are defined.

3.1.2 Avoided Cost Model (ACM)

The Avoided Cost Model (ACM), developed by E3 (2018), is used in demand-side cost-effectiveness proceedings at the California Public Utilities Commission (CPUC) to evaluate California’s DER program components. We use this model to proxy for the avoided cost associated with a DER unit output, enabling us to calculate the cost-shifting measurements when coupled with private economic savings from DER-CAM. The ACM calculates the cost avoided by the utility by not producing and delivering one extra unit of energy. This calculation is made by dividing the map into 16 Climate Zones in California, these zones are called forecasting climate zones (FCZ), where each one has its commercial electricity supplier¹⁶. The cost itself is composed of nine components: Energy, Losses, Ancillary Services, Cap and Trade, GHG Adder, Societal Criteria Pollutant, Capacity, Transmission, and Distribution costs.

Energy and Losses give the hourly marginal cost of providing a unit of energy from the wholesale market to end-users (adjusted for line losses). Ancillary services give the marginal cost of providing reliable services to the grid to keep it stable¹⁷. Cap and Trade costs give the marginal cost of CO₂ emissions associated with the marginal generation technology based on projections of California’s cap-and-trade policy. The

¹⁶These utilities can serve more than one zone. The largest ones are Southern California Edison (SCE), Pacific Gas and Electric (PG&E) and Los Angeles Department of Water and Power (LADWP).

¹⁷EVs providing behind-the-meter services are easily coupled with the ACM since the utility sees them as a (mobile) battery. For in-front-of-the-meter services, some modifications should be made in the method to avoid counting the same service twice, since the model already accounts for the ancillary service procurement cost component.

GHG Adder and Societal Criteria Pollutant costs give the avoided costs associated with reducing the need to procure additional renewable output to meet Renewable Portfolio Standards requirements. We group these six components in our analysis under Energy-based costs. The last three components are referred to as capacity-related cost components. Generation capacity gives the avoided costs from not procuring additional production capacity to meet peak demand. Transmission and distribution capacity gives the costs of expanding capacity to meet system peak demand. We set the ACM on the Climate Zone 9, Los Angeles suburb areas, and SCE utility territory, as this setting accurately proxies the avoided costs for our sample. The model computes 2020, 2025, 2030, and 2035 levelized avoided cost so that each year can be the reference for the next four, accounting for twenty years in total¹⁸. To achieve numerical traceability, DER-CAM uses three representative day-types per month: weekday, weekend day, and peak day. The calculation of the weekday and weekend day is done using average values across the month. For the peak day, the maximum observed load during one day is filtered and used as the peak day profile¹⁹. The yearlong hourly data computed by the ACM is therefore transformed into these three representative profiles to match dimensionally the results from DER-CAM.

We regress the real hourly weekday and weekend avoided cost profiles (as a dependent variable) on the representative average avoided profile day of each month to find how well the average profiles capture the real avoided cost variation. We calculated the average R-squared value for all four years (energy plus capacity avoided costs). The satisfactory values of 0.8305 for weekdays and 0.8906 for weekends are obtained.

Fig. 3.2 shows the breakdown of peak avoided costs for Climate Zone 9 per 12 months and 24 hours in 2020 divided into energy- and capacity-related avoided costs. Along the year, there are marked variations for both energy-related and capacity-related costs caused by the different season characteristics. In general, during spring months, low marginal avoided costs are observed while the hydro production is high,

¹⁸20 years will be the period taken to calculate the net present value of the investment, which coincides with Solar PV lifetime.

¹⁹A useful data-processing tool was developed by Lawrence Berkeley National Laboratory to convert the load data into representative peak, weekday, weekend profiles for each month (LBNL; 2019).

CHAPTER 3. RATE DESIGN WITH DISTRIBUTED ENERGY RESOURCES AND ELECTRIC VEHICLES: A CALIFORNIAN CASE STUDY

Month	Hour																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	64.63	63.66	62.72	62.68	63.69	76.75	93.93	123.55	90.49	81.98	76.91	73.87	70.64	70.75	73.80	77.15	93.99	117.19	117.93	103.62	99.22	81.55	74.03	69.11
2	63.36	60.83	58.82	58.83	61.73	72.92	124.04	118.71	92.90	70.67	67.23	65.28	0.00	0.00	64.95	68.92	81.96	105.57	130.33	116.38	108.63	90.75	73.93	65.74
3	57.98	57.66	56.12	57.30	72.04	106.52	117.37	104.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	75.14	115.88	149.19	118.10	100.97	81.00	70.90	63.76
4	59.14	56.42	59.12	64.85	78.06	103.99	101.22	29.64	0.00	0.00	54.21	50.51	53.92	60.21	62.08	0.00	0.00	85.86	130.20	120.47	90.21	76.72	62.87	59.26
5	57.12	56.45	56.40	57.20	71.62	95.50	36.97	0.00	0.00	29.25	82.13	90.38	85.40	98.74	125.07	72.60	100.33	132.57	211.16	162.04	101.44	83.13	68.64	62.45
6	61.45	60.43	61.97	61.79	66.78	76.48	67.84	27.94	29.63	31.90	40.22	48.13	58.84	92.83	141.76	322.79	372.68	528.62	783.64	319.04	124.78	97.30	83.52	66.28
7	63.35	62.89	61.32	60.41	67.81	72.09	72.12	70.54	28.27	29.05	34.98	39.31	44.91	51.83	121.82	133.05	151.83	184.68	208.24	121.29	97.03	76.43	70.64	70.36
8	63.96	61.63	60.22	61.30	65.40	84.74	83.06	76.99	85.49	105.40	93.43	104.83	127.34	182.30	296.63	320.68	452.29	564.82	513.94	256.75	129.01	97.31	81.99	71.94
9	73.61	69.15	66.77	64.08	64.28	86.41	85.48	71.41	77.87	91.27	95.87	108.21	125.76	156.62	233.77	357.69	516.34	914.08	599.01	264.15	120.52	97.94	85.69	80.13
10	73.75	70.01	68.41	70.46	85.13	118.81	129.42	94.97	74.53	28.01	31.03	40.86	107.11	123.33	147.07	219.63	464.89	660.09	444.38	213.37	181.61	131.87	103.82	86.98
11	91.32	84.20	78.20	74.27	77.96	103.07	130.64	107.84	86.09	74.80	73.41	73.65	73.77	74.38	77.91	102.64	136.29	238.74	208.17	135.53	132.75	113.30	90.61	87.86
12	81.14	77.17	73.43	75.07	79.31	95.26	123.95	115.34	86.98	76.18	68.94	66.61	66.41	66.97	69.48	81.62	120.55	147.87	134.66	124.31	122.80	105.82	105.05	91.92

(a) Energy-related Peak Marginal Avoided Costs (\$/MWh)

Month	Hour																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.84	0.08	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.61	3.54	2,024.86	7,925.93	9,050.50	8,813.61	239.63	101.94	0.36	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	4.04	181.41	652.27	8,686.98	7,116.88	2,250.61	485.97	1.78	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	1.66	5,209.01	12,934.90	16,584.56	22,171.92	22,822.83	5,784.20	1,705.36	4.52	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.47	4.86	2.74	0.02	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(b) Capacity-related Peak Marginal Avoided Costs (\$/MWh)

Month	Hour																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	64.63	63.66	62.72	62.68	63.69	76.75	93.93	123.55	90.49	81.98	76.91	73.87	70.64	70.75	73.80	77.15	93.99	117.19	117.93	103.62	99.22	81.55	74.03	69.11
2	63.36	60.83	58.82	58.83	61.73	72.92	124.04	118.71	92.90	70.67	67.23	65.28	0.00	0.00	64.95	68.92	81.96	105.57	130.33	116.38	108.63	90.75	73.93	65.74
3	57.98	57.66	56.12	57.30	72.04	106.52	117.37	104.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	75.14	115.88	149.19	118.10	100.97	81.00	70.90	63.76
4	59.14	56.42	59.12	64.85	78.06	103.99	101.22	29.64	0.00	0.00	54.21	50.51	53.92	60.21	62.08	0.00	0.00	85.86	130.20	120.47	90.21	76.72	62.87	59.26
5	57.12	56.45	56.40	57.20	71.62	95.50	36.97	0.00	0.00	29.25	82.13	90.38	85.40	98.74	125.07	72.60	100.33	132.57	211.16	162.04	101.44	83.13	68.64	62.45
6	61.45	60.43	61.97	61.79	66.78	76.48	67.84	27.94	29.63	31.90	40.22	48.13	58.84	92.83	141.76	322.80	372.69	528.65	784.48	319.11	124.78	97.30	83.52	66.28
7	63.35	62.89	61.32	60.41	67.81	72.09	72.12	70.54	28.27	29.05	34.98	39.38	45.52	55.37	2,146.68	8,058.97	9,202.33	8,998.29	447.87	223.23	97.39	76.43	70.64	70.36
8	63.96	61.63	60.22	61.30	65.40	84.74	83.06	76.99	85.49	105.40	93.43	104.83	127.39	186.33	478.04	972.95	9,139.27	7,681.69	2,764.54	742.72	130.79	97.31	81.99	71.94
9	73.61	69.15	66.77	64.08	64.28	86.41	85.48	71.41	77.87	91.27	95.87	108.25	127.42	5,365.64	13,168.68	16,922.25	22,688.26	23,736.91	6,383.21	1,969.51	125.04	97.94	85.69	80.13
10	73.75	70.01	68.41	70.46	85.13	118.81	129.42	94.97	74.53	28.01	31.03	40.86	107.11	123.33	147.07	219.63	473.36	664.95	447.12	213.38	181.61	131.87	103.82	86.98
11	91.32	84.20	78.20	74.27	77.96	103.07	130.64	107.84	86.09	74.80	73.41	73.65	73.77	74.38	77.91	102.64	136.29	238.74	208.17	135.53	132.75	113.30	90.61	87.86
12	81.14	77.17	73.43	75.07	79.31	95.26	123.95	115.34	86.98	76.18	68.94	66.61	66.41	66.97	69.48	81.62	120.55	147.87	134.66	124.31	122.80	105.82	105.05	91.92

(c) Total Peak Marginal Avoided Costs (\$/MWh)

Figure 3.2: Marginal peak avoided costs profile for Forecasting Climate Zone 9 in 2020.

and during summer, on the other hand, high marginal avoided costs are present because the system strongly depends on natural gas power plant generation to match the demand and cope with the duck curve challenge driven by high solar PV production²⁰.

From an intraday perspective, there are significant variations during the middle of the day and evening hours, especially for the spring and summer months. The avoided costs are driven mostly by energy-related costs, but from July to September, from 2 PM until 9 PM, the capacity-related costs by far outweigh the energy-related costs, thus driving the total avoided cost. All this high variability in the total avoided costs show that the value of storage (stationary batteries and electric vehicles) is strongly dependent on the period, season, and charge and discharge strategies.

We couple the ACM with results from DER-CAM to calculate the avoided costs for each facility under specific tariffs. We also study two different cases to calculate the average avoided costs of the facilities. In case 1, the facility peak day never overlaps with the system peak avoided costs; instead, it overlaps with the typical avoided costs for a weekday during a specific month. This case is the most likely to occur in day-by-day operations. In case 2, the private facility peak overlaps precisely with the system peak avoided costs profile, meaning when the system is more constrained. These two cases show practically the same qualitative results, differing only in the amount of final aggregated and average avoided costs. They provide bounds for each tariff and technology mix, showing the limits that it is possible to have within cases with more than one facility peak day; in our case, we assumed three peak days per month. Not only will the demand reduction during the system constrained hours to be the decisive factor in terms of total avoided costs, but the discharging and charging strategies during the different hours will also have an influence. The last metric, cost-shifting, measures the difference between the private savings and the avoided costs of the system, i.e. the amount of money not recovered by the utility due to the presence of DERs²¹. This can be used as an equity proxy for tariffs since positive cost-shifting

²⁰During the summer months (July, August, and September) when the system highly depends on costly natural gas plants, the generation capacity costs are the major part of capacity costs. Network capacity costs surpass generation capacity costs in the following month due to the absence of these peak power plants.

²¹A positive value of cost-shifting means that the utility has a deficit in their budget caused by the DERs; on the other hand, a negative one represents a surplus, which can lead to a decrease in tariff value.

may imply a rise in tariffs for all consumers. The higher the cost-shifting, the higher the propensity to raise tariffs to recover all the utility costs, mainly those related to the electric network usage, contributing to the death spiral of utilities (Simshauser; 2016). Ideally, zero cost-shifting means that the annual savings of the private facilities are precisely the avoided costs for the utility. This means that the tariff is perfectly adapted to avoiding inequalities between those who have DERs and those who do not. However, it is hard to achieve this goal given the distortions in electricity bills caused by the DERs under ill-adapted tariffs.

3.2 Data

The next section presents and justifies the choice of input data and parameters to run the model.

3.2.1 Load profiles

To find the private value impact of the installed DERs, we need to define what kind of sites to consider and the techno-economic characteristics of the resources. The load profile of commercial sites will be used for several reasons: DERs can play an essential role in electricity consumption reduction in the buildings sector, as around half of the global electricity demand today is in this sector²²; Secondly, the load profile peak is synchronized with the PV production during the day, leading to higher economic gains without the need for financial incentives for renewable such as feed-in-tariffs or net-metering schemes.

The five load profiles used shown in Figure 3.3 are the average peak day profile for September from commercial reference sites developed by the U.S. Department of Energy (DoE; 2013)²³, which include a medium office, restaurant, warehouse, retail, and a medium mall. We transform the yearly data into DER-CAM weekday, weekend, and peak load profiles as done with the avoided cost data. We also regress the real hourly weekday and weekend profiles (as a dependent variable) on the representative

²²It has also accounted for 52% of global electricity demand growth since 2000, contributing nearly 55% (7,200 TWh) to global growth through 2040 (IEA; 2018).

²³These datasets are hourly profile data over a year for several commercial sites representing approximately 70% of the commercial buildings in the U.S.

average profile day of each month to find how well the average profiles capture the real demand variation. The calculated average R-squared value for all five building loads is then 0.8647 for weekdays and 0.7303 for weekends.

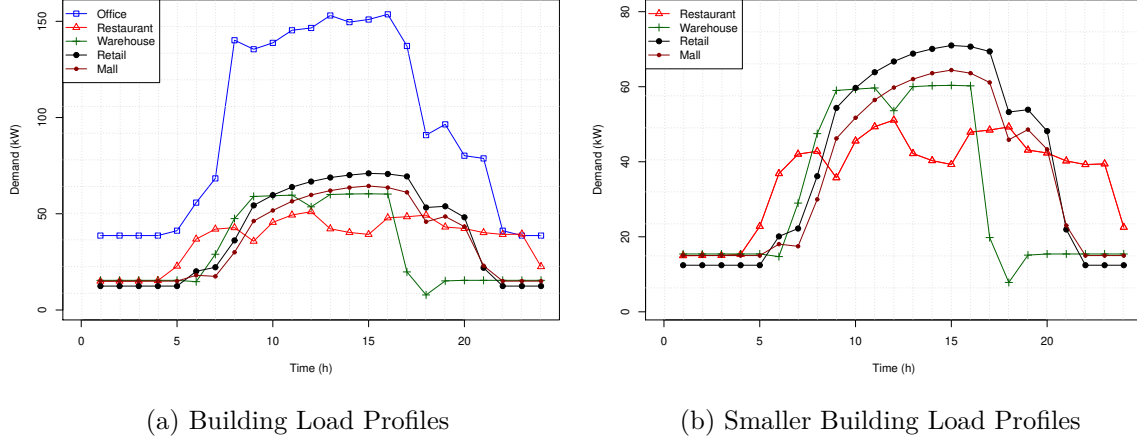


Figure 3.3: Commercial building load profiles.

3.2.2 Electricity retail rates

The diversity offered by SCE’s retail rates couple perfectly with the assortment of DERs applied in this study. Energy- and capacity-based tariffs, with high demand charges, make a reliable scenario to analyze the sensitivity of many parameters due to tariffs. Fig. 3.4 shows three different commercial and industrial (C&I) tariffs based on the rates proposed by Southern California Edison’s C&I tariff book for general services (GS2) with a maximum demand ranging from 20 kW to 200 kW (SCE; 2019b). All of them are three-part tariffs, which include fixed, energy, and capacity charges. The difference lies in the weighting of each part: the temporal granularity is a time-of-use (TOU) approach with on-peak, mid-peak, off-peak and even super-off-peak periods during winter. Lastly, the rates are uniformly adopted under SCE’s territorial service zones²⁴. We will use three tariff structures in total: an energy-based tariff (TOU-ENE), a capacity-based tariff (TOU-CAP), and a coincident peak demand tariff (TOU-COIN) in which all demand charges are shifted towards a specific hour, in our case, the coincident hour varies between 5 and 7 PM over the year due to the highest grid constraints

²⁴The detailed rate values during summer and winter periods are presented in Tables A.2 and A.3.

observed in a given month²⁵. The coincident hour for a month is set a month before by the utility, so commercial buildings can formulate beforehand their strategies to reduce demand charges. In SCE's C&I tariff book, the adopted retail tariffs TOU-ENE and TOU-CAP correspond to TOU-E and TOU-D while TOU-COIN is a counterfactual tariff based on coincidental demand charges. SCE proposed these tariffs TOU-D and TOU-E to frame better the grid constrained period and the cost of using the network by shifting the attributed on-peak period from around midday toward early evening. In addition, SCE customers are encouraged to compare their current energy costs to other rate options and select the best rate plan. Finally, no complementary assistance programs (e.g., feed-in-tariffs and net-metering) were applied alongside the rates to check whether DER investments would still be profitable under these conditions. It is important to measure how mature DER investments are without utility financial support since great uncertainties are present around these assistance programs. In the case of feed-in-tariffs, in which the utility buys the excess energy from the PVs at a price equal or higher than the applied retail rate, the program called Renewable Market Adjusting Tariff (ReMAT) by CPUC to incentivize the adoption of small renewable generators (less than 3 MW) was suspended for all new contracts under SCE territory (CPUC; 2018). Regarding net-metering schemes, SCE gives the possibility of billing the net energy at a certain point in time via the program NEM 2.0 (SCE; 2021). However, an imminent change of this program towards a new NEM 3.0 may have a strong impact on the project's profitability (IOUs; 2021).

Besides the rates applied to the private facility, the rates applied to EV owners during home charging are essential to justify the economic gains of the spread between the two rates. The applied charge is a weighted average off-peak domestic time-of-use electric vehicle charging (TOU-EV-1) rate adapted from SCE's tariff book according to the season (SCE; 2019a), resulting in an energy price $P_{ev} = 0.1103$ \$/kWh.

3.2.3 DER Parameters

Numerous parameters of technology and market data are needed to obtain reliable results according to the scenario. Capital and operational costs for DERs were obtained

²⁵The Table A.4 shows the complete list of coincidental hours adopted monthly by the utility.

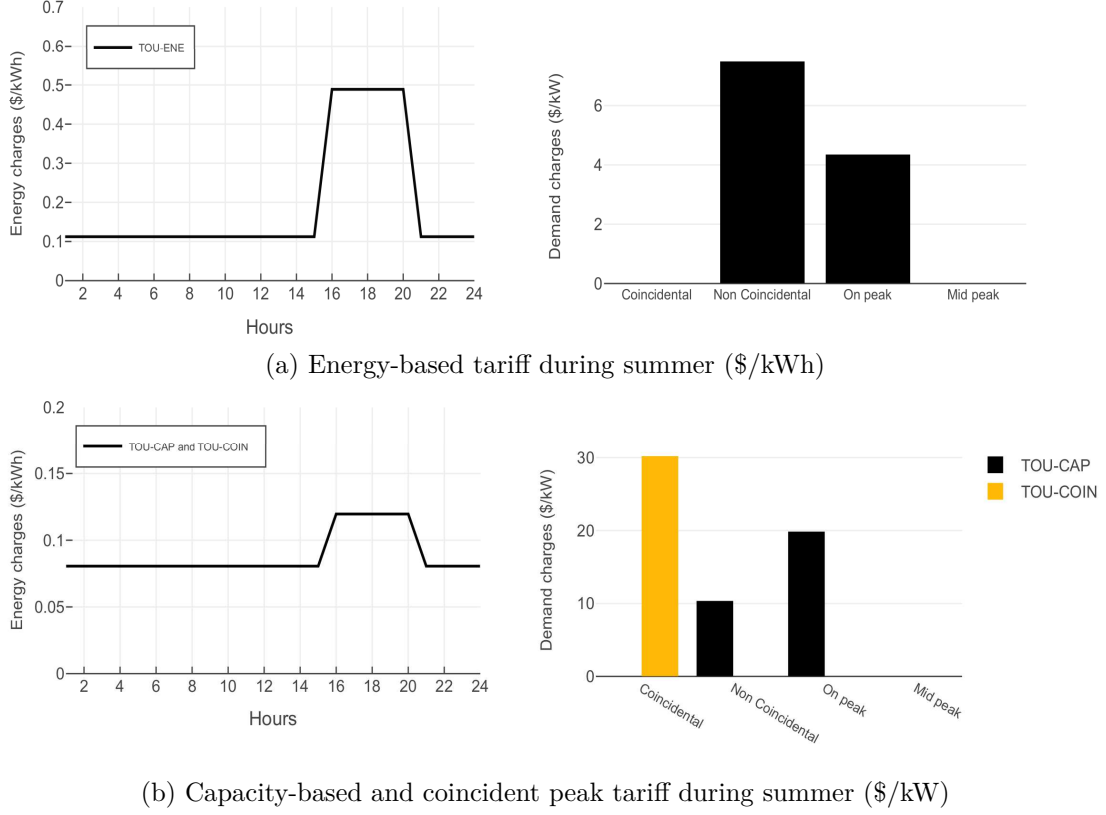


Figure 3.4: Electricity tariff formats.

by selecting values from a list of options after extensive benchmarking. Two cost scenarios are defined to compare different cost reduction trajectories. First, in both exogenous and endogenous investment analysis, we adopt a conservative scenario in which we select mid-range values found in the literature with their public subsidies, if applicable. To complement the endogenous analysis, an optimistic scenario considering a significant cost decrease of DERs is assessed.

For the solar PVs, we take a peak efficiency of 19.1%, which corresponds to a multi-crystalline panel taking the highest market share globally (NREL; 2019). The investment costs per KW found in the literature range from 1,250 to 3,237 \$/kW²⁶ (Beck et al.; 2017; Cardoso et al.; 2017; Fu et al.; 2017; Hanna et al.; 2017; Koskela et al.; 2019; NREL; 2020; Tervo et al.; 2018). There is also a wide range of values for their lifetime, from 20 to 30 years. Finally, the following specifications were selected

²⁶More precisely, these values are calculated as \$/kWac, meaning that the investment already includes the power inverter to transform the direct current into alternate current to be used in a local grid.

for the conservative scenario: 2,100 \$/kW (Fu et al.; 2017), 25 years of lifetime (Sheha and Powell; 2019) and 0.66 \$/kW per month (McLaren et al.; 2018) as operation and maintenance costs. In the optimistic scenario, we adopt the value of 1250 \$/kW in line with the cost projected by NREL (2020) for commercial PVs in their advanced technology scenario by 2025²⁷.

Besides the market parameters, battery energy storage systems (BESSs) and EVs have extra technical parameters linked to the battery functioning compared to solar PVs. First, a fixed cost of \$500 (Beck et al.; 2017) is established to account for the mandatory battery system costs regardless of the size of the battery, such as the initial installation labor and the structural support. The investment costs per kWh, as in the case of solar PVs, vary widely in the literature, from 350 to 1050 \$/kWh for lithium-ion battery technology (Beck et al.; 2017; Cardoso et al.; 2017; Doroudchi et al.; 2018; Fu et al.; 2018; Hanna et al.; 2017; IRENA; 2017; Koskela et al.; 2019). The selected value was 465 \$/kWh (Doroudchi et al.; 2018). However, adding the lower bound of the subsidy offered by SCE's storage rebate incentive program, up to 250 \$/kWh (SCE; 2017), turns the final cost into 215 \$/kWh. In the optimistic scenario, the value of 100 \$/kWh was selected. This value is the goal of the battery industry for making electric vehicles competitive with internal combustion engine vehicles without subventions. Their lifetime varying from 5 to 15 years, we select 10 years (Sheha and Powell; 2019; Tesla-Powerwall; 2020); the fixed maintenance is already included in the investment costs per kWh value. Second, several technical parameters must also be defined. We thus set a charging and discharging efficiency of 90% (Tesla-Powerwall; 2020), a maximum charging and discharging rate of 30%, and a state of charge between 20% and 90% to avoid extra battery degradation.

In the case of electric vehicles, the costs will be associated with the installation of the charging station by the local facility while the vehicle itself is owned by the employees of the building. The level 2 charging stations, ranging from 4 kW to 20 kW, are mostly found in commercial buildings and workplaces due to the higher charging power needed to compensate for the shorter connection period compared to home

²⁷The lowest costs per kW of PVs are found in utility-scale projects by scaling up project size and portfolios. Since they are larger than commercial and residential PV projects, the great size enables them to reduce operation and maintenance expenses.

charging. Here, we take a 7.7 kW DC bidirectional charging station, excluding the need for users to install an extra onboard charger to allow vehicle-to-grid capabilities when the station, not the vehicle, does the DC-AC conversion. Currently, there is no large-scale commercial production of bidirectional charging stations; for this reason, costs for bidirectional chargers come from expert insights. It is possible to order a charging station with the desired specifications for 3,850 \$/station. CPUC gives 50% of its charging station base cost rebate via the SCE Charge Ready program for workplaces (CPUC; 2016); thus, the final price would be around 1,900 \$/Station. The charging station cost in the optimistic scenario depends on the technological progress in the power electronics industry. We assume a similar cost reduction as in the battery case, and we adopt the value of 1,000 \$/Station without rebates. To calculate the investment costs per kWh as an input to the model (\$/kWh) defined by Equation A.3, it is necessary to define an average battery capacity according to the Californian scenario of the vehicles connected to each charging station at the facility. Calculating the top sold EV weighted average in California during 2018 according to IHS-Markit (2019), we obtain the value of 58 kWh battery per vehicle which results in a cost of accessing the EV battery of 32.75 \$/kWh in the conservative scenario and 16.37 \$/kWh in the optimistic one, dividing the cost of installing a charging station per the average battery capacity. A lifetime of ten years and fixed operation and maintenance costs of 0.28 \$/kWh per month (10% of the investment costs per kWh per year) were also taken. Table 3.1 summarizes all the costs taken for the different DERs.

Table 3.1: Adopted DER costs.

	Solar PV	Battery	Electric Vehicles
Fixed cost	-	Cons*: \$ 500 Opt: \$ 0	-
Cost per kW(h) (After subsidies)	Cons: 2,100 \$/kWac Opt: 1,250 \$/kWac	Cons: 215 \$/kWh Opt: 100 \$/kWh	Cons: 32.74 \$/kWh Opt: 16.37 \$/kWh
Lifetime	20 years	10 years	10 years
O&M (per month)	0.66 \$/kW	0	0.28 \$/kWh
Subsidy	-	Cons: 250 \$/kWh (SCE incentive program) Opt: -	Cons: \$1,950 (50% of station cost) (SCE workplace rebate) Opt: -

*The acronym 'Cons' stands for the conservative scenario and 'Opt' for the optimistic scenario.

Specifically for EVs, there are several parameters to be defined with regard to

the state of charge and connecting hours at the facility or home. Similar to the BESS, the adopted charging and discharging efficiency is 90%, the allowed state of charge ranges between 20% and 90% to avoid further degradation. One real limitation to the minimum state of charge is ensuring enough energy for the EVs to make their trip back home safely. In California, a battery-electric vehicle goes on average 42 kilometers a day, meaning 21 kilometers per trip (INL; 2015), which accounts for 8 kWh assuming an EV consumes 19 kWh/100 km. Consequently, the minimum state of charge during the disconnection anywhere is the standard 20% plus 12% to ensure at least round trip, so the final value is 32%. By contrast, the minimum state of charge to connect at the facility grid is 73%, which accounts for the average consumption to make the trip from home to the commercial building plus a small reserve margin.

In our scenarios, the home charging episodes occur between 9 PM and 7 AM, which is when the EV is parked at home under the off-peak tariff period with cheaper electricity, whereas the connection at the facility grid occurs at 9 AM and they disconnect at 7 PM (Stadler et al.; 2013). The EVs are not connected to the buildings on the weekends for two main reasons. First, most of the employees would not be working in offices, warehouses, and retails. Second, defining the random mobility patterns during these days for the remaining building types (restaurants and malls) lies outside the scope of this paper. Fig. 3.5 summarizes all the parameters visually for the EV case. The final parameters model the battery degradation according to equation A.4: the capacity loss per normalized Wh is $8.70 \cdot 10^{-5}$, the future replacement cost is 200 \$/kWh for the conservative scenario and 100 \$/kWh for the optimistic one.

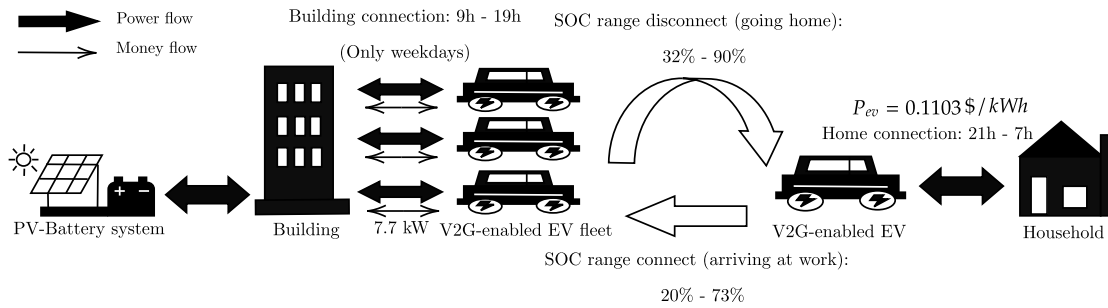


Figure 3.5: Electric vehicle parameters and time schedule.

4 Results

The following section presents and justifies the analysis of both exogenous and endogenous investments. We focus our analysis on four of the metrics in Figure 3.1: net present value, avoided costs, cost-shifting, and EV remuneration. Since charge and discharge strategies and demand reduction will be implicit in the calculation of the chosen metrics, they will be mainly used to explain the dynamics behind the primary metrics.

4.1 Exogenous investment

The main objective of the exogenous investment is to fix the amount of DERs installed beforehand (see A for additional DER sizing details). The model chooses the discharging and charging strategies to minimize the total cost, thus studying the variability of these strategies according to each tariff structure independently. The sensitivity to the tariff design is critical to measure how the strategies differ by isolating the impact of adjusting tariffs. The exogenous investment isolates the impact of adjusting tariffs while having a fixed amount of installed DER. In the current context, it can be seen as a change of regulation in which customers are obliged to move from one tariff scheme to another (after the grandfathering period) after investing in DERs. An example would be a customer under an energy-based tariff with a considerable amount of installed PV who now faces high demand charges under a capacity-based tariff. Then, it might not necessarily have the lowest possible cost at the start. Nevertheless, the exogenous sizing is unlikely in real life since one DER size does not fit all tariffs, it allows to measure the effect on customer investments.

4.1.1 Net present value

This section assesses the private financial value of installing DERs under the discussed electricity rates. The net present value (NPV) is an economic indicator of whether the investment made by the private facilities will be profitable. We considered a nominal discount rate of 8%, a time horizon of 20 years (the lifetime of solar PVs), and an

inflation rate of 1.5%²⁸. Before calculating the NPV, it is essential to analyze the changes in total electricity costs as we move from one base case without DERs under the former tariff type to one with DERs installed under all presented rates²⁹.

Tariff design has a strong influence on battery and EV charging and discharging strategies, which in turn affect the electricity costs. The main objective is to charge the battery and EV during off-peak periods to achieve energy arbitrage objectives and not to compromise private peak demand during that process. With respect to discharging strategies, there are several incentives to adopt storage, such as energy arbitrage, offset coincident peak Maximum Demand Charges (MDC), non-coincidental MDC, and on-peak MDC. These are all summarized in Table A.1 along the time at which they occur for each tariff. More details on the charging and discharging episodes can be found in the Table A.

Table 3.2 gives the result for the four technology scenarios where general observations can be made, and the average total electricity costs are available in Table A.8. First, the PV+BESS is the scenario where there is the most significant cost reduction, followed closely by the PV+EV+BESS. BESSs have a spillover effect on EVs, supporting them to discharge more than they would if they were alone. The gap between electricity cost reduction between those two scenarios (PV+BESS and PV+EV+BESS) thus decreases. The PV generation is not synchronized with on-peak demand periods under these tariffs, reducing the total electricity savings. Under the capacity type, the cost reductions are almost the same as for coincident peak tariffs due to a similar discharging strategy being adopted when there is no PV production at the end of the afternoon. Finally, under the energy tariff, the electricity cost shortfall outruns the other ones since the PV generation is highly valued.

According to our calculations, the most substantial positive return is under the TOU-ENE tariff due to the high contribution of PV generation to decrease energy

²⁸For a yearly time period i , the net present value is calculated by :

$$\sum_{i=1}^{20} \frac{\text{Annualized cash flow} \cdot (1 + \text{inflation})^i}{(1 + \text{nominal discount rate})^i}$$

²⁹For baseline tariff $j \in \{TOU - CAP, TOU - ENE\}$ and tariff $k \in \{TOU - CAP, TOU - COIN, TOU - ENE, \}$, the percentage change in total electricity costs (TEC) of moving from the baseline tariff j to the new tariff k with

technology $i \in \{PV + BESS, PV + EV, PV + EV + BESS\}$ is calculated by : $\frac{TEC_k^i - TEC_k^{Base}}{TEC_j^{Base}}$.

Table 3.2: Average percentage total electricity costs change (%).

PV+BESS		TOU-CAP	TOU-COIN	TOU-ENE
	Baseline			
	TOU-CAP	-50.2	-49.9	-58.9
	TOU-ENE	-43.9	-43.3	-51.4
PV+EV		TOU-CAP	TOU-COIN	TOU-ENE
	Baseline			
	TOU-CAP	-37.2	-35.5	-48.2
	TOU-ENE	-32.9	-30.9	-42.3
PV+EV+BESS		TOU-CAP	TOU-COIN	TOU-ENE
	Baseline			
	TOU-CAP	-46.7	-42.6	-55.1
	TOU-ENE	-41.0	-37.0	-48.2

charges even without any complementary financial help such as feed-in tariffs or net-metering schemes. However, PVs seem to be oversized under all the other rates, leading to negatives returns and implying the need for storage.

Second, the BESS coupled with PVs is the best scenario considering NPV under all the tariffs. The same results are applied to the storage mix but with a lower return. We would expect considerably higher returns when moving towards the coincident capacity tariff. However, in some facilities, the load at the coincident peak time is so small that even with a 100% offset of the demand, the total energy costs with an installed DER would exceed the total energy costs of not having any DER at all.

Third, the EVs as the standalone storage have the worst performance in all the scenarios observed in this NPV analysis. EV charging with PV surplus is not enough to financially compensate the high investments made in solar panels and charging stations. Moreover, batteries perform economically better than EVs under all tariffs due to the higher availability and extended discharging periods. They also present the lowest financial return under coincidental tariff because their capability to offset demand is directly linked to the utility's coincidental hour. During half of the year, the coincidental hour is around 7 PM, meaning that EVs cannot discharge at this time since they are already disconnected from the building. All the results concerning net present values using the scenario without any DER installed for each tariff as the

baseline are summarized in Table 3.3.

4.1.2 Avoided costs

The total avoided costs will, in theory, be directly linked to the demand reduction during system on-peak hours (5-8 PM) depending on the weighting on these periods for each tariff. Following the method proposed, we also study two different cases to calculate the facilities' average avoided costs: Case 1, when the facility peak day overlaps with the typical avoided costs for a weekday, and Case 2, when the private facility peak overlaps precisely with the system peak avoided costs profile.

We analyze three different technology scenarios, comparing them to the base case scenario without any DERs under our three representative tariff structures. The first observation is that peak demand reduction due to PV generation is not negligible due to the synchronization of the load profile with the PV generation. The highest demand hours occur mostly when the PV generates electricity, leaving few early morning and early evening hours to be offset by storage. The system peak time is less affected by the PVs because it occurs when the generation starts to come down. However, the private peak is also relatively reduced.

In Table 3.4, the PV+BESS scenario shows the highest percentage reduction for system peak demand and for private peak demand except under coincident peak tariffs³⁰. Under TOU-COIN, the BESS is charged with a significant amount of energy during non-coincident periods to offset the demand of coincident periods creating a higher private demand than before but in another time window. Regarding PV+EV+BESS, the demand reduction is similar to the PV+BESS scenario because now the battery supports the EV discharge before departure, crossing the threshold where the EV battery use cost (degradation plus energy) exceeds the gains.

When BESS is present, the TOU-ENE and TOU-CAP tariffs effectively enhance the demand reduction during the system and private peak times due to their incentive to discharge during the on-peak time. EVs alone offset more demand under the energy tariff TOU-ENE compared to TOU-CAP since they have a low discharge power rate

³⁰Tables A.5, A.6 and A.7 are provided for more details about the monthly demand reductions according to the technology scenarios under different tariffs.

Table 3.3: Net present value by rates and technology scenarios (\$).

Net present value with Solar PV+BESS			
	TOU-CAP	TOU-COIN	TOU-ENE
Mean	-17,518	-21,543	33,772
(St. Dev.)	(18,286)	(35,044)	(20,822)
#> 0 ^a	1	2	5
Net present value with Solar PV+EV			
	TOU-CAP	TOU-COIN	TOU-ENE
Mean	-71,684	-89,815	-17,767
(St. Dev.)	(40,185)	(50,996)	(16,246)
#>0	0	0	0
Net present value with Solar PV+EV+BESS			
0	TOU-CAP	TOU-COIN	TOU-ENE
Mean	-25,651	-53,365	19,142
(St. Dev.)	(21,677)	(37,884)	(17,814)
#>0	0	0	4

^a#>0 values counts the facilities with positive NPVs.

Table 3.4: Average peak demand reduction.

Average system peak demand reduction (%)			
	TOU-CAP	TOU-COIN	TOU-ENE
PV+BESS	-38.7	-44.5	-42.8
PV+EV	-13.5	-18.8	-24.5
PV+EV+BESS	-33.5	-30.1	-37.5
Average private peak demand reduction (%)			
	TOU-CAP	TOU-COIN	TOU-ENE
PV+BESS	-47.5	-8.3	-45.4
PV+EV	-27.2	-17.3	-27.2
PV+EV+BESS	-44.1	-20.3	-43.1

under this capacity tariff.

Recalling that the PV tends to offset a significant amount of the demand in the middle of the day, the discharge strategies of energy and capacity tariffs will be similar for case 1 using BESS. Their on-peak periods are the same, which increases the avoided costs, as it gives more incentive to discharge during this time window. The coincident peak rate increases the avoided costs even more by better framing the specific time window with the highest avoided capacity costs for the system. Contrary to the PV-only scenario in which most of the avoided costs are energy-related (67% against 32% from capacity-related costs as shown in Boampong and Brown (2019)), in the BESS case, the capacity costs account for almost half of the total in all tariffs. This fact indicates that the battery is discharging during time periods when the system is constrained and has the highest avoided capacity costs and charging when there are the lowest capacity costs (see the average result over 20 years for PV and PV+BESS in Table 3.5).

EVs have the lowest total avoided costs among all the storage technologies, where most of those costs are energy-related, while the capacity-related avoided costs appear more during summer periods. Because EVs are not present during weekends in our scenarios, the energy not exchanged with the grid will reduce the total avoided costs for the EV alone compared to the other scenarios. They present low avoided costs under the capacity tariff, but the performance is better under coincidental and energy tariffs. According to their discharging strategy, they have more incentive to offset demand during a short period or arbitrage energy along the day, leading to higher avoided costs. The combination EV+BESS performs mid-way between the other two technology scenarios with storage, as shown in Table 3.5.

With regard to cases 1 and 2 (Table A.9), the main difference lies in the results of private facility week day multiplied by system peak day and private facility peak day multiplied by system peak day profile. Usually, when the two peak days coincide, the avoided costs will be high when the avoided capacity costs are higher in this case. Nevertheless, this will depend on when the load peak occurs in the facility and whether coincident peak tariffs are applied.

First, if the private peak load occurs in the early morning, the facility will tend

Table 3.5: Average avoided costs - Case 1 (\$).

Avoided costs of solar PV+BESS - Case 1			
	TOU-CAP	TOU-COIN	TOU-ENE
Total mean	17,501	17,589	17,201
(St. Dev.)	(8,503)	(8,431)	(8,400)
Energy	9,042	8,644	8,767
(St. Dev.)	(4,447)	(4,348)	(4,332)
Capacity	8,459	8,684	8,434
(St. Dev.)	(4,090)	(4,177)	(4,108)
Avoided costs of solar PV+EV - Case 1			
	TOU-CAP	TOU-COIN	TOU-ENE
Total mean	10,104	12,436	14,826
(St. Dev.)	(5,534)	(5,962)	(7,427)
Energy	6,578	6,798	7,326
(St. Dev.)	(3,460)	(3,336)	(3,735)
Capacity	3,525	5,638	7,500
(St. Dev.)	(2,081)	(2,676)	(3,740)
Avoided costs of solar PV+EV+BESS - Case 1			
	TOU-CAP	TOU-COIN	TOU-ENE
Total mean	14,459	15,067	16,127
(St. Dev.)	(7,448)	(7,639)	(8,308)
Energy	8,078	7,732	8,355
(St. Dev.)	(4,160)	(3,950)	(4,267)
Capacity	6,381	7,334	7,771
(St. Dev.)	3,299	(3,739)	(4,049)

to offset it during the day, leaving less energy to be discharged in the late afternoon, as occurs on weekdays. Hence the avoided costs during a weekday would be higher than the peak day.

Second, coincident peak tariffs will postpone the charge to later hours just before the coincidental period. The avoided costs during the discharge for the private peak days will not outweigh the costs for the charge during the weekday. The difference between avoided costs for discharge and cost of charge between the two cases (case 2 minus case 1) will therefore be negative.

4.1.3 Cost-shifting

Table 3.6 shows, for case 1, the cost-shifting in absolute values and relative to the corresponding private gains. The capacity tariff has significantly lower cost-shifting than the energy tariff since the PV does not bring as high electricity gains in this case. For instance, the increased private gains outweigh the higher avoided costs under the energy tariff. Regarding the coincident peak tariff, the cost-shifting is the lowest in absolute values due to higher avoided costs and lower electricity savings than the capacity tariff TOU-CAP. This fact happens because batteries and EVs are incentivized to discharge during the variable grid-constrained periods and increase the avoided costs. While the avoided costs remain practically the same for batteries, they increase for EVs, leading to lower cost-shifting values. This last finding is interesting, showing that EVs can increase both electricity savings and avoided costs. This makes them suitable candidates to incentivize private gains and alleviate grid constraints at the same time under this type of tariff³¹.

4.1.4 Value created by electric vehicles

Although the scenarios with negative NPV are unlikely, the analysis of the EV revenue under different tariffs is still pertinent. The goal is to identify preliminary evidence from this sensitivity analysis before the endogenous investment assessment. In general, according to Fig. 3.6c, the value created by energy services compared to the sum of

³¹The results of case two in Table A.10 are analogous to case one, and the qualitative analysis is roughly the same.

compensations is the highest under coincident demand tariff for both cases (PV+EV and PV+EV+BESS), where EVs can offset demand charges under a shorter period compared to on-peak demand and even non-coincidental demand, which can last for several hours. Therefore, under the capacity tariff (TOU-CAP), EVs without battery support are not well-adapted to covering all this time window to offset demand. For the energy tariff (TOU-ENE), the battery degradation component exceeds all others, suggesting that more kWhs needing financial compensation are exchanged via the EV. Unlike the many studies on EVs providing energy services to the grid, we consider battery degradation an important factor influencing remuneration. Yet if the capacity loss per normalized Wh of $8.70 \cdot 10^{-5}$ and future replacement cost of 200 \$/kWh are considered out of date, a share of the total amount can still be part of the sharing of value between the facility and EV owners.

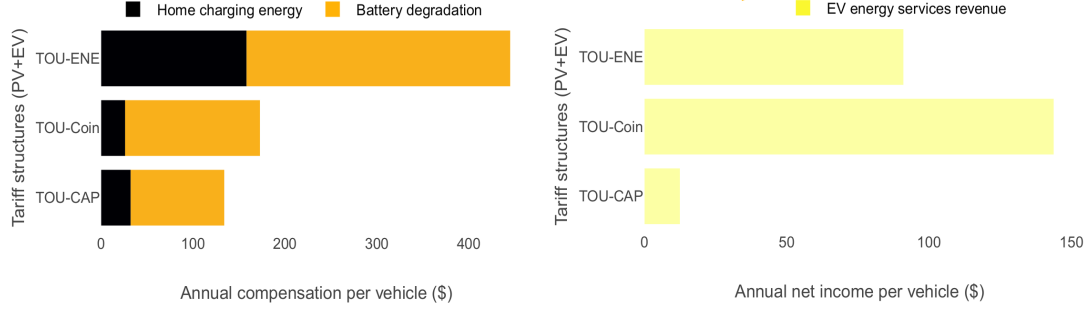
The number of EVs connected to the grid also directly influences the total revenue per vehicle in both scenarios. For instance, the PV+EV scenario remuneration per EV is considerably lower than the PV+EV+BESS one due to the higher number of vehicles present (twice as many). The competition between them thus decreases the amount received by any vehicle.

4.2 Endogenous investment

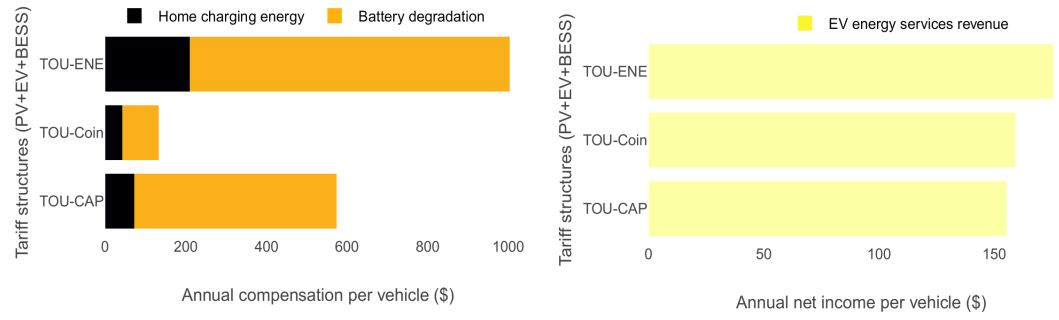
This last section considers the endogenous investments, i.e., letting the model choose the optimal amount of DER for each facility to minimize their total costs. The previous exogenous assessment was made to explore the effects of changing tariffs and their influence on the discussed measures: private financial value, avoided costs, cost-shifting, and EV remuneration. Now, this section will extend the analysis by demonstrating what investments facilities might make, acting rationally. Two DER cost scenarios are discussed for the endogenous investments: a conservative and an optimistic one. In the first scenario, we select mid-range values found in the literature with their public subsidies. The latter accounts for a considerable decrease in DER prices due to technological progress and learning-by-doing effects.

Table 3.7 shows the mean capacity installed in the facilities of each DER type and how many facilities choose to install it by the tariff. Regarding the conservative

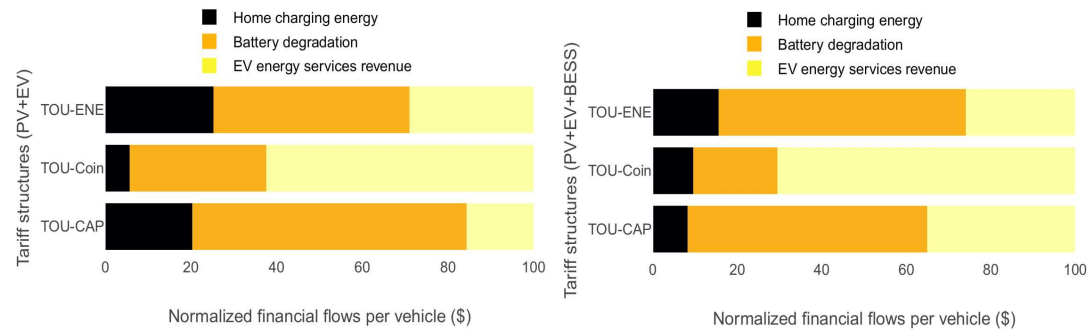
CHAPTER 3. RATE DESIGN WITH DISTRIBUTED ENERGY RESOURCES AND ELECTRIC VEHICLES: A CALIFORNIAN CASE STUDY



(a) Average EV compensation (left) and net income (right) per vehicle per year - PV+EV case (\$).



(b) Average EV compensation (left) and net income (right) per vehicle per year - PV+EV+BESS case (\$).



(c) Normalized financial flows per vehicle per year - PV+EV case (left) and PV+EV+BESS case (right). (\$).

Figure 3.6: Average EV financial flow breakdown per vehicle - Exogenous case.

scenario, the energy tariff TOU-ENE incentivizes the highest amount of PVs to be installed, confirming the high valuation of solar PV generation under this type of rate. No PVs were installed in any of the facilities under coincident tariffs due to the low demand offset during the coincidental period. The model also chooses to use stationary batteries in all facilities both to offset maximum demand charges and arbitrage energy between different time windows. Under the capacity rate, less storage is needed to be profitable due to the lower on-peak demand to be reduced at these hours of the day. For energy rates, the opposite holds, as the TOU-ENE tariff needs more storage to arbitrage energy toward late afternoon when there is not enough solar PV electricity generation. Under coincident peak tariff class, the number of facilities adopting EVs is the highest among all tariffs, in which four buildings adopted this type of storage. This shows that they are suitable candidates for offsetting coincidental maximum demand charges during a short time window; however, the amount of kWh accessed is highly dependent on the coincidental hours. If the coincidental hour is fixed at 6 PM along the year, for example, instead of being variable between 5 - 8 PM, the amount of kWh of EVs accessible would be almost seven times higher and they would be present in all buildings³². In this matter, Table 3.7 should be interpreted carefully. Although the number of facilities installing EV charging stations is the highest under TOU-COIN among all tariffs for both coincidental hour scenarios, the mean capacity of EVs is highly variable.

As expected, due to the cost reduction of DERs, the total amount of installed DER increases considerably in the optimistic scenario. Solar PVs are now adopted under all types of tariffs, including the TOU-COIN and stationary batteries are the main type of storage. Even with equivalent cost reduction, EVs are not preferably adopted by buildings. For instance, under TOU-COIN and TOU-ENE, batteries substituted all the available vehicles. It is now possible for the buildings to offset all the coincidental demand using only cheap batteries instead of EVs that are away when coincidental hours arise at 7 PM during half of the year. The availability is also linked with the investment under TOU-ENE tariff since now energy arbitrage can be cheaply

³²An average of 475.4 kWh of EVs is invested by the buildings under TOU-COIN if the coincident hour is fixed at 6 PM as shows Table A.11.

done on all week days and weekends.

Regarding private financial returns, we analyze the average electricity cost reduction and the net present value considering all investment costs (see Table 3.8). Although in some cases with exogenous investments, the electricity cost reduction might be greater, the total cost also depends on the DER costs and EV expenditures. In the endogenous case, all these cost terms will be minimized to have the highest possible NPV. Energy tariffs have, in general, the highest electricity reduction and NPV due to the solar PV generation being in phase with the load profile. Economic gains under the capacity tariff are moderately reduced when the solar PV does not efficiently reduce non-coincidental demand. In these cases, the facilities, therefore, rely on storage to offset on-peak and non-coincidental demands. Still, at some point, the costs of storage outweigh the gains of reducing the demand.

These two facts thus bound the maximum NPV considerably lower than the corresponding energy tariff, the exception being coincident peak tariffs. Looking closer at this tariff, TOU-COIN rate shows a higher NPV than TOU-CAP with almost the same electricity change. TOU-COIN presents the highest NPV among all tariffs due to the reduction of electricity costs with smaller investments; however, the situation changes between the two cost scenarios. When buildings manage to offset 100% of coincidental demand using cheap battery storage, the NPV reaches a maximum in which no additional investment in storage brings more financial benefits. This constraint prevents a significant increase of NPV under TOU-COIN when compared to other tariffs, especially TOU-CAP. Finally, the highest NPV in the optimistic scenario is found to be the TOU-ENE tariff due to the high economic return of solar PV generation.

As expected from the exogenous results, the highest avoided costs are found under energy tariff in which there is more solar PV generation and more installed storage to arbitrage energy towards on-peak periods. In the exogenous case, the sometimes oversized solar exports contribute to the higher share of energy-related avoided costs. In comparison, in the endogenous case, the capacity costs are the highest share under all tariffs due to the proportionally higher storage share than solar PVs. Unsurprisingly, under the energy tariff TOU-ENE, the avoided costs are greater than the other ones justified by the higher investment in storage and solar PV. Even so, the main incentive

Table 3.6: Average cost-shifting measures by technologies and tariffs - Case 1 (\$).

	TOU-CAP	TOU-COIN	TOU-ENE
PV+BESS	8,004	7,583	12,542
(St. Dev.)	(5,433)	(4,026)	(6,419)
% of savings	31.4	30.1	42.2
PV+EV	8,936	5,412	9,611
(St. Dev.)	(5,635)	(2,585)	(5,293)
% of savings	46.9	30.3	39.3
PV+EV+BESS	9,381	6,420	11,770
(St. Dev.)	(5,767)	(2,966)	(5,840)
% of savings	39.3	29.9	42.2

Table 3.7: Average DER amount in endogenous case.

	Conservative scenario			Optimistic scenario		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
PV (kW)	32.2	0.0	77.2	137.8	83.8	145.8
(St. Dev.)	(21.0)	(0.0)	(25.3)	(66.1)	(38.2)	(73.8)
#> 0 ^a	5.0	0.0	5.0	5.0	5.0	5.0
BESS (kWh)	83.2	183.2	235.2	418.6	258.8	442.4
(St.Dev.)	(65.4)	(103.6)	(73.0)	(207.9)	(152.4)	(219.7)
#>0	5.0	5.0	5.0	5.0	5.0	5.0
EV (kWh)	116.3	72.3	273.7	77.7	0.0	0.0
(St. Dev.)	(58.5)	(29.2)	(273.1)	(47.5)	(0.0)	(0.0)
#>0	3.0	4.0	3.0	3.0	0.0	0.0

^a#>0 values count the facilities with positive DER capacity installed.

Table 3.8: Private financial gains - Endogenous case.

Average total electricity costs - Endogenous case (\$)						
	Conservative scenario			Optimistic scenario		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
Basecase	50,144	43,729	57,517	50,144	43,729	57,517
(St. Dev.)	(23,538)	(20,931)	(27,012)	(23,538)	(20,931)	(27,012)
With DER	37,554	30,887	27,685	13,020	16,927	12,174
(St. Dev.)	(17,452)	(13,845)	(16,713)	(6,341)	(8,956)	(5,374)
Average percentage total electricity costs change - Endogenous case (%)						
	Conservative scenario			Optimistic scenario		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
Baseline						
TOU-CAP	-24.94	-24.97	-60.89	-73.87	-53.15	-89.86
TOU-ENE	-22.42	-21.39	-52.77	-64.68	-45.72	-78.35
Average net present value (NPV) - Endogenous case. (\$)						
	Conservative scenario			Optimistic scenario		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
Mean NPV	30,718	77,518	55,558	160,710	150,596	248,208
(St. Dev.)	(22,225)	(47,911)	(29,053)	(77,811)	(84,651)	(118,181)
#> 0 ^a	5	5	5	5	5	5

^a#>0 values count the facilities with positive NPV.

to invest in storage is to reduce maximum demand charges, for this type of tariff, the spread between on-peak and off-peak is reasonably high. This justifies the adoption of more storage than the capacity tariff.

Cost-shifting issues are more critical among energy tariff due to more significant private savings, as shown in Table 3.9. In the optimistic scenario, cost-shifting concerns increase substantially, except for TOU-CAP, driven by an increase in DER investment for all tariffs. The avoided costs increase considerably more than the savings from reduced electricity consumption, reflecting a significant decrease in absolute and relative cost-shifting values for the capacity tariff. Otherwise, in the energy rate case, the private savings and total avoided costs values grow at a similar rate, contributing to cost-shifting. Finally, the coincident peak tariff follows the same trend as the energy tariff, for which we obtained the second-lowest cost-shifting among all rates. The results of case 2 for the endogenous case where the system peak day coincides with that in the facility are shown in Table A.12, and they are qualitatively analogous to the exogenous case.

The last point to be analyzed is the EV net income for the endogenous case

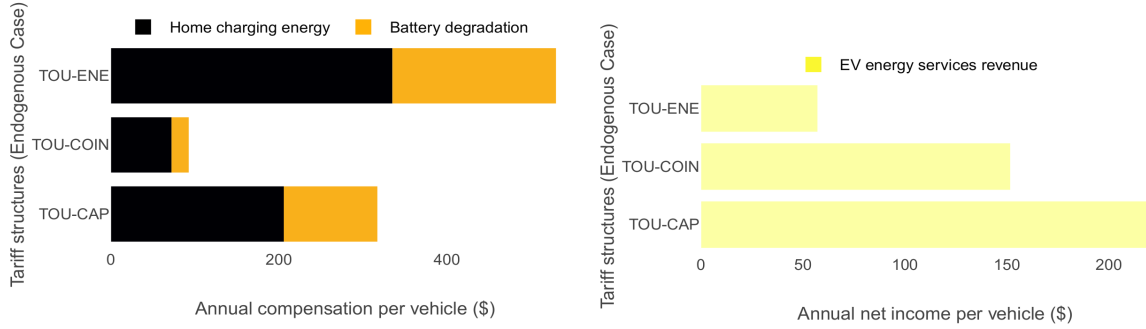
Table 3.9: Average avoided costs and cost-shifting - Endogenous case. (\$)

Avoided costs - Endogenous case 1						
Conservative scenario				Optimistic scenario		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
Total Mean	6,278	9,363	22,127	33,330	20,450	34,390
(St. Dev.)	(4,005)	(5,405)	(10,142)	(16,158)	(9,901)	(17,196)
Energy	2,625	2,575	8,645	15,558	9,327	16,129
(St. Dev.)	(1,713)	(1,573)	(3,484)	(7,483)	(4,415)	(7,887)
Capacity	3,653	6,789	13,482	17,772	11,122	18,261
(St. Dev.)	(2,434)	(3,839)	(7,294)	(8,701)	(5,487)	(9,350)
Cost-shifting - Endogenous case 1						
Conservative scenario				Optimistic scenario		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
Total Mean	6,312	3,479	7,704	3,794	6,353	10,953
(St. Dev.)	(4,338)	(2,227)	(1,972)	(5,452)	(3,989)	(5,937)
% from savings	50.1	27.1	25.8	10.2	23.7	24.2

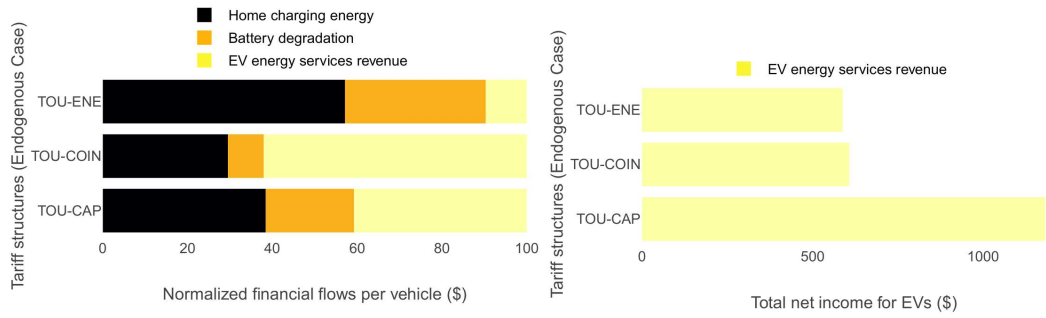
shown in Fig. 3.7 with more numerical details present in table A.13. The endogenous investment will install the optimum amount of charging stations in the facilities to minimize their costs, so the remuneration of the EVs is a result of the optimization problem. Consequently, as opposed to batteries, charging stations were not installed in all the facilities according to each tariff structure studied in the conservative scenario. First, under capacity tariff, the total net income and the net income per vehicle are the highest, demonstrating the ability of EVs when coupled with stationary batteries to offset demand during an extended period. Under energy tariffs, the net income from energy services to the facility is the smallest share among all tariffs due to the competition from stationary batteries, which are more cost-efficient on the energy arbitrage task since they are present all day and during the weekends. Finally, under coincident peak tariffs, the stations enable the EVs to provide high value to the facilities by offsetting the coincident peak demand. The TOU-COIN rate shows the highest number of facilities adopting EVs and an annual average net income of \$ 151.5 per EV, in which the highest share of the remuneration does not depend on battery degradation and electricity home pricing³³. Finally, the financial flow is notably reduced in the optimistic scenarios as batteries are prioritized over EVs. Only under TOU-CAP the vehicles still appear as electric storage due to their synergy with batteries, but BESS

³³The net income is even higher when coincidental hours defined by the system operator arise sooner, in the case of fixed coincidental at 6 PM, it can reach around \$426 per vehicle. The Table A.14 compares the average financial flow in those two cases for the conservative and optimistic scenario.

are by far the primary storage source. In this case, with a net income of around \$ 25, the attractiveness of providing this type of energy service may not be enough to convince EV owners.



(a) Average EV compensation (left) and net income (right) per vehicle per year - Endogenous case.



(b) Normalized financial flows per vehicle per year (left) and total net income for EVs (right) - Endogenous case. (\$)

Figure 3.7: Average EV financial flow breakdown per vehicle - Endogenous case (Conservative scenario).

5 Discussion and policy implications

The development of smart-charging and vehicle-to-grid technologies reinforces the concept of using the EV as a DER. Endogenous investment analysis confirms that if commercial buildings have the possibility to install bidirectional charging stations to reduce the electricity bill, this would be profitable, especially under conservative cost scenarios (refer to Table 3.7). The inclusion of EVs in the DER portfolio alongside batteries and solar PVs expands the investment choices that heterogeneous buildings may have, consequently increasing the number of profitable scenarios for them. In all

tariff scenarios in which EVs were present, a positive net income was observed for EV owners. This indicates that the episodes of charging at home and discharging in the commercial facility grid surpassed the ones of charging using commercial grid electricity and discharging at home. Even though solar electricity was available to charge the vehicles during their parking time, this locally generated electricity was not often used to charge them. This finding suggests that the synchronization between EVs and solar PVs in commercial buildings as the one found in [Kuang et al. \(2017\)](#) highly depends on the possibility to arbitrage energy from another source, for instance, EV owners home energy. A home time-of-use tariff set with a low off-peak rate can be a fair economic signal to drive the vehicle charging and alleviate grid congestions, but it will undermine the synergy between EVs and PVs.

It is essential to point out that the revenues obtained by EV owners rely on the hypothesis of systematic charging episodes at home, which has been found inaccurate from analysis of real-life EV driving and charging behavior ([Western Power Distribution; 2019](#)). EV owners should be incentivized to connect their vehicles more often to their home charging infrastructure to ensure energy arbitrage and follow-up revenue. The annual net income per vehicle found, which varied between \$57 and \$218 with the highest revenue found under TOU-CAP, illustrates the drawback of assessing theoretical remuneration for bill management services based on energy storage analysis as in [Thompson and Perez \(2020\)](#). The final remuneration is strongly dependent on which tariffs the facilities and vehicle owner's home are under and the specific constraints of vehicles such as availability. Energy services could be stacked, or the revenue split strategy between parties could be reviewed to increase EV remuneration using vehicle-to-grid services. First, regarding stacked services, in [Black et al. \(2020\)](#) a demonstration project in California showed the viability of using EV fleets to manage the facility electricity bill via demand reduction and provide ancillary services to the local utility. Another option could be to reevaluate the fifty-fifty split of revenue. In our analysis, the cost of installing a charging station is fully recovered via direct energy savings brought by EVs with bidirectional capabilities; however, charging stations in commercial facilities may have a positive effect on attractiveness to customers and employee satisfaction. These effects can have a beneficial effect on the general facility

budget, allowing them to reduce their share of the value created by EVs.

General policy recommendations to regulators can be made using tariffs as instruments to push certain technologies forward. Energy tariffs provide the highest incentive to invest in solar PV production and will often be profitable to private facility investors. Even so, this is the worst case for cost-shifting in both the conservative and optimistic scenario of DER costs. If a local regulator seeks to increase the share of solar generation in the energy mix, a first step would be to incentivize energy tariff adoption. However, if high cost-shifting values are already present, adopting a coincident peak tariff can alleviate this issue in the short term. Finally, if the average cost of DERs continues to fall quickly, the capacity tariff would be an alternative to slow down cost-shifting increases due to high DER penetration. This is the only case in which the growth of avoided costs could outweigh the increase in cost savings, showing that the trade-off between maximizing avoided costs and minimizing cost-shifting found by Boampong and Brown (2019) should be nuanced under capacity tariffs in an optimistic cost scenario. The regulatory changes of this nature should be carefully planned since for a fixed investment, solar PV adopters would incur high financial losses when moving from an energy tariff to another with high weight in demand charges (as shown in Table 3.2). Here, another trade-off between reducing cost-shifting levels and reducing solar PV revenues is observed.

6 Conclusion

This study describes how electricity rates influence crucial elements to be considered before investing in DERs at a private facility and how they can affect cost recovery from the utility's perspective. We considered several factors in our analysis, e.g., charging and discharging strategies, demand reduction, net present value, avoided costs, cost-shifting, and EV remuneration in two different types of investments: exogenous and endogenous. We simulated different technology combinations of PVs, BESSs, and EVs to assess the private investment part and the avoided cost model to account for the impact on the utility side. First, we considered the exogenous investment to understand the underlying mechanism in which the DER management system reacts

under different price signals, i.e., distinct tariff designs. In addition, this type of investment is useful to study the effects of retail rates on both private and utility sides with the same amount of DERs installed in all particular facilities. To extend the analysis, the endogenous investment then revealed what course the investments made by the facilities could take since they would try to minimize their investment costs. Two scenarios using different DER costs were studied in this case: a conservative scenario and an optimistic one.

The exogenous analysis showed that the final electricity bill reduction was directly linked to the charge and discharge strategies, determining the demand reduction over different periods. We found that solar PVs reduced electricity bills significantly under the energy tariff TOU-ENE for all DER combinations compared to other tariffs. Whereas, on the utility side, the tariffs with high demand charges often presented lower cost-shifting. This finding underlines the negative impact that a regulatory change aiming to reduce cost-shifting values for buildings already under energy tariff and high solar PV would have on their budget.

The endogenous investment model revealed how the facility would invest rationally to minimize its costs. For the conservative scenario, the average DER capacity installed often used EV+BESS to reduce its electricity costs, indicating that the mix can work together to support the facility grid, each one bringing its benefits. Coincident peak tariff was noteworthy for the results for conservative endogenous investments, in which we obtained the highest NPV and the lowest cost-shifting. The drawback of this kind of rate is that there is a danger of creating a demand peak elsewhere in the daytime, probably early morning (8–10 AM) or even later evening (9–11 PM). In the optimistic scenario, TOU-COIN is not as attractive as before for buildings due to the limited gains obtained after offsetting all coincident demand, so there is no more investment from this point. Nevertheless, only under TOU-CAP, the avoided costs increase more than electric savings by using cheap storage to target several hours of the day. The shift from energy-based tariffs towards coincidental and capacity-based tariffs can alleviate cost-shifting values caused by strong DER penetration.

The last aspect we analyzed is the EV net income obtained from energy services provided to the facility. Their availability and the tariff in which the buildings are

under have an essential impact on their adoption by facilities, and consequently, on their revenues. Regarding EVs, the net income revenue varied between \$57 and \$218, with the highest revenue found under TOU-CAP. Although bill management can be the topmost remunerated service for EVs, it still strongly depends on the tariff and the contract to split gains between EV owners and the facilities. In addition, the optimistic scenario showed that batteries substituted almost all the available vehicles, capturing their share of the value created under all tariffs.

Our results could be used as a roadmap for other countries and regions seeking to invest in solar PV generation, stationary batteries, and electric vehicles. They help weigh up tariff effects under several parameters of analysis. The strongest barrier to apply the same methodology using a different region is the lack of public available ACM. The ACM used in this work was developed especially for the Californian electric system and made publicly available. Although many utilities of countries may have this kind of model for their systems, it is only for internal purpose utilization. Minimizing total costs is the approach most often taken in the literature due to the attractiveness of the profits that DERs can bring, although multi-objective optimization taking into account CO₂ emission reduction is also well-represented. The electrification of other sectors (heating) can also be a part of a future analysis with the addition of other DERs such as heat pumps. For instance, they can provide extra flexibility to buildings if coupled properly in the DER mix³⁴. Studies are needed using fairness functions between heterogeneous agents with and without installed DERs to minimize the inequalities created by the tariff applied. The tariff schemes used in this paper are existing rates, but more granular time-specific tariffs with more levels for time-of-use periods besides super off-peak periods or more location-specific tariffs components now warrant investigation.

³⁴The methodology allows the coupling of different types of DERs since the DER-CAM model has this option. A paper written by the DER-CAM team (Steen et al.; 2015) explains how the modeling of heat pumps is done.

7 References

- Beck, T., Kondziella, H., Huard, G. and Bruckner, T. (2017). Optimal operation , configuration and sizing of generation and storage technologies for residential heat pump systems in the spotlight of self-consumption of photovoltaic electricity, *Applied Energy* **188**: 604–619.
URL: <http://dx.doi.org/10.1016/j.apenergy.2016.12.041> 73, 74
- Black, D., Macdonald, J., Deforest, N. and Gehbauer, C. (2020). *Los Angeles Air Force Base Vehicle-to-Grid Demonstration.* 93
- BloombergNEF (2019). Battery Pack Prices Fall As Market Ramps Up With Market Average, (December).
URL: <https://about.bnef.com/blog/battery-pack-prices-fall-as-market-ramps-up-with-market-average-at-156-kwh-in-2019/> 56
- Boampong, R. and Brown, D. P. (2019). On the Network Value of Behind-the-Meter Solar PV plus Energy Storage : The Importance of Retail Rate Design. 57, 58, 61, 62, 82, 94
- Borenstein, S. (2016). The economics of fixed cost recovery by utilities, *Electricity Journal* **29**(7): 5–12. 60
- Borne, O. (2019). Vehicle-to-grid and flexibility for electricity systems : To cite this version : Vehicle-To-Grid and Flexibility for Electricity Systems : from Technical Solutions to Design of Business Models. 65
- Brown, D. P. and Sappington, D. E. (2018). On the role of maximum demand charges in the presence of distributed generation resources, *Energy Economics* **69**: 237–249. 57
- Brown, T. and Faruqui, A. (2014). Structure of Electricity Distribution Network Tariffs : Recovery of Residual Costs, (August). 57
- Burger, S. P., Jenkins, J. D., Batlle, C. and Pérez-arriaga, I. J. (2019). Restructuring Revisited Part 2 : Coordination in Electricity Distribution Systems, *The Energy Journal* **40**. 60
- Burger, S. P., Knittel, C. R., Pérez-arriaga, I. J. and Schneider, I. (2020). The Efficiency and Distributional Effects of Alternative Residential Electricity Rate Designs, *The Energy Journal* **41**(1): 199–240. 60
- CA.GOV (2020). Governor Newsom Announces California Will Phase Out Gasoline-Powered Cars and Drastically Reduce Demand for Fossil Fuel in California’s Fight Against Climate Change, (September).
URL: <https://www.gov.ca.gov/2020/09/23/governor-newsom-announces-california-will-phase>

-out-gasoline-powered-cars-drastically-reduce-demand-for-fossil-fuel-in-californias-fight-against-climate-change/ 58

Cardoso, G., Stadler, M., Mashayekh, S. and Hartvigsson, E. (2017). The impact of ancillary services in optimal DER investment decisions, *Energy* **130**: 99–112. 64, 73, 74

CEC (2019). California renewable energy overview and programs.

URL: <https://ww2.energy.ca.gov/renewables>. Accessed: December 13, 2019 58

Costello, K. and Hemphill, R. (2014). “electric utilities’ ‘death spiral’: Hyperbole or reality?”, *The Electricity Journal* **27**: 10. 57, 60

CPUC (2016). Charge ready and market education program.

URL: <https://www.cpub.ca.gov/zevChargingInfrastructure.aspx>. Accessed: July 17, 2019 75

CPUC (2018). Renewable feed-in tariff (fit) program.

URL: <https://www.cpub.ca.gov/feedintariff/>, Accessed: July 29, 2019 72

CPUC (2019). Self-generation incentive program.

URL: <https://www.cpub.ca.gov/sgip>. Accessed: December 13, 2019 58

Dameto, N. M., Chaves-Avila, J. P. and San Roman, T. G. (2020). Revisiting Electricity Network Tariffs in a Context of Decarbonization, Digitalization, and Decentralization, *Energies* (June). 60

DoE, U. (2013). Commercial reference buildings.

URL: <https://openei.org/doe-opendata/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-states>, Accessed: 30 August 2019 70

Doroudchi, E., Alanne, K., Okur, Ö., Kyyrä, J. and Lehtonen, M. (2018). Approaching net zero energy housing through integrated EV, *Sustainable Cities and Society* **38**(August 2017): 534–542.

74

E3 (2018). Avoided cost model, acm.

URL: <https://www.ethree.com/tools/acm-avoided-cost-model/>, Accessed: 21 October 2019 62, 66

Eid, C., Codani, P., Perez, Y., Reneses, J. and Hakvoort, R. (2016). Managing electric flexibility from Distributed Energy Resources: A review of incentives for market design, *Renewable and Sustainable Energy Reviews* **64**: 237–247. 61

Freitas Gomes, I., Perez, Y. and Suomalainen, E. (2020). Coupling small batteries and PV generation : A review, *Renewable and Sustainable Energy Reviews* **126**(March): 109835.

URL: <https://doi.org/10.1016/j.rser.2020.109835> 59

CHAPTER 3. RATE DESIGN WITH DISTRIBUTED ENERGY RESOURCES AND ELECTRIC VEHICLES: A CALIFORNIAN CASE STUDY

- Fu, R., Feldman, D. and Margolis, R. (2018). U . S . Solar Photovoltaic System Cost Benchmark : Q1 2018 U . S . Solar Photovoltaic System Cost Benchmark : Q1 2018, (November). 56, 74
- Fu, R., Feldman, D., Margolis, R., Woodhouse, M. and Ardani, K. (2017). U . s solar photovoltaic system cost. 73, 74
- Hanna, R., Ghonima, M., Kleissl, J., Tynan, G. and Victor, D. G. (2017). Evaluating business models for microgrids : Interactions of technology and policy, *Energy Policy* **103**(August 2016): 47–61. 73, 74
- Hoarau, Q. and Perez, Y. (2019). Network tariff design with prosumers and electromobility : Who wins , who loses ?, *Energy Economics* **83**: 26–39.
URL: <https://doi.org/10.1016/j.eneco.2019.05.009> 61
- IEA (2018). World energy outlook, *France, Paris* . 56, 70
- IEA (2020). Global EV Outlook 2020 to electric mobility. 56, 58
- IHS-Markit (2019). Best selling all-electric cars in california in 2018.
URL: <https://electrek.co/2019/03/06/tesla-model-3-electric-car-sales-surge-california/> Accessed: August 20, 2019 75
- IHS-Markit (2020). Average Cost Of Batteries To Drop Below \$100/kWh By 2023, (October).
URL: <https://www.greencarcongress.com/2020/09/20200924-ihs.html> 56
- INL (2015). Electric vehicle mile traveled (evmt): On road results and analysis. 76
- INL (2016). Domestic ev tariff. idaho national laboratory.
URL: <https://avt.inl.gov/sites/default/files/pdf/arra/PluggedInSummaryReport.pdf>, Accessed: July 29, 2019 64
- IOUs, C. (2021). Distributed generation successor tariff workshop: Joint iou proposal.
URL: <https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=6442468353>, Accessed: May 24, 2021 72
- IRENA (2017). Electricity storage and renewables: Costs and markets to 2030. 74
- Kam, M. V. D. and Sark, W. V. (2015). Smart charging of electric vehicles with photovoltaic power and vehicle-to-grid technology in a microgrid ; a case study, *Applied Energy* **152**: 20–30. 59
- Kaschub, T., Jochem, P. and Fichtner, W. (2016). Solar energy storage in German households: profitability, load changes and flexibility, *Energy Policy* **98**: 520–532. 59

- Koskela, J., Rautiainen, A. and Järventausta, P. (2019). Using electrical energy storage in residential buildings – Sizing of battery and photovoltaic panels based on electricity cost optimization, *Applied Energy* **239**(October 2018): 1175–1189. 73, 74
- Kuang, Y., Chen, Y., Hu, M. and Yang, D. (2017). Influence analysis of driver behavior and building category on economic performance of electric vehicle to grid and building integration, *Applied Energy* **207**: 427–437.
URL: <https://doi.org/10.1016/j.apenergy.2017.07.006> 59, 93
- Küfeoğlu, S. and Pollitt, M. G. (2019). The impact of PVs and EVs on domestic electricity network charges : A case study from Great Britain, *Energy Policy* **127**(August 2018): 412–424. 61
- LBNL (2019). Berkeley’s data processing tool.
URL: <https://building-microgrid.lbl.gov/der-cam-tools>, Accessed: 21 October 2019 67
- Lee, C.-y. and Heo, H. (2016). Estimating willingness to pay for renewable energy in South Korea using the contingent valuation method, *Energy Policy* **94**: 150–156. 56
- McLaren, J., Anderson, K., Laws, N., Gagnon, P., Diorio, N. and Li, X. (2018). Identifying Critical Factors in the cost effectiveness of solar and battery storage in commercial buildings in Commercial Buildings, *National Renewable Energy Laboratory. NREL PR-6A20-70813* (February). 74
- Momber, I., Gómez, T., Member, S., Venkataramanan, G., Member, S., Stadler, M., Beer, S., Lai, J., Marnay, C. and Battaglia, V. (2010). Plug-in Electric Vehicle Interactions with a Small Office Building : An Economic Analysis using DER-CAM, pp. 1–8. 64
- NREL (2019). Best research-cell efficiency chart, 54.
URL: <https://www.nrel.gov/pv/cell-efficiency.html>, Accessed in 18 March 2019 73
- NREL (2020). Annual Technology Baseline: Commercial PV, (November).
URL: <https://atb.nrel.gov/electricity/2020/index.php?t=sd> 56, 73, 74
- Nykqvist, B. and Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles, **5**(April): 100–103. 56
- Pearre, N. S. (2019). Review of research on V2X technologies , strategies , and operations, *Renewable and Sustainable Energy Reviews* **105**(April 2018): 61–70. 61
- Perez-Arriaga, I. J., Jenkins, J. D. and Batlle, C. (2017). A regulatory framework for an evolving electricity sector: Highlights of the MIT utility of the future study, *Economics of Energy & Environmental Policy* **6**(1): 71–92. 56

CHAPTER 3. RATE DESIGN WITH DISTRIBUTED ENERGY RESOURCES AND ELECTRIC VEHICLES: A CALIFORNIAN CASE STUDY

- Pollitt, M. G. (2018). Electricity Network Charging in the Presence of Distributed Energy Resources : Principles , Problems and Solutions, **7**(1): 89–104. 57
- SCE (2017). Self-generation incentive program - handbook.
URL: <https://www.sce.com/business/generating-your-own-power/incentive-program>. Accessed: July 17, 2019 74
- SCE (2019a). Domestic ev tariff. southern california edison.
URL: https://library.sce.com/content/dam/sce-doclub/public/regulatory/tariff/electric/schedules/residential-rates/ELECTRIC_SCHEDULES_TOU-EV-1.pdf, Accessed: July 29, 2019 72
- SCE (2019b). Tariff books. southern california edison.
URL: <https://www.sce.com/regulatory/tariff-books/rates-pricing-choices>. Accessed: July 17, 2019 58, 71
- SCE (2021). Net metering program.
URL: <https://www.sce.com/business/generating-your-own-power/net-energy-metering>, Accessed: May 24, 2021 72
- Schittekatte, T. and Meeus, L. (2020). Least-Cost Distribution Network Tariff Design in Theory and Practice, *Ssrn* **41**(5). 57
- Schittekatte, T., Momber, I. and Meeus, L. (2018). Future-proof tariff design: Recovering sunk grid costs in a world where consumers are pushing back, *Energy Economics* **70**: 484–498. 60, 61
- Schumacher, K., Krones, F., McKenna, R. and Schultmann, F. (2019). Public acceptance of renewable energies and energy autonomy: A comparative study in the French, German and Swiss Upper Rhine region, *Energy Policy* **126**(November 2018): 315–332. 56
- Sheha, M. N. and Powell, K. M. (2019). An economic and policy case for proactive home energy management systems with photovoltaics and batteries, *The Electricity Journal* **32**(1): 6–12. 74
- Simshauser, P. (2016). Distribution network prices and solar PV: Resolving rate instability and wealth transfers through demand tariffs, *Energy Economics* **54**: 108–122. 60, 61, 70
- Sioshansi, R. (2016). Retail electricity tariff and mechanism design to incentivize distributed renewable generation, *Energy Policy* **95**: 498–508. 60
- Stadler, M., Kloess, M., Groissböck, M., Cardoso, G., Sharma, R., Bozchalui, M. C. and Marnay, C. (2013). Electric storage in California’s commercial buildings, *Applied Energy* **104**: 711–722. 64, 76
- Steen, D., Stadler, M., Cardoso, G., Groissböck, M., DeForest, N. and Marnay, C. (2015). Modeling of thermal storage systems in MILP distributed energy resource models, *Applied Energy* **137**: 782–792. 96

CHAPTER 3. RATE DESIGN WITH DISTRIBUTED ENERGY RESOURCES AND ELECTRIC VEHICLES: A CALIFORNIAN CASE STUDY

Tervo, E., Agbim, K., DeAngelis, F., Hernandez, J., Kim, H. K. and Odukomaiya, A. (2018). An economic analysis of residential photovoltaic systems with lithium ion battery storage in the United States, *Renewable and Sustainable Energy Reviews* **94**(January): 1057–1066. 73

Tesla-Powerwall (2020). Tesla powerwall technical specifications.

URL: <https://www.tesla.com/powerwall>, Accessed: January 20, 2020 74

Thompson, A. W. and Perez, Y. (2020). Vehicle-to-Everything (V2X) energy services , value streams , and regulatory policy implications, *Energy Policy* **11**(July): 111136.

URL: <https://doi.org/10.1016/j.enpol.2019.111136> 61, 65, 93

Western Power Distribution (2019). Final Electric Nation Customer Trial Report. 93

* * *

The image shows a musical score for the song "Wave" by Antônio Carlos Jobim. The score is written for piano and voice. The piano part is in the bass clef, and the vocal part is in the treble clef. The key signature is two sharps (F# and C#), and the time signature is common time (C). The piano part features a steady eighth-note accompaniment in the right hand and a more complex bass line in the left hand. The vocal part consists of a melody with some grace notes and a final phrase. The dynamic marking *mp* (mezzo-piano) is used throughout. The score is divided into four measures by vertical bar lines.

Antônio Carlos Jobim - *Wave*.

* * *

Chapter 4

New EV rate design: An MPEC assessment

* * *

High penetration of electric vehicles (EVs) will deeply impact the management of electric power systems. To avoid costly grid reinforcements and the risk of load curtailment due to EV charging, indirect load control via adapted economic signals is a solution proposed by many utilities. Charging costs can be reduced by a domestic tariff applied only to EV charging using a dedicated measurement method of the load, while enhancing the flexibility offered by EVs. We develop a game-theoretical model expressed and treated as a Mathematical Program with Equilibrium Constraints (MPEC) to capture the interaction between a National Regulatory Authority (NRA) designing these tariffs and heterogeneous agents. First, we analyze the conditions in which EV-only tariffs can be applied for domestic slow charging sessions by comparing different energy profiles. Second, we study the impact of EV charging on different tariff structures to identify the most efficient way of recovering network costs. The submetering concept under a pure volumetric tariff can bring yearly gains varying from \$64 to \$110 compared to the flat rate. It depends on the share of investments on grid reinforcement that remain to be made. Finally, we derive policy implications from the results and earmark more sophisticated tariff designs for further investigation.

* * *

1 Introduction¹

The shift towards a low-carbon economy requires a great reduction of CO₂ emissions coming from the transportation sector, which accounts for 24% of direct emissions (IEA; 2020). To reduce CO₂ emissions, electric vehicles (EVs) are required to substitute ICE vehicles to achieve the decarbonization goals established during international environmental summits. Between 150 and 230 million vehicles are expected to be on the roads around the world by 2030, thus potentially causing future issues for power systems. This research aims to consider the challenges that might be imposed on the management of the grid as a result of the high penetration of EVs (Salah et al.; 2015). To avoid costly grid reinforcements and the risk of load curtailment due to EV charging, indirect price control, via adapted economic signals, is a solution adopted by many utilities (Knezović et al.; 2017). These economic signals, given to the EV users via a network tariff and energy price profiles, can have different structures. Users, who seek to minimize their electricity bills, are then led to a different final utilization pattern. Most household electricity meters do not separate the rates used for household electricity needs from the one used to charge privately owned EV, known as “whole-house” rate. Today, in some countries, users have the option of a domestic time-of-use (TOU) rate applied exclusively to EV charging. This tariff is called the EV-only rate. Users under this measurement method can reduce charging costs and promote the flexibility offered by EVs via adapted price signals.

Several pilots were conducted in the U.S (California, Minnesota, Texas) to test the technical feasibility and customer acceptance of these rates (Smart Electric Power Alliance; 2019). Californian-state electric investor-owned utilities (IOUs) already offer these types of rates in their portfolio for dwellings. For instance, Pacific Gas & Electricity (PG&E) and San Diego Gas & Electric (SD&E) allow residential customers to be billed at a tiered rate for home appliances while for EV charging, a specific time-of-use plan is adopted (PGE; 2021; SDGE; 2021). However, as installing a second meter is mandatory for these cases, EV-only rates have not been widely adopted due to the extra equipment’s high associated costs. The need for separate wiring and

¹This work is a collaboration with Adam Abdin, Jakob Puchinger and Yannick Perez.

metering renders such market segmentation expensive and cumbersome (Borenstein et al.; 2021). One alternative to avoid upfront costs or fees for residential customers on a second meter is submetering. In this case, the metering infrastructure, inside the electric vehicle supply equipment (EVSE), can be used to measure the electricity coming from the grid specifically for EV charging. The technological progress of smart meters, communication networks, and data management will allow the submetering configuration to be adopted by many utilities for billing purposes. For the US case, an official decision on submetering by the regulator in California is expected in 2021 after the conclusion of the submetering pilots (CPUC; 2021). Advanced metering infrastructure (AMI) in the case of electricity is being rolled out in different paces in the E.U and U.S. For instance in the E.U, as of July 2018, all but two member states had conducted at least one cost-benefit analysis for a large-scale rollout of smart meters to at least 80% by 2020. However, only a few of those members reached the target, while the majority postponed the achievement of this milestone to 2030 (European Commission; 2020). In the U.S, by the end of 2020, 75% of U.S. households already had an AMI installation in their homes (Cooper and Shuster; 2021).

To the best of our knowledge, no study assesses the effects on users and network tariff design of the adoption of two different rates for the same household simultaneously. We investigate this configuration supposing the submetering scheme has a dedicated protocol allowing the communication between the owner’s EVSE and the utility for billing purposes. Our integrated approach considering diverse energy profiles and the impact on tariff design allows for having a fair investigation on the solution cost-effectiveness. We find that a total gain varying from \$ 64 and \$ 110 per year is achievable depending on the state of the grid. Users willing to adopt that solution, when possible, can collect the spread between flat and time-of-use profiles, which is not offset by network tariff increase in the case of volumetric tariffs. The structure of this paper is as follows. First, an overview of the problem is given to explain the motivation of the research, with a literature review support. The data used are then presented, along with the setup proposed. In section 5, the results are presented showing energy profile assessment and network tariff impacts. In section 6, we discuss the results and derive policy implications. Finally, the last section comprises the conclusion.

2 Literature review

In this section, we analyze two main strands of the literature. The first concerns the interaction between EVs, distributed energy resources, and tariff design which has received much attention recently. This is mainly due to the great penetration of DER into the grid, which may change the way utilities charge their customers. The second looks at the EV demand-side flexibility assessment that analyses how smart charging and V2G can simultaneously bring remuneration via energy services and support the grid. This work locates itself at the intersection between these two strands by tackling dedicated EV tariffs which can defer network investments by adopting smart charging.

A vast body of literature investigates the impacts of different electricity rates, including energy prices and network tariffs, on specific end-users possessing DERs. The impacts on their decisions are assessed either with tariffs defined exogenously (Ansarin et al.; 2020; Avau et al.; 2021; Backe et al.; 2020; Freitas Gomes et al.; 2021) or using equilibrium models in which grid tariffs are determined endogenously as the results of a bi-level approach (Askeland et al.; 2021; Hoarau and Perez; 2019; Schittekatte and Meeus; 2020). In all these cases, only one tariff structure is analyzed at a time for users with only one metering scheme. Hoarau and Perez (2018) analyses the interaction between tariff design and DERs with EVs to measure the most cost-efficient configuration and the fairest for heterogeneous agents. For Hoarau and Perez (2018), the more a tariff structure gives incentives for DERs, the less beneficial it is for EVs. Using a similar framework, Askeland et al. (2021) highlights that an EV agent can spread the EV charging evenly throughout the day to minimize the agents' individual peak load regardless of the overall load situation. This can be problematic if prospective costs drive grid costs since the coincident peak can go up followed by a tariff increase. This type of cost if recovered via cost-reflective tariffs can benefit both prosumers who can invest in DERs and consumers who are not able according to Schittekatte and Meeus (2020).

A subset of this literature specifically investigates tariffs and best practices for EV charging (Hildermeier et al.; 2019; King and Datta; 2018; Küfeoğlu et al.; 2019). Hildermeier et al. (2019) argues that customer education is key, in particular, to attract

new user groups, who are not already convinced of the specific advantages of managed EV charging. For EV-only tariffs, this effort would probably duplicate since more information regarding bill savings optimization and metering infrastructure should be explained. However, if adequate information about tariffs and behavior is provided, users usually choose more complex tariffs (Mayol and Staropoli; 2021). In the same line, Küfeoğlu et al. (2019) supports the idea that energy utilities must offer consumers more options for TOU tariffs, not only allow for greater demand-side management but also encourage uptake of V2H technology. Finally, King and Datta (2018) points out that submetering is indeed a far less expensive option than the installation of a separate meter for the EV. Moreover, they explain that standards are already available to ensure appropriate billing using the submeter approach. The accuracy of it can be set at the same level as already existing standards from electricity meters.

The second strand of literature studying EV demand-side flexibility raises attention to the challenges and opportunities expected during EV uptake. Knezović et al. (2017) provide a roadmap with key recommendations for supporting active EV involvement in grids to provide flexibility services such as investment deferral, load, and voltage services. One barrier highlighted is the lack of standardized smart-meter functionalities and interoperability among all participants. In the same line, Salah et al. (2015) argues that price incentives can help to exploit available load flexibility embedded in EV charging, whilst if ill-designed, they can lead to a significant increase of peak loads in times of low prices. Lastly, it is worth pointing out the value streams of numerous V2G services (Thompson and Perez; 2020). In our framework, network investment deferral supported by EV flexibility in a context with renewable energy as explored by Hemmati and Mehrjerdi (2020), can contribute to an accessible cost-reflective tariff.

3 Method

In this section the game-theoretic model is presented. First, the solution method to determine the main results is summarized. Then, the equations of the optimization problems of both levels are described in detail.

3.1 Model overview

This section describes the model used to pursue the main goals of this research. We develop a bi-level game-theoretical optimization model to capture the interaction between a National Regulatory Authority (NRA) and the dwellings. The upper-level represents the NRA responsible for setting network tariffs to maximize the social welfare subject to grid cost-recovery, total DER investment costs, and the cost of final electricity usage of the dwellings. In the lower-level, the dwellings seek to minimize their electricity costs according to the final tariff structure applied. The dwellings' decisions include new investments in DER investment decisions and optimal scheduling of electric vehicle charging which, in turn, depend on the tariff applied. Therefore, there is a clear interdependence between the lower level charging, investment decisions, and the tariff design. The interdependence requires finding an equilibrium solution of which can only be properly captured within a bi-level optimization approach as previously described. At first, we deal only with the lower level to find the most adapted energy profile for each agent owning EVs. In this case, the lower level is formulated as a Mixed Integer Linear Programming (MILP) taking the network tariffs as exogenous variables. Then, to assess the impact on network tariff, the bi-level model is expressed and treated as a Mathematical Program with Equilibrium Constraints (MPEC), in which the equilibrium game-theoretic solution for both NRA and the dwellings will be the one in which no unilateral deviation in their decisions will be profitable, defined as a Nash equilibrium. The complete solution framework is summarized in Figure 4.1. The full model formulation and the techniques used to transform and solve the MPEC are detailed step by step in the B.

3.2 Upper-level problem formulation: the regulator

3.2.1 Regulator objective function

The main objective of the regulator is to decide on the network tariff to maximize social welfare while ensuring cost-recovery and the individual optimization problems of the agents. Within this context, social welfare maximization can be assumed to be equivalent to cost minimization for all interacting agents since, in addition to the network

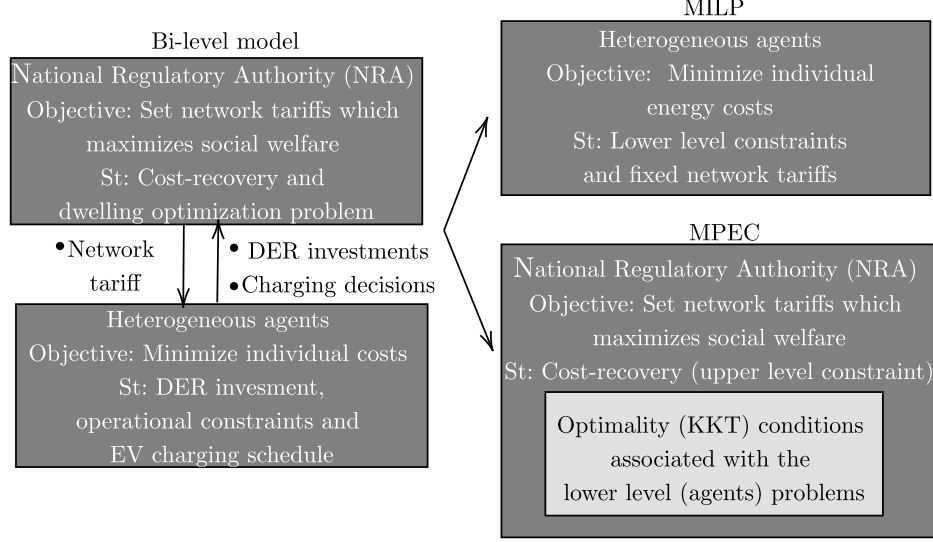


Figure 4.1: Methodological framework.

costs, the investment and energy costs of dwellings are also included in the minimization problem of the regulator. As a consequence, Equation 4.1, which represents the NRA cost function, accounts for the sum of DER investments costs ($Cost^{DER}$), energy charges ($Cost^P$) and network charges ($Cost^N$) for the agents:

$$\min Cost^{NRA} = Cost^{DER} + Cost^P + Cost^N \quad (4.1)$$

The first term of the regulator's objective function is the investment decisions of the dwellings. It is represented by Equation 4.2 in which a customer c would seek to optimally decide to install a certain capacity of solar PV (ic_c^{PV}) and battery (ic_c^S), if it is profitable to do so, with an annualized investment costs I^{PV} and I^S , for solar PV and battery, respectively. This is formulated as:

$$Cost^{DER} = \sum_{c \in C} (I_c^S * ic_c^S + I_c^{PV} * ic_c^{PV}) \quad (4.2)$$

The total net energy costs to satisfy electricity demand for all agents is calculated in Equation 4.3. We assume one retailer supplying all the customers. However, more than one energy profile can be considered according to the rate chosen. For instance, charging the vehicles under an EV-only tariff will require a time-of-use profile whereas the house electricity consumption could be considered under a flat one. Energy charges

account for the total energy imports ($imp_{c,h}^P$) minus total exports back to the grid ($exp_{c,h}^P$) at a certain price for buying ($PBE_{c,h}^P$) and another for selling ($PSE_{c,h}^P$) energy. If the buying and selling prices are the same, the rate is said to be symmetric in terms of energy. Finally, the parameter W stands for the scaling factor to provide costs on a temporal basis. To calculate the yearly operational costs, W takes the value of $W = \frac{\text{Total number of hours per year}}{H}$ in which H is the number of hours for the time horizon considered. The net energy costs are then described as:

$$Cost^P = \sum_{c \in C} \sum_{h \in H} W_h * (imp_{c,h}^P * PBE_{c,h}^P - exp_{c,h}^P * PSE_{c,h}^P) \quad (4.3)$$

The last term of the objective function accounts for the network costs calculated according to Equation 4.4). The cost of operating and reinforcing the distribution grid is borne by the distribution system operator (DSO) who is assumed to recover its costs via a regulated grid tariff. We assume two types of costs: sunk costs and prospective costs. The sunk costs are those incurred in the past to build and reinforce the grid in order to meet the demand in the future. Prospective costs are variable and depend on the maximum cumulative load of all customers. The variable agc is the additional grid capacity needed to ensure proper functioning with an annualized incremental cost for grid capacity I^{DSO} . This can be formulated as described in the following equation:

$$Cost^N = SunkCosts + I^{DSO} * agc \quad (4.4)$$

3.2.2 Grid capacity constraints

The grid capacity needed to ensure the power delivery to the customers depends on their hourly imports and exports. Because different customers can import and export energy at the same time, the aggregated net electricity flow is the variable needed to size additional grid investments. This flow is calculated as the absolute value of aggregate trading of all customers. To maintain the linearity of the problem, Equation B.5 and B.6 will calculate the hourly sum of net imports and net exports as just one term of that equation will be nonzero, then the sum of both Equation B.7 will measure the aggregated hourly demand.

$$e_h^G = \left| \sum_{c \in C} imp_{c,h}^P - exp_{c,h}^P \right|, \forall h \in H \quad (4.5)$$

Then the total grid capacity, defined as the sum of existing (*egc*) and the additional capacity (*agc*), should be always greater or equal than the hourly imports (or exports) of all the customers' demands, as formulated in Equation 4.6:

$$egc + agc \geq e_h^G \forall h \in H \quad (4.6)$$

3.2.3 DSO cost-recovery constraint

An important constraint of the upper level is the cost-recovery of grid costs by the DSO via the network tariff. In our framework, the regulator is fully in charge of setting the tariffs and we assume that all costs can be recovered via a three-part tariff formulation including volumetric (*vnt*), capacity (*cnt*), and a fixed (*fnt*) elements as in Equation 4.7. The three terms, depend, respectively on the net energy of each agent (€/kWh), each consumer maximum peak (€/kW) or the number of customers *n* (€/customer). Net-metering options are also considered by the parameter (*NM*) which can assume different values according to the tariff structure. For example, the user can be charged for the net amount of energy consumed (*NM* = 1), only for imports (*NM* = 0), or for both imports and exports back to the grid (*NM* = -1). This formulation allows the regulator to adopt the tariff which achieves the highest social welfare taking into account the customer reactions. The full cost-recovery constraints is described as:

$$Cost^N = \sum_{c \in C} \sum_{h \in H} W * (imp_{c,h}^P - NM * exp_{c,h}^P) * vnt + \sum_{c \in C} p_c * cnt + n * fnt \quad (4.7)$$

3.3 Lower-problem formulation: the agents

3.3.1 Agents objective function

The objective function of the agents in the lower level is to minimize their total costs subject to the tariff applied by the regulator. It is formulated according to Equation

4.8 as the sum of investments costs in DER ($Cost_c^{DER}$), energy charges ($Cost_c^P$) and network charges ($Cost_c^N$). The term $Cost_c^{DER}$ is only present for the prosumers, as they are able to invest in solar-PV panels and batteries to reduce their peak demand and general energy consumption from the grid.

$$Min Cost_c = Cost_c^{DER} + Cost_c^P + Cost_c^N \quad (4.8)$$

The following Equations 4.9-4.11 detail each term of the lower-level objective function. First, DER investments costs are the sum of annualized solar-PV and batteries investments as stated in Equation 4.9. The energy charges for each customer are related to the type of energy rate that they adopted among the retailer's offer, as indicated in Equation 4.10. Then, network charges calculated by Equation 4.11 are the charges paid for grid utilization by each customer. If we consider a dedicated measurement of power and energy for EVs, it will create another connection point which can be physical, using an extra meter, or virtual, via submetering. This is crucial for network tariff design purposes since EVs can then be considered as an additional agent separated from the dwelling, even if the dwelling will still bear the costs of the charging or collect the revenue by discharging into the grid.

$$Cost_c^{DER} = I_c^S * ic_c^S + I_c^{PV} * ic_c^{PV}, \forall c \in C \quad (4.9)$$

$$Cost_c^P = \sum_{h \in H} W * (imp_{c,h}^P * PBE_{c,h}^P - exp_{c,h}^P * PSE_{c,h}^P), \forall c \in C \quad (4.10)$$

$$Cost_c^N = \sum_{h \in H} W * (imp_{c,h}^P - NM * exp_{c,h}^P) * vnt + p_c * cnt + fnt, \forall c \in C \quad (4.11)$$

3.3.2 Agents peak power constraint

The amount of capacity charges paid by each user depends on their peak power consumption over a time period. As the installed grid capacity must ensure that both bidirectional power flows can be managed, the peak power can occur while customers are importing or exporting energy as described in Equation 4.12. Since only one term on the left side of the inequality can be non-zero at each time step, we can measure

their maximum imported or exported power to calculate the amount of capacity-based charges that should be paid. This is described as:

$$imp_{c,h}^P + exp_{c,h}^P \leq p_c, \forall c \in C, h \in H : (\mu_{c,h}^G) \quad (4.12)$$

The agents represented by the lower level optimization problem are submitted to several constraints which are described by Equations 4.13-4.30 and their respective dual variables. These equations describe the investment options available for DERs and their interaction with dwelling load and electric vehicles, and are detailed in the following section.

3.3.3 Electric vehicle capacity constraint

The main purpose of EVs is to fulfill the mobility needs of their owners. However, when idle, they can be considered as a battery able to inject energy back to the grid while maintaining a certain amount of energy for driving. Equation 4.13 describes how the state of charge (SOC) of the EV battery ($s_{c,h}^{EV}$) depends on its state in the previous time-step ($s_{c,h-1}^{EV}$), the charging decision ($d_{c,h}^{\Delta EV+}$), discharging decision ($d_{c,h}^{\Delta EV-}$) and consumption while driving ($D_{c,h}^{\Delta EV-}$). This formulation can potentially lead to discharging and charging episodes happening at the same time-step. Nevertheless, positive converter losses and energy costs will prevent this from occurring due to associated costs in the objective function². The losses in the storage system are represented by the converter losses parameter (L^S) and battery self-discharge parameter (R_c). Initial conditions are needed to account for overnight charging and initial state of charge. In order to enable it, the last time-step is linked to the first one, as stated in Equation 4.14 which assumes that the initial and final states of the battery should be equivalent. Finally, the state of charge is determined by the parameter SOC_0^{EV} in Equation 4.15 defined below:

²The solutions are verified ex-post to ensure that the realistic behavior happens for all agents over the entire time-horizon.

$$s_{c,h}^{EV} = S_{c,h-1}^{EV} * (1 - R_c^{EV}) + d_{c,h}^{\Delta EV+} * (1 - L^{EV}) - d_{c,h}^{\Delta EV-} * (1 + L^{EV}) - D_{c,h}^{\Delta EV-},$$

$$\forall c \in C, h \in H \setminus \{1\} : (\lambda_{c,h}^{EV1}) \quad (4.13)$$

$$s_{c,1}^{EV} = S_{c,H}^{EV} * (1 - R_c^{EV}) + d_{c,1}^{\Delta EV+} * (1 - L^{EV}) - d_{c,1}^{\Delta EV-} * (1 + L^{EV}) - D_{c,1}^{\Delta EV-},$$

$$\forall c \in C :$$

$$(\lambda_{c,1}^{EV1}) \quad (4.14)$$

$$s_{c,H}^{EV} = SOC_0^{EV}, \forall c, h \quad (\lambda_c^{EV2}) \quad (4.15)$$

Moreover, Equations 4.16-4.19 describe the operational limits for the EVs battery. First, Equation 4.16 and 4.17 ensure that the state of charge of the battery remain within a certain range to avoid extra battery degradation. By limiting the state of charge, we implicitly remove the need to include the degradation costs directly in the objective function. Regarding power levels, the parameters $(P_{c,h}^{EVch})$ in Equation 4.18 for charging and $(P_{c,h}^{EVdis})$ in Equation 4.19 for discharging are responsible for limiting power transfers depending on the type of electric vehicle charging equipment (EVSE) adopted. These constraints are described as:

$$s_{c,h}^{EV} \leq \overline{E}_{c,h}^{EV}, \forall c \in C, h \in H : (\mu_{c,h}^{EV2}) \quad (4.16)$$

$$s_{c,h}^{EV} \geq \underline{E}_{c,h}^{EV}, \forall c \in C, h \in H : (\mu_{c,h}^{EV3}) \quad (4.17)$$

$$d_{c,h}^{\Delta EV+} \leq P_{c,h}^{EVch}, \forall c \in C, h \in H : (\mu_{c,h}^{EV4}) \quad (4.18)$$

$$d_{c,h}^{\Delta EV-} \leq P_{c,h}^{EVdis}, \forall c \in C, h \in H : (\mu_{c,h}^{EV5}) \quad (4.19)$$

3.3.4 Battery storage investment constraints

A stationary battery allows the user to shift load temporally and store the electricity surplus generated by solar PV. Analogous to the EVs charging and discharging equations, Equation 4.20 describes how the state of charge of the battery ($s_{c,h}$) depends on its state in the previous time-step ($s_{c,h-1}$), the charging decision ($d_{c,h}^{\Delta+}$) and discharging decision ($d_{c,h}^{\Delta-}$). In this case, we let the optimization define the initial state of charge of the battery since it will depend on the total amount of battery installed which is, also, a decision variable.

$$s_{c,h} = s_{c,h-1} * (1 - R_c) + d_{c,h}^{\Delta+} * (1 - L^S) - d_{c,h}^{\Delta-} * (1 + L^S), \forall c \in C, h \in H \setminus \{1\} : (\lambda_{c,h}^{S1}) \quad (4.20)$$

$$s_{c,1} = s_{c,H} * (1 - R_c) + d_1^{\Delta+} * (1 - L^S) - d_1^{\Delta-} * (1 + L^S), \forall c \in C : (\lambda_{c,1}^{S1}) \quad (4.21)$$

The capacity installed will be decided by the model, if it is profitable for each agent, by choosing the variable ic_c^s bounded by a maximum capacity limit (U_c^s) as stated in Equation 4.22. For certain agents who do not have the possibility to install any battery capacity, the maximum value can be set to zero.

$$ic_c^s \leq U_c^s, \forall c \in C : (\mu_c^{S1}) \quad (4.22)$$

As in the EVs' case, Equations 4.23-4.26 describe the operational limits for the stationary battery. The parameters ($S^{\%max}$) and ($S^{\%min}$) are the percentage of maximum and minimum charge levels allowed, respectively. Regarding power levels, the charging factor (P_c^{ch}) in Equation 4.25 and discharging factor (P_c^{dis}) in Equation 4.26 represent the maximum limits of power transfers according to the storage system specifications described as the following:

$$s_{c,h} \leq ic_c^s * S^{\%max}, \forall c \in C, h \in H : (\mu_{c,h}^{S2}) \quad (4.23)$$

$$s_{c,h} \geq S^{\%min} * ic_c^s, \forall c \in C, h \in H : (\mu_{c,h}^{S3}) \quad (4.24)$$

$$d_{c,h}^{\Delta+} \leq ic_c^s * P_c^{ch}, \forall c \in C, h \in H : (\mu_{c,h}^{S4}) \quad (4.25)$$

$$d_{c,h}^{\Delta-} \leq ic_c^s * P_c^{dis}, \forall c \in C, h \in H : (\mu_{c,h}^{S5}) \quad (4.26)$$

3.3.5 Solar-PV investment constraints

The capacity of solar-PV installed is, also, endogenously decided within the model. If it is profitable for each agent through the variable ic_c^{PV} bounded by a maximum capacity limit (U_c^{PV}) as stated in Equation 4.27. For certain agents incapable of installing any solar PV, the maximum value can be set to zero. The amount of energy produced will depend on the solar availability in kW/kWp ($G_{c,h}^{PV}$) and the users do not have the option of curtailment, meaning that they have to export the surplus of electricity generated in any given time period.

$$ic_c^{PV} \leq U_c^{PV} \forall c \in C : (\mu_{c,h}^{PV1}) \quad (4.27)$$

3.3.6 Energy balance equation

The energy balance equality couples all the investment and operational decisions with the load demand profile of each customer ($D_{c,h}$) as stated in Equation 4.28. The terms $imp_{c,h}^L$ and $exp_{c,h}^L$ allow modeling the interaction between an EV, which is metered separately, and the household loads. By treating the EV as a separate agent, it can buy electricity under an EV-only rate and transfer power to the house, if needed, which is itself under a different rate. In this manner, Equation 4.29 ensures the supply-demand balance ensuring that all the imports are equal to exports. Similarly, the households that may invest in DERs will have their own interaction with their electric vehicles. Now, dwellings can invest in DERs and arbitrage energy between the two different retail tariffs, for example, by charging the EV with a battery at a flat rate. It is also possible to charge the EV using local solar energy instead of relying on buying

electricity from the grid, significantly increasing the complexity of the interactions. To restrain the relation between EVs and the prosumers type of households, another equilibrium equation (Equation 4.30) is added. The auxiliary parameter α_c will forbid the other agent types to interact with the dwellings under EV-only rates by setting it to zero. An analogy can be made with local market modeling. In our case, an EV and a specific type of household form a local market in which they can interact with others only via the main grid. These interactions are described in Equations 4.28-4.30 as follows:

$$D_{c,h} + d_{c,h}^{\Delta EV+} - d_{c,h}^{\Delta EV-} + d_{c,h}^{\Delta+} - d_{c,h}^{\Delta-} - ic_c^{PV} * G_{c,h}^{PV} = imp_{c,h}^P - exp_{c,h}^P + \alpha_c * (imp_{c,h}^L - exp_{c,h}^L), \forall c \in C, h \in H : (\lambda_{c,h}^{EB}) \quad (4.28)$$

$$\sum_{c \in C_{EV}} (imp_{c,h}^L - exp_{c,h}^L) = 0, \forall h \in H : (\lambda_h^{L_{EV}}) \quad (4.29)$$

$$\sum_{c \in C_{EV/DER}} (imp_{c,h}^L - exp_{c,h}^L) = 0, \forall h \in H : (\lambda_h^{L_{EV/DER}}) \quad (4.30)$$

Additional constraints can be added to enforce the interaction between the EV and the house in which they are connected as stated in Equations 4.31 and 4.32. These equations will limit the amount of energy that a vehicle can import from the house according to the existing energy resources (battery and PV). Reciprocally, the house also can only import energy from the vehicle if it is ready to discharge at any hour. The model allows to avoid V2H by forcing the constraint of Equation 4.32 to zero while allowing V2G via the energy balance equation 4.28.

$$imp_{EV,h}^L \leq d_{c,h}^{\Delta-} + ic_c^{PV} * G_{c,h}^{PV}, \forall c \in (C_{EV} \cup C_{EV/DER}), \forall h \in H : (\mu_{c,h}^{impL}) \quad (4.31)$$

$$imp_{c,h}^L \leq d_{EV,h}^{\Delta EV-}, \forall c \in C_{EV}, \forall c \in (C_{EV} \cup C_{EV/DER}), \forall h \in H : (\mu_{c,h}^{impL2}) \quad (4.32)$$

4 Case study: setup and input data

In this section, the setup and input data for a case study using the bi-level model is described. First, the general setup of the numerical example will be explained as a starting point. Then, the data regarding agents such as load profiles, solar insolation, and energy tariff profiles are presented alongside the data of EVs and DERs. Finally, the baseline electricity bill is followed by the grid cost structure.

4.1 Setup

In the case study, two behaviors are considered regarding the option that agents have to invest in DERs like solar PV and stationary batteries: prosumer and consumer behavior. Moreover, when EVs are considered, a combination resulting in four different types of agents is observed: prosumer with EV, consumer, prosumer, and consumer with EV. Within this configuration, a 50% share of prosumers is analyzed. Although it seems a high share for today's global level, in a mid-term perspective, the amount of prosumer agents is expected to increase. Increasing environmental awareness and DER technology cost reduction contribute to boost the number of consumers becoming prosumers. Given smart charging, V2G, and submetering are considered, the number of possible scenarios could rapidly increase. To limit the number of agents and scenarios, V2G will only be adopted by the prosumers with EVs since they can be considered as full-innovators and less risk-averse. Submetering will be adopted for those who can obtain higher gains according to the first MILP model results. With reference to the share of EVs, a 50% of EV owners is considered among the agents. This proportion will be relative to the total vehicle stock present if the remaining agents are considered to have ICE vehicles³. Smart charging is essential to limit the risk of surpassing the

³The factors influencing the shift to prosumer behavior will have an important impact on the electric mobility uptake. Current zero-emission vehicle policy support and ICE bans in more than 20 countries by 2030-2035 will contribute to the high penetration of EVs in the market (IEA; 2021).

maximum capacity of the grid during peak, therefore, it will be considered a common practice among all EV owners. The representation of the agents will depend on which type of EV rate they are under and if they are able to make DER investments as shown in Figure 4.2:

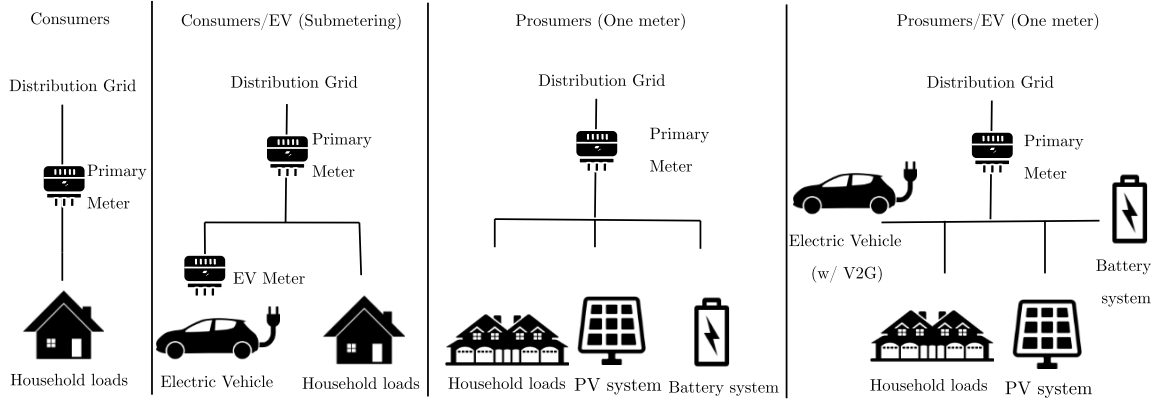


Figure 4.2: Topology configuration of all agents.

For instance, the topology configuration of the agents complexifies when moving towards prosumers with submetered EVs. In this case, one rate is applied specifically for EV charging using the existing EVSE meter and the other for the remaining loads including DERs. It is possible, in theory, to arbitrage energy within the same household collecting the spread between these rates at the condition that investments in DERs or V2G are made. The assessment using the MILP model considers different energy profiles, topologies, and DER costs, so EV owners could choose the options that reduce their total cost.

The first analysis will consider only different energy profiles (flat or time-of-use) whilst the network charges will be fixed according to the baseline electricity bill. This baseline scenario will be used as a reference to all other counterfactual scenarios with respect to energy and network cost variation. The grid costs expected to be recovered via tariffs depend on the state of the grid, in other words, if all the investments were already made the costs are considered to be sunk, or if there are still investments to be made, they are considered to be prospective. Once the model is calibrated with input data, the MPEC formulation will allow for evaluating the variation of grid charges for the agents according to how the regulator sets the tariffs.

4.2 Load and solar profiles

The adopted 48-hour load profiles correspond to the inelastic hourly demand for the prosumers who have the capacity and the means to invest in DERs and for the consumers who are not able to. Total annual electricity consumption of 10,000 kWh is adopted for prosumers, which is equivalent to the average consumption of a U.S residential utility customer (EIA; 2020). The value for consumers is chosen to be 5,500 kWh, being equivalent to the average French dwelling consumption (Odyssee Mure; 2019). The difference in total consumption between them is explained by a positive correlation frequently observed in the literature between income and electricity usage (Borenstein; 2012; Burger et al.; 2020). Peak demand values for a typical household tend to occur in the early evening while having a second smaller peak in the morning. Here, they differ for both agents, a peak of 4,8 kW for prosumers and 3,2 kW for consumers are calibrated, which leads to a coincidental peak of 8 kW without any EV and DER investments.

With respect to the solar profile, a 48-hour profile with two different insolation peaks is used. The first one with higher insolation represents a typical shiny day in which there is direct sunlight without any external interference during all periods. Whereas the second can represent a cloudy or a rainy day where the solar irradiation is deeply reduced, leading to less electricity production by solar PVs. The day with the smaller peak of insolation is synchronized with the day presenting the higher peak of electricity consumption. Finally, both load and solar profiles are described by Figure 4.3.

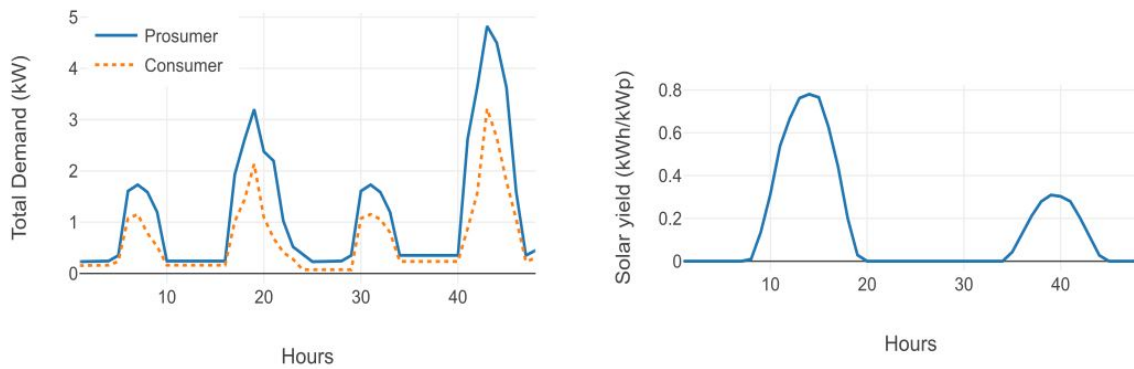


Figure 4.3: Load and solar profiles.

4.3 EV and DER data

Electric vehicle charging constitutes a large share of the residential electricity bill especially for owners with important mobility needs. According to a pilot conducted in the United Kingdom exploring user behavior related to home charging, the value of 3,500 kWh corresponds to the average yearly consumption of vehicles with batteries greater than 35 kWh (Western Power Distribution; 2019). This amount is equivalent to the average electricity consumption of a dwelling in the U.K. An EVSE allowing a maximum input power of 7 kW is adopted, then, the peak caused by EVs will depend on the type of rate applied since it is possible to spread out the charging over the day by using smart charging.

From the yearly EV energy consumption it is possible to derive the daily energy needs for mobility purposes. First, based on the average energy consumption per kilometer of 194 Wh/km (Electric Vehicle Database; 2021a), the daily traveled distance of around 50 km/day is calculated⁴. This distance is in line with the one found for EVs in European countries like Italy, France and Germany (Pasaoglu et al.; 2014) and in California (California Energy Commission; 2019). Therefore, the daily energy need of 9,7 kWh is estimated for the case study based on these data⁵.

To avoid extra battery degradation, the battery state of charge is advised to remain between a specific range and to have a limited depth of discharge. It is assumed that the battery capacity of full-electric vehicles corresponds to the average value of 60 kWh (Electric Vehicle Database; 2021b) and the SOC is allowed to vary between 6 and 54 kWh (10-90% respectively). Finally, the assumption regarding connection hours is defined as observed in the British EV charging pilot. The majority of EVs disconnect at 7 A.M. from their homes and plug-in back at 5 P.M. (see B for more details). Conversion losses from power electronics converters in the EVSE of 5% and a negligible self-discharge rate complete the technical parameters of EVs.

The cost of technologies such as solar PV has a strong impact on the size of DER investments of the agents and vary substantially across utility, commercial, and residential sectors (NREL; 2020). The adopted cost of installing solar PV is around

⁴Daily travel distance = $\frac{\text{Yearly average consumption}}{\text{Efficiency} * \text{Days in a year}} = \frac{3,500 \text{ kWh}}{194 \frac{\text{Wh}}{\text{km}} * 360 \text{ days}} = 50.1 \frac{\text{km}}{\text{day}}$

⁵Daily energy needs = $\frac{\text{Yearly average consumption}}{\text{Days in a year}} = \frac{3,500 \text{ kWh}}{360 \text{ days}} = 9.7 \frac{\text{kWh}}{\text{day}}$

900 \$/kWp, which can be considered low in the context of residential-scale systems. However, we use this optimistic scenario to illustrate a situation where it is cost-optimal for the agents to invest in these systems. Direct subsidies can also support the argument of using this cost for end-users. On the other hand, net metering will not be considered since it may over-incentivize solar PV investments and cause strong fairness issues among agents. A discount factor of 5% and a lifetime of 20 years translates into an annualized cost of 72 \$/kWp.

Stationary batteries have been benefiting from the cost decrease of automotive batteries at a pack level. The adopted cost for them is 150 \$/kWh, which corresponds to the current weighted average cost of a battery pack for electric vehicles (IEA; 2021). In addition, the annualized cost of 19.4 \$/kWh is obtained by using a similar discount factor of 5% and a lifetime of 10 years. Regarding the technical parameters, we assume conversion losses of 5% and a self-discharge rate of 0.1% per hour. The presence of self-discharge only in the stationary battery systems and not for EV batteries corresponds to the assumption that battery management systems (BMS) in EVs are more efficient⁶. Finally, analogous to the EV battery case, the SOC is allowed to vary between 10% and 90% of the total battery capacity.

4.4 Baseline electricity bill

A reference scenario is needed to compare the outcome of the optimization model for further analysis. The baseline electricity bill is a counterfactual bill defining energy and network costs in dollars for each agent. Furthermore, Renewable Energy Support (RES) and taxes are also main components in the majority of electricity offers for households. The weighted average breakdown of electricity offers in 2019 provided by the ACER marketing monitoring report (ACER; 2020) indicates that the share of energy costs will be 45% and network charges account for 33% if the amount of RES is split equally between them, whereas the taxes will account for the remaining 22%. Electricity prices vary considerably across countries in different regions, for

⁶By not allowing the battery to function outside its operating margins with respect to temperature, for example, the self-discharge will be greatly reduced, therefore, remaining negligible for functioning purposes.

instance, the average price for E.U was 21.6 euro cents/kWh (ACER; 2020) while in the U.S the average was found to be 10.6 cents/kWh (EIA; 2019). The average value of 16.3 cents/kWh will be used as the reference for the bill calculation coupled with the breakdown information. Table 4.1 shows in detail the final bill for each agent.

Table 4.1: Electricity bill components

	Breakdown	Cost in bill (\$/kWh)	Consumer (\$)	Consumer/EV (\$)	Prosumer (\$)	Prosumer/EV (\$)
Energy	45%	0,073035	406	662	731	986
Network	33%	0,053559	298	485	536	723
Other charges	22%	0,035706	198	323	357	482
Total costs	100%	0,163	902	1470	1624	2192

Until now, the energy costs were assumed to be invariant over time, meaning that a flat energy profile is adopted. Nevertheless, this type of energy profile is not suitable to incentivize households to reduce their consumption during a certain period of the day or to install DERs for peak shaving and valley filling purposes. Time-of-use energy profiles can be the appropriate economic signal to fulfill these objectives, therefore, two extra TOU profiles are proposed for evaluation. The first denominated TOU1 has the highest relative value synchronized with the private peak, incentivizing the agents to offset coincidental demand and reduce their own peak. Then, the second profile TOU2 supports solar PV adoption since its relative value around the period of solar production is the greatest among all profiles. In order to render them comparable, both TOU profiles are calibrated so that the final consumer bill in the basecase scenario would be the same regardless of the choice of energy profiles. The final average price of TOU rates will be often lower than the equivalent flat rate due to the high number of mid-peak and off-peak hours. However, the final electricity bill is slightly higher. This fact shows how complex tuning energy profiles can be, depending mostly on what kind of incentives the utility purposes. For instance, increasing on-peak charges to avoid grid congestion or decrease the off-peak level to encourage users to shift their consumption. We point out that the rates selected are not symmetric, which means that the compensation for injecting electricity into the grid is not at the same level as the cost of withdrawing electricity. Users are subjected to a 10% compensation related to the energy price at the moment of the injection according to the type of tariff⁷. All energy profiles are described in Figure 4.4:

⁷The future of policies regarding PV injection prices is quite uncertain. Due to the high cost-

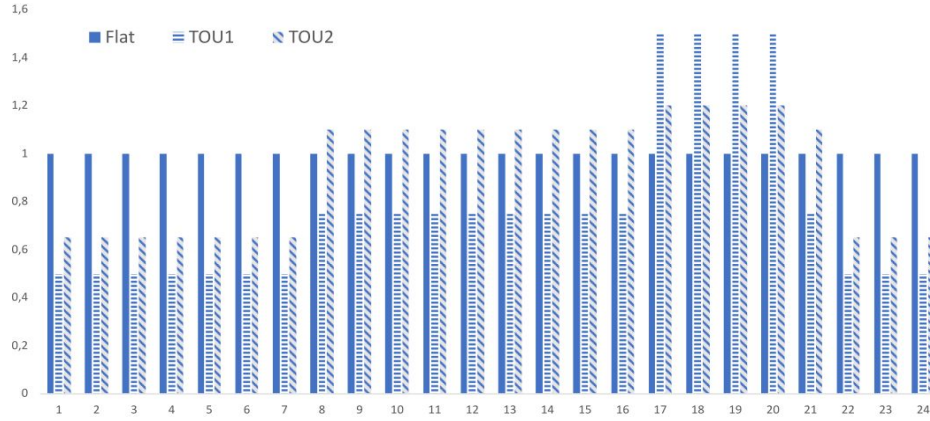


Figure 4.4: Energy profiles.

4.5 Grid cost structure

Several factors constitute the grid cost structure which makes the assumptions regarding the structure complex to make. For instance, fixed operating costs, sunk capital costs, variable operating costs, and network losses are part of the cost needed to be recovered by network operators. According to [Simshauser and Downer \(2016\)](#), with respect to an electricity distribution system, the fixed and sunk capital costs will comprise 70-80% of the total cost structure. This indicates that traditional distribution grids are over-dimensioned for the current demand, practice which is described as "fit-and-forget".

Nevertheless, the penetration of new distributed energy resources (stationary batteries, solar PV, and heat pumps) and electric vehicles will substantially change this scenario. Grid reinforcements may be necessary to cope with the peak load increase caused by these technologies mainly if their use is not properly coordinated. The economic feasibility of substituting grid capacity with local flexibility can be assessed by using forward-looking grid costs. The forward-looking aspect states that the reduction of network utilization cannot reduce the costs of the current network infrastructure, which are sunk, but only defer future network investments by reducing coincident peak load ([Govaerts et al.; 2019](#)). Therefore, this element, also named prospective costs, signal the long-run costs of the network to the agents.

As in [Schittekatte and Meeus \(2020\)](#), we adopt three scenarios for the analysis:

shifting levels in some locations, indirect incentives for installing PVs such as feed-in-tariffs and compensations for energy injection are ought to substantially decrease ([IOUs; 2021](#)).

100% sunk costs, 50% sunk and 50% prospective and 100% prospective grid costs. For the first scenario, the *SunkCosts* parameter of Equation 4.4 corresponds to \$ 2,040, which is the sum of network charges of all agents in the baseline electricity bill (see Table 4.1). For the second scenario, half of this costs is adopted in the latter parameter, while the increment annualized costs I^{DSO} , representing the prospective costs will be 63.8 \$/kW⁸. Finally, the full prospective scenario is pictured with increment annualized costs of 127 \$/kW while there is no sunk costs⁹. Even though grid costs are lumpy and vary depending on site-specific properties, these values allow us to have a fair representation of grid cost structure.

5 Results

In this section, we present the results of the our numerical example. We begin by analyzing the impact of different energy profiles for EV owners on the final electricity bill under the fixed basecase volumetric network tariff. Then, once the energy profiles are set for the agents owning an EV, we assess the effects of different network tariff designs on the final bill. We end by discussing and some policy implications are highlighted.

5.1 Energy profile assessment

A retailer's electricity offer usually has several types of rates given the difference in time granularity for customers. Flat or time-varying rates are proposed for residential customers, so they are encouraged to compare current energy costs to other rate options and select the best rate plan (SCE; 2019). The aim of this section is to retain the cost-efficient solution, i.e, one meter or submetering, by choosing a combination of energy profiles; grid charges are exogenously fixed beforehand to minimize the energy costs. The logic behind this choice is to anticipate EV owner's action regarding the choice of rates assuming that a single consumer decision does not have an impact on the other

⁸ $I^{DSO} (50\% \text{ prospective}) = \frac{0.5 * \text{Average sunk costs}}{\text{Average coincident peak}} = \frac{0.5 * 510 \$}{4 \text{ kW}} = 63.7 \frac{\$}{\text{kW}}$

⁹We reinforce the assumption that EV charging done via smart-charging will not deeply affect the coincidental peak demand. Therefore, the average peak used for prospective costs calculation corresponds to the coincident peak without any EV or DER installed.

consumers' choices, therefore having negligible impact on the network tariff design.

The agents possessing an EV are analyzed individually using the MILP model described in modeloverview with respect to their total costs. All three energy profiles are adopted for the agents using only one meter (flat, TOU1, TOU2), while for the submetering configuration, a combination of a flat rate for the houseloads and TOU1 or TOU2 for EV charging will be considered. According to our setup, only prosumers will have the option of adopting V2G technologies since they are considered full-innovators. We split the analysis of consumers who are not able to invest in DER and prosumers who can. Both Figures 4.5 and 4.6 show the variation of the total cost for consumers and prosumers owning an EV under different energy profiles.

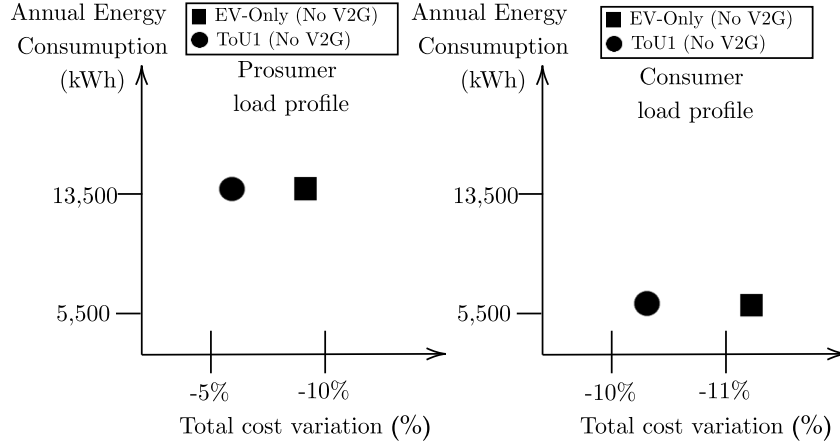


Figure 4.5: Energy cost variation without DER investment.

First, Figure 4.5 show the cost variation of two rate choices compared to the flat baseline rate for two different load profiles. This clearly reveals the positive impact of submetering by applying EV-only tariffs for agents who are not able to invest in DER. For the prosumer load profile, the cost reduction obtained by adopting an EV-only solution (Flat rate for the house plus TOU1 for the EV) surpasses the whole-house TOU1 tariff by around 2%, while for the consumer profile, half of this value is obtained. In conclusion, the greater the energy consumption of the households, the higher are the bill savings brought by the submetering solution.

Prosumers who are ready to invest in DER may have different choices regarding the type of solution to adopt. Figure 4.6 shows that whole-house TOU tariffs are

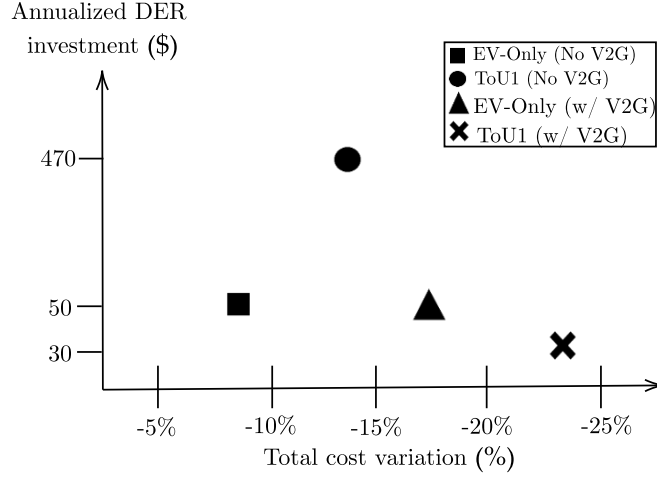


Figure 4.6: Energy cost variation with DER investment.

preferred since they bring higher energy cost reduction with or without V2G. This preference is due to the higher cost-effectiveness of arbitraging energy from off-peak to peak hours using a stationary battery or V2G under the whole-house TOU1. On the other hand, EV-only tariffs do not incentivize the adoption of DERs, especially batteries, considering that they will be charged under a flat rate which is not financially attractive. A great share of spread is already obtained by adopting the different tariffs for the submetering solution, reducing the gains brought by DERs¹⁰. The detailed results for both solutions are shown in Table B.1.

Finally, based on these results we are able to choose the energy profiles and type of solution for each agent who owns an EV for further analysis. For prosumers with EVs and V2G, the whole-house TOU1 tariff will be adopted due to the lowest costs observed among the options. For consumers who possess an EV, the submetering solution coupling flat rate for the house loads and TOU1 for the EV charging will be adopted for the same reason of cost-effectiveness. For the comparison scenario, all agents able to invest in DER will adopt TOU1 and passive consumers will select flat rates.

¹⁰This scenario could differ according to price, for instance, simulations with a more conservative PV cost of 1,500 \$/kWp indicates that EV-only tariffs are more cost-effective than ToU, without the need for great investments in DER. The full data of this scenario is presented in Table B.2

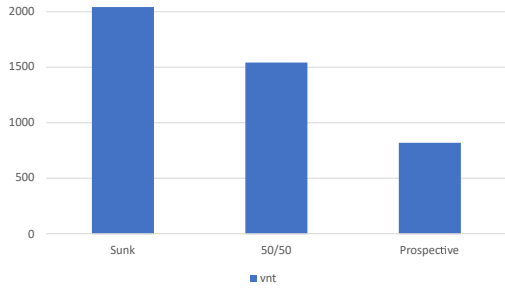
5.2 Network costs impact

With the energy profiles defined for all agents, it is possible to identify the impacts on network costs caused by EVs and submetering solutions. The MPEC model allows for simulating several tariff designs that can be used to recover grid costs by the network operator. We adopt two possible tariffs structures for this purpose: a pure volumetric tariff which is the most common way of billing customers in the current residential sector and a three-part tariff including capacity and fixed charges. A technology scenario using V2G technology and submetering is also included. This represents a total of four scenarios which includes the two different tariffs structures and the possibility of adopting EV submetering coupled with V2G.

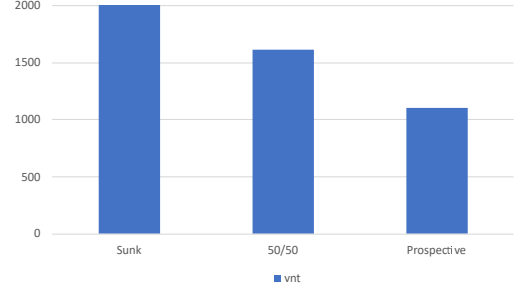
First, the changes in total network costs are going to be presented according to all three grid cost structure scenarios. Then, individual costs variation and their manner of allocation according to different tariff designs will be explored. We focus on the submetering solution including the variation that it may cause in network costs to verify its cost-effectiveness. The cumulative network costs for all scenarios based on three grid costs structure is presented below in Figure 4.7:

Our main observation is the higher the share of prospective costs in the network cost structure, the lower the total grid costs. This is due to the implicit cooperative behavior of all agents once variable costs are present and dependent on the coincident peak. In the case of 100% sunk costs, prosumers invest as much as possible in DERs to avoid grid charges and shift more of it to the consumers. We are going to focus on the scenarios with prospective costs given the exhaustive sunk costs analysis in (Hoarau and Perez; 2019; Schittekatte et al.; 2018). Notwithstanding, in both cases with prospective charges, prosumers invest in DERs to reduce their contribution to coincident peak increase, while EV owners also use smart-charging to avoid constrained hours. As a consequence, the tariff will decrease for all agents since the coincident peak that drives network variable costs is greatly reduced.

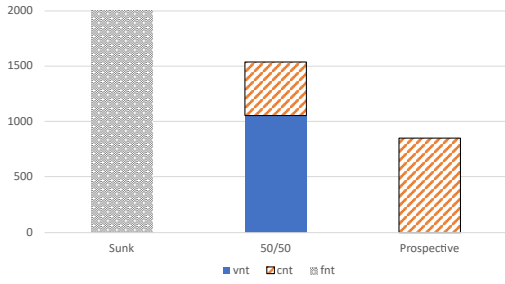
We note a perceptible increase in the cumulative network charges for the scenarios with V2G and submetering containing variable charges (see Table B.3 for more numerical details). The underlying logic is that V2G greatly reduces the need for



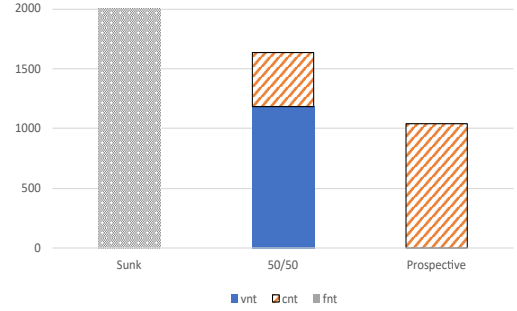
(a) Volumetric tariff.



(b) Volumetric tariff with V2G and EV sub-metering.



(c) Three-part tariff.



(d) Three-part tariff with V2G and EV sub-metering.

Figure 4.7: Total network costs.

battery investment. Unlike the stationary batteries, EVs are away from home during greater part of the day. Thus the required charging episodes for driving needs share the same peak period as those required for energy arbitrage. Consequently, an increase in the coincident peak occurring in off-peak period increases the network tariff. A possible solution to alleviate a coincident peak increase during off-peak periods involves charging EV at work or using public charging infrastructure. If this type of charging is incentivized, users could spread the EV charging for all hours of the day, which would have a positive impact on the total grid costs to be recovered.

The shift from volumetric to three-part tariff does not significantly change the network costs, albeit impacting users in its allocation. Prospective costs, if recovered via capacity charges, will benefit those who can reduce their private peak by investing in storage or adopting V2G technology. While under volumetric tariff, storage will be mostly used to arbitrage energy from on-peak to off-peak periods and lower the coincident peak. This will optimize the energy usage of prosumers without deeply interfering with the charges paid by consumers. There will then be fewer fairness

issues under the volumetric tariff in which consumers will be spared of high cost-shifting levels as shown in Figure 4.8.

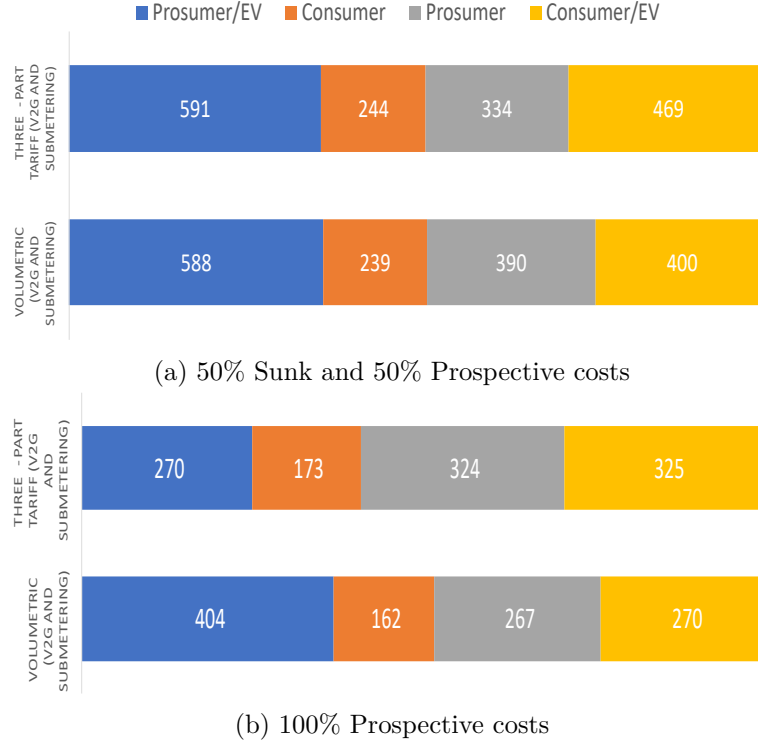


Figure 4.8: Network cost breakdown.

Comparing the volumetric tariff with a three-part tariff, consumers will experience a 1.5% and 3.7% reduction of grid charges for the 50% sunk 50% prospective and 100% prospective scenario, respectively. The same trend is observed for consumers with an EV, but in this case, the magnitude of the reduction is around 14% and 11%. Clearly, volumetric tariff favors the agents possessing an EV (submetered or not) who cannot invest in DERs. Nevertheless, it is essential to determine the total charges for this agent to evaluate the cost-efficiency of the submetering solution. Gains obtained from energy savings could be outweighed by increases in network charges due to other agent's reactions to the type of tariff applied. Therefore, Figure 4.9 computes the total costs for consumers with EV with regard to different tariffs and technological scenarios.

A dedicated tariff for EVs excluding house loads will create a positive spread with respect to energy charges as first described in section 5.1. The extended analysis, which includes the variation of network costs caused by other agent responses in this context,

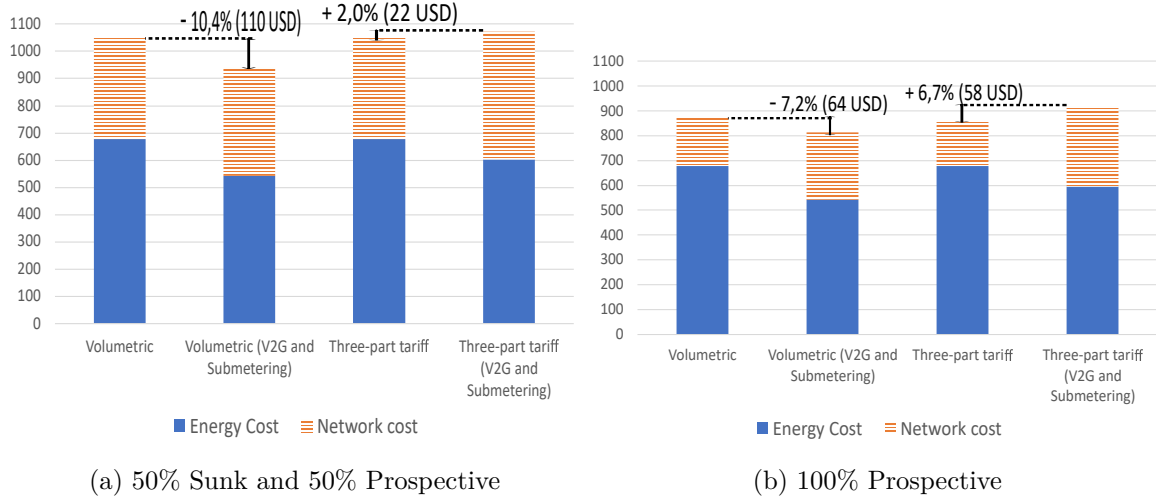


Figure 4.9: Total costs of Consumer/EV agent for all four scenarios.

will shed light on the potential of this solution. Under the volumetric tariff, the rise of network costs driven by a slight increase in coincident peak does not outrun the reduction in energy costs. The final bill reductions observed are around 10.4% and 7.2% for the 50% sunk 50% prospective and 100% prospective scenario, respectively. In the case of three-part tariffs, the outcome is not as favorable. The capacity charges applied to agents will transfer the network savings by prosumers to consumers, including the EV with submetering. In this case, the rise of network charges will surpass the energy savings by having two different tariffs. Therefore, a final rise of 2.0% and 6.7% is observed.

6 Discussion and policy implications

The integrated assessment of submetering exploring energy and network charge variation showed that this solution brings added value to EV charging. Submetering simplifies the indirect load control of EVs by using a specific economic signal for charging while leaving other appliances available to be under another rate. The adoption of an adequate smart-meter placed upstream that can properly communicate with the EVSE meter are imperative to achieving this. Pilots and demonstration projects are essential not only to prove the feasibility of the concept but also to establish future protocols and adjust the technology appliances involved. The transaction costs involved

in adjusting and optimizing the usage of the EVSE meter would be counterbalanced in a short period taking into consideration the variety of services potentially available. This configuration of meters also allows for other EV energy services such as frequency regulation that can be done using V2G without the need to buy or rent a dedicated meter. Stacked energy services potentially allow for fairer revenues for EV owners where the proposed submetering solution extends the service portfolio using smart-meters.

With respect to rate plans offered by utilities, the gains obtained from submetering can be enhanced with high on-peak charges or super off-peak periods proposed by some electricity providers, for example. We tuned our counterfactual time-varying energy profiles with respect to a flat energy tariff, so that the energy costs, in the end, would be practically the same. However, in real-life tariff books, the spread between a flat rate and the price levels of a domestic time-of-use proposed could be higher than the one captured in our results. We showed that the concept can bring fair yearly gains varying from \$64 to \$110 if well managed. However, the exact benefit remains sensitive regarding the rate plans available from each utility. Regulators should then incentivize utilities to propose more time-varying rate plans to boost demand-side management for users including EVs and DERs.

Finally, two different tariffs give users more flexibility to optimize the electricity bill for a particular load like electric vehicles. Moreover, the "type-of-use" tariffs can also be applied for other loads such as heat pumps. In theory, three tariffs driving different appliances in the same household could bring higher electricity bill savings if well optimized. This framework would substantially complexify user's understanding of the bill, which could discourage them from adopting this solution. Another drawback is the risk of badly designing a rate plan that could over-incentivize a specific type of load usage and bring deficit to the utility budget. The concept of price discrimination applied in these tariffs should be carefully taken into account to avoid any subsequent fairness issues between customers.

7 Conclusion

The adoption of an electricity rate designed specifically to charge EVs at home enables charging costs reduction for a myriad of dwellings. Assuming that household demand without flexible loads is quasi-inelastic, separating the billing of EV charging gives a fair incentive to adopt domestic EV-only rates. We develop a game-theoretical model, expressed, and treated as a Mathematical Program with Equilibrium Constraints (MPEC), to capture the interaction between a National Regulatory Authority (NRA) and the dwellings. This type of modeling is essential to determine the network tariff endogenously depending on the reactions of all agents. With the uptake of domestic EV-only tariffs, the grid operators will also have the necessary information about charging events and could better accommodate other EVs while avoiding costly grid reinforcements. NRAs on their end can adapt a tariff structure that gives incentives for DER and a separate one for EV adoption.

A fair energy cost reduction is observed with EV-only tariff for the adopter while keeping the network charges fixed. However, by recovering grid costs via a three-part tariff that contains capacity charges, the network costs increase offset the gains brought by energy savings. Under a pure volumetric tariff, fairness issues were nuanced, resulting in well-allocated network costs distribution in which consumers experience a higher decrease in their charges. In addition, the submetering concept can bring yearly gains varying from \$64 to \$110 under this type of tariff.

Our results could be used to support the creation of new local projects useful to demonstrate the cost-benefit of this solution applied to a specific context. The majority of pilot projects currently concentrated in the U.S may not sufficiently represent all diversity of contexts in which EV-only tariffs could work properly. Extending the number of pilots to other countries is essential to identify all possible barriers. With respect to future work, an extension of the problem for regulators in neighboring countries could frame the economic spillover between them. Different EV penetration, DER levels, and adoption rate of EV-only tariffs could provide a more reliable framework. Moreover, surveys including the option of EV-only tariffs to customers to assess their acceptance is crucial for better the design of this type of tariffs.

8 References

- ACER (2020). Annual Report on the Results of Monitoring the Internal Markets in 2019 Electricity and Natural Gas. 124, 125
- Ansarin, M., Ghiassi-Farrokhfal, Y., Ketter, W. and Collins, J. (2020). Cross-subsidies among residential electricity prosumers from tariff design and metering infrastructure, *Energy Policy* **145**(July): 111736.
URL: <https://doi.org/10.1016/j.enpol.2020.111736> 108
- Askeland, M., Backe, S., Bjarghov, S. and Korpås, M. (2021). Helping end-users help each other : Coordinating development and operation of distributed resources through local power markets and grid tariffs, *Energy Economics* **94**: 105065.
URL: <https://doi.org/10.1016/j.eneco.2020.105065> 108
- Avau, M., Govaerts, N. and Delarue, E. (2021). Impact of distribution tariffs on prosumer demand response, *Energy Policy* **151**(February): 112116.
URL: <https://doi.org/10.1016/j.enpol.2020.112116> 108
- Backe, S., Kara, G. and Tomasgard, A. (2020). Comparing individual and coordinated demand response with dynamic and static power grid tariffs, *Energy* **201**: 117619.
URL: <https://doi.org/10.1016/j.energy.2020.117619> 108
- Borenstein, S. (2012). The redistributive impact of nonlinear electricity pricing, *American Economic Journal: Economic Policy* **4**(3): 56–90. 122
- Borenstein, S., Fowlie, M. and Sallee, J. (2021). Designing electricity rates for an equitable energy transition. 107
- Burger, S. P., Knittel, C. R., Pérez-arriaga, I. J. and Schneider, I. (2020). The Efficiency and Distributional Effects of Alternative Residential Electricity Rate Designs, *The Energy Journal* **41**(1): 199–240. 122
- California Energy Commission (2019). Joint iou electric vehicle load research. 123
- Cooper, A. and Shuster, M. (2021). Electric Company Smart Meter Deployments: Foundation for a Smart Grid (2021 Update), (April). 107
- CPUC (2021). Summary of cpuc actions to support zero-emission vehicle adoption.
URL: <https://www.cpuc.ca.gov/zev/>. Accessed: March 25, 2021 107
- EIA (2019). Electric power monthly. energy information administration.
URL: <https://www.eia.gov/electricity/>. Accessed: March 25, 2021 125

EIA (2020). Electricity use in homes. energy information administration.

URL: <https://www.eia.gov/tools/faqs/faq.php?id=97&t=3>. Accessed: June 25, 2021 122

Electric Vehicle Database (2021a). Energy consumption of full electric vehicles.

URL: <https://ev-database.org/cheatsheet/energy-consumption-electric-car>. Accessed: March 25, 2021 123

Electric Vehicle Database (2021b). Useable battery capacity of full electric vehicles.

URL: <https://ev-database.org/cheatsheet/useable-battery-capacity-electric-car>. Accessed: March 25, 2021 123

European Commission (2020). *Benchmarking Smart Metering Deployment in EU-28*, number December. 107

Freitas Gomes, I., Perez, Y. and Suomalainen, E. (2021). Rate design with distributed energy resources and electric vehicles : A Californian case study, *SSRN* (March).

URL: <https://fsr.eui.eu/publications/?handle=1814/69861> 108

Govaerts, N., Bruninx, K., Le Cadre, H., Meeus, L. and Delarue, E. (2019). Spillover effects of distribution grid tariffs in the internal electricity market: An argument for harmonization?, *Energy Economics* **84**. 126

Hemmati, R. and Mehrjerdi, H. (2020). Investment deferral by optimal utilizing vehicle to grid in solar powered active distribution networks, *Journal of Energy Storage* **30**(April): 101512.

URL: <https://doi.org/10.1016/j.est.2020.101512> 109

Hildermeier, J., Kolokathis, C., Rosenow, J., Hogan, M., Wiese, C. and Jahn, A. (2019). Smart ev charging: A global review of promising practices, *World Electric Vehicle Journal* **10**(4): 1–13. 108

Hoarau, Q. and Perez, Y. (2018). Interactions between electric mobility and photovoltaic generation: A review, *Renewable and Sustainable Energy Reviews* **94**(October): 510–522.

URL: <https://doi.org/10.1016/j.rser.2018.06.039> 108

Hoarau, Q. and Perez, Y. (2019). Network tariff design with prosumers and electromobility : Who wins , who loses ?, *Energy Economics* **83**: 26–39.

URL: <https://doi.org/10.1016/j.eneco.2019.05.009> 108, 130

IEA (2020). Tracking transport report. 106

IEA (2021). Global EV Outlook 2021, *Global EV Outlook 2021* . 120, 124

IOUs, C. (2021). Distributed generation successor tariff workshop: Joint iou proposal.

URL: <https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=6442468353>, Accessed: May 24, 2021 126

- King, C. and Datta, B. (2018). EV charging tariffs that work for EV owners, utilities and society, *Electricity Journal* **31**(9): 24–27.
URL: <https://doi.org/10.1016/j.tej.2018.10.010> 108, 109
- Knezović, K., Marinelli, M., Zecchino, A., Andersen, P. B. and Traeholt, C. (2017). Supporting involvement of electric vehicles in distribution grids: Lowering the barriers for a proactive integration, *Energy* **134**: 458–468. 106, 109
- Küfeoğlu, S., Melchiorre, D. A. and Kotilainen, K. (2019). Understanding tariff designs and consumer behaviour to employ electric vehicles for secondary purposes in the United Kingdom, *Electricity Journal* **32**(6): 1–6. 108, 109
- Mayol, A. and Staropoli, C. (2021). Giving consumers too many choices: a false good idea? A lab experiment on water and electricity tariffs, *European Journal of Law and Economics* **51**(2): 383–410.
URL: <https://doi.org/10.1007/s10657-021-09694-6> 109
- NREL (2020). Annual Technology Baseline: Commercial PV, (November).
URL: <https://atb.nrel.gov/electricity/2020/index.php?t=sd> 123
- Odyssée Mure (2019). Electricity consumption per dwelling. odyssée-mure.
URL: <https://www.odyssee-mure.eu/publications/efficiency-by-sector/households/electricity-consumption-dwelling.html>. Accessed: June 25, 2021 122
- Pasaoglu, G., Fiorello, D., Martino, A., Zani, L., Zubaryeva, A. and Thiel, C. (2014). Travel patterns and the potential use of electric cars - Results from a direct survey in six European countries, *Technological Forecasting and Social Change* **87**: 51–59.
URL: <http://dx.doi.org/10.1016/j.techfore.2013.10.018> 123
- PGE (2021). Ev rates. pacific gas and electric company.
URL: https://www.pge.com/en_US/residential/rate-plans/rate-plan-options/electric-vehicle-base-plan/electric-vehicle-base-plan.page. Accessed: March 25, 2021 106
- Salah, F., Ilg, J. P., Flath, C. M., Basse, H. and Dinther, C. V. (2015). Impact of electric vehicles on distribution substations : A Swiss case study, *Applied Energy* **137**: 88–96.
URL: <http://dx.doi.org/10.1016/j.apenergy.2014.09.091> 106, 109
- SCE (2019). Tariff books. southern california edison.
URL: <https://www.sce.com/regulatory/tariff-books/rates-pricing-choices>. Accessed: July 17, 2019 127

- Schittekatte, T. and Meeus, L. (2020). Least-Cost Distribution Network Tariff Design in Theory and Practice, *The Energy Journal* **41**(5). 108, 126
- Schittekatte, T., Momber, I. and Meeus, L. (2018). Future-proof tariff design: Recovering sunk grid costs in a world where consumers are pushing back, *Energy Economics* **70**: 484–498.
URL: <https://doi.org/10.1016/j.eneco.2018.01.028> 130
- SDGE (2021). Ev plans. san diego gas and electric.
URL: <https://www.sdge.com/residential/pricing-plans/about-our-pricing-plans/electric-vehicle-plans>. Accessed: March 25, 2021 106
- Simshauser, P. and Downer, D. (2016). On the Inequity of Flat-rate Electricity Tariffs Author (s): Paul Simshauser and David Downer Source : The Energy Journal , JULY 2016 , Vol . 37 , No . 3 (JULY 2016), pp . 199-229 Published by : International Association for Energy Economics Stable URL : <https://www.jstor.org/stable/44075655> On the Inequity of Flat-rate Electricity Tariffs, **37**(3): 199–229. 126
- Smart Electric Power Alliance (2019). Residential Electric Vehicle Rates That Work, (November): 1–46. 106
- Thompson, A. W. and Perez, Y. (2020). Vehicle-to-Everything (V2X) energy services , value streams , and regulatory policy implications, *Energy Policy* **11**(July): 111136.
URL: <https://doi.org/10.1016/j.enpol.2019.111136> 109
- Western Power Distribution (2019). Final Electric Nation Customer Trial Report. 123

* * *

*Le véritable voyage, ce n'est pas de parcourir le désert
ou de franchir de grandes distances sous-marines, c'est
de parvenir en un point exceptionnel où la saveur de
l'instant baigne tous les contours de la vie intérieure.*

Antoine de Saint-Exupéry - *Le petit prince*

* * *

Chapter 5

General Conclusion

This dissertation has investigated several key impacts of electric mobility in an energy transition context, motivated by climatic aspects (reducing greenhouse gases) and health aspects (decreasing air pollution). We explore the relations between electric vehicles and distributed energy resources in a multidimensional framework. A smooth introduction of EVs mainly requires an adapted regulatory framework for power systems. In this context, electricity rates will be fundamental to unlock EV's role as a DER without undervaluing the user's mobility needs. This final section is composed of three parts. The first part summarizes key takeaways of each chapter of the dissertation. The second part revisits the findings to establish transversal links and conclusions. The final part proposes several leads for future research.

1 Summary of contributions

1.1 Chapter 2

In our analytical framework, the coupling between PV–EV–battery relates to different layers of analysis. The synergies of the coupling between distributed battery resources and photovoltaic power generation will help decarbonize the electric power and mobility sectors while profitable - if well managed - to most agents involved: system operators, regulators, ordinary consumers, etc. To frame the most critical aspects involving the coupling itself, we proposed an analytical framework with three layers of research: Technical, economic, and societal. We showed that technological progress regarding PVs, batteries, and EVs has often been a step ahead of policies and regulations, causing actors' strategies to be outdated and impeding the optimal utilization of each resource. For example, in the uncoordinated PV boom caused by unadapted Feed-in-Tariffs schemes and in the V2G limited market participation due to the lack of adapted market design.

Policy innovation on user acceptance could assure that the other way around becomes true: with policies ahead of technical progress, adapted ecosystems for technological development can emerge. Policies could prepare the field to accommodate Distributed Energy Ressources (DERs) and accelerate their adoption based on the techno-economic models and socio-technical analysis results. Our analysis identifies the gaps warranting further investigation, and we propose a timeline for research purposes. In the short term, the focus should be on adjusting policies and regulations to extract the maximum benefit of EV/PV coupling. More tariff design studies showing the effects of EVs coupled with PVs and stationary batteries could help policymakers finding an adapted rate for the synergy. Regarding policies, to the best of our knowledge, no joint policy for EV/PV coupling has been studied in the literature, while it could accelerate both DERs deployment.

In summary, emerging technologies (e.g., microgrids, vehicle-to-grid, and blockchain) will reshape PV–EV–battery synergy, forcing electricity grid operators to adjust grid management. Second, inappropriate economic regulations (e.g., obsolete tariff and ancillary services market designs) and outdated strategies formulated by the automo-

tive sector could jeopardize all the potential benefits of EV/PV coupling. Then, user acceptance appears to be a decisive variable in whether people are willing to invest in distributed energy systems.

1.2 Chapter 3

Following the literature gaps found in the second chapter, this study focuses on Distributed Energy Resources (DERs) investments at private facilities. We assess how electricity rates affect DERs investment from the private facilities' perspective and cost recovery from the utility's perspective. We simulated different technology combinations of Photovoltaic power (PV), electric storage systems (BESSs), and Electric Vehicles (EVs) to evaluate the private investment part and the avoided cost model to account for the impact on the utility side.

We found that solar PVs significantly reduced electricity bills under the energy tariff (for a fixed DER investment scenario and all DER combinations). Whereas, on the utility side, the tariffs with high demand charges often presented lower cost-shifting. This finding underlines the possible negative budget impact of a regulatory change aiming to reduce cost-shifting values for buildings already under energy tariff and high solar PV. The endogenous investment model revealed how the facility would invest rationally to minimize its costs. For the conservative scenario, the average DER capacity installed often used EV+BESS to reduce its electricity costs, indicating that the mix can work together to support the facility grid, each one bringing its benefits.

Coincident peak tariff yielded remarkable results for conservative endogenous investments, in which we obtained the highest net present value and the lowest cost-shifting. The drawback of this kind of rate is that there is a danger of creating a demand peak elsewhere in the daytime, probably early morning (8–10 AM) or even later evening (9–11 PM). Then, in the optimistic scenario, a peak-coincident tariff becomes less attractive for buildings due to the limited gains obtained after offsetting all coincident demand; investments cease from that point. Under capacity tariffs, however, avoided costs increase more than electric savings because cheap storage targets several hours of the day. The shift from energy-based tariffs towards coincidental and capacity-based tariffs can alleviate cost-shifting values caused by strong DER pene-

tration.

The last aspect we analyzed is the EV net income obtained from energy services provided to the facility. EV availability and applicable electricity tariffs scheme have an essential impact on facilities' adoption of EV capacities and associated revenues. Regarding EVs, the net income revenue varied between \$57 and \$218, with the highest revenue found under capacity tariffs. Although bill management can be the topmost remunerated service for EVs, it still strongly depends on the tariff and the contract to split gains between EV owners and the facilities. In addition, the optimistic DER cost scenario showed that batteries substituted almost all the available vehicles, capturing their share of the value created under all tariffs.

1.3 Chapter 4

The adoption of an electricity rate explicitly designed to charge Electric Vehicles (EVs) at home enables charging costs reduction for many dwellings. Assuming that household demand without flexible loads is quasi-inelastic, separating EV charging bills gives a fair incentive to adopt domestic EV-only rates. We develop a game-theoretical model, expressed and treated as a Mathematical Program with Equilibrium Constraints (MPEC), to model the interaction between a National Regulatory Authority (NRA) and the dwellings. This type of modeling is essential to determine the network tariff endogenously depending on the reactions of all agents.

With the uptake of domestic EV-only tariffs, the grid operators will also have the necessary information about charging events and better accommodate other EVs while avoiding costly grid reinforcements. NRAs can adapt a tariff structure that incentivizes Distributed Energy Resources (DERs) and EVs adoption separately. A fair energy cost reduction for adopters is observed with an EV-only tariff while keeping the network charges fixed. However, network costs may offset energy savings if grid costs are recovered via a three-part tariff containing capacity charges. Under a pure volumetric tariff, fairness issues were nuanced, resulting in well-allocated network costs distribution in which consumers experience a higher decrease in their charges. In addition, the submetering concept can bring yearly gains varying from \$64 and \$110 under this type of tariff – we confirmed submetering's positive effect on EV charging val-

ues through an integrated assessment exploring energy and network charge variation. Submetering simplifies the indirect load control of EVs by using a specific economic signal for the charging while leaving other appliances available to be under another rate.

2 Transversal considerations

The chapters of this dissertation are heterogeneous in their methods but linked regarding the main subject studied. We analyzed the impacts of electricity rates in two different sectors: commercial and residential. There are particularities in those sectors which need specific policies recommendations for each. First of all, the load profiles in commercial sites are similar to a bell-shaped curve, while households display the typical 'humped-camel shape.' This is crucial to assess how investments in Distributed Energy Resources (DERs) will occur and which tariffs will support them. As solar photovoltaic power (PV) generation is already synchronized with part of the load present in commercial facilities, the cost-effectiveness of investing in solar energy is high from the start. Moreover, under existing incentive programs such as feed-in-tariff and net-metering with volumetric tariffs, over-adoption of solar PV may be observed, as in California and Australia. The direct consequence is the increase of cost-shifting levels. Our recommendation in chapter 3 was that a coincident peak tariff in the short-term followed by capacity tariffs in a mid-term period could alleviate some cost-shifting issues. However, it does not mean that this solution would also work effectively for the residential sector. As seen in chapter 4, capacity charges would only over-incentivize the adoption of storage and bring back the fairness problems in the residential sector. It is known that solar PV coupled with net-metering would bring important fairness issues among customers under volumetric tariffs, but EVs could help to counterbalance this issue.

Another important consideration is the EV owner's behavior. The widespread of V2X technology among EV drivers would increase their options of providing energy services to third parties or themselves. The net income obtained by providing bill management services to commercial facilities depends on systematic overnight charg-

ing. Similarly, arbitraging energy at home under a time-of-use tariff also requires this type of behavior. The risk of having a higher coincident peak created by EV charging around dawn and early morning is high if not well coordinated. This fact could increase network costs for all users. In this context, the connection hours based on EV drivers' mobility patterns would define what type of service among the ones studied would bring higher gains. If the user leaves and arrives early at home (leaving around 7 AM and coming back at 5 PM as adopted in chapter 4), the complementary charging at work and the discharge during on-peak periods at home will be profitable for them and avoid network increase for other users. Otherwise, if it is a late worker (leaving around 7 AM and coming back at 7 PM as adopted in chapter 3), the bill management service provided for the commercial facility and a coordinated charging at home will be the most cost-efficient solution.

3 Future works

Finally, potential avenues for future work can be derived from this manuscript. When dealing with electric vehicles and different DERs, there is a myriad of research questions that could be assessed within this context. Chapter 2 provides an educational framework pointing out critical literature gaps which need further information. Moreover, we can also offer future steps for research within our applied modeling frameworks.

First, the recurrent inclination when dealing with DERs behind the meter is adding more technologies and improving the granularity analysis. For instance, heat pumps could also be used by consumers to react to the network tariff design. Accounting for these electricity-consuming devices could bring new insights regarding synergy between DERs. Moreover, demand response could also be included. All the load profiles used in our chapters were inelastic, leaving peak shifting to batteries or EVs. Demand response could compete with them for this type of service. Larger databases for different classes of customers, different consumer profiles, longer time series could also be used to do specific case study analyses.

Modeling EV problems require a spatio-temporal approach. The adoption of

deterministic parameters based on pilot data can provide fair results. Nevertheless, including uncertainties around driving needs and connection hours could provide additional insights. Uncertainties in an equilibrium framework complexify the resolution of the problem due to the increased number of scenarios that should be simulated. The grid costs structure could also be more detailed by including network losses, fixed costs, and the cost of bidirectional flows. In this context, enabling locationally more granular network tariffs would require more detailed modeling of the distribution network, complicating the possibilities of finding an equilibrium regarding consumers' reactions. This would allow studying the cost-inefficiency of uniform tariffs over territory without taking local constraints into account. New methods of resolution with respect to equilibrium problems could be applied to solve this issue. Reinforcement learning is a promising concept that can perfectly couple to the framework of adding uncertainties or the network itself.

Energy communities can also be modeled to assess the effects they may have on grid tariffs. The cooperative behavior within a community could be modeled as a local market that can bring additional gains to all participants and other network users. Alternatively, this framework including distributed energy resources and EVs could be translated inside peer-to-peer power markets. Peer-to-peer markets would be a way to connect multiple small producers to multiple small consumers. Both local markets with the prices defined by a supply-demand equilibrium condition in the neighborhood and peer-to-peer markets enabled by smart contracts connecting specific end-users deserve more investigation.

Chapter A

Appendix to Chapter 3

Optimization program

The endogenous model is fully described in this section with the main variables reflecting the charge and discharge decisions, solar, battery, and electric vehicle optimum capacity along with its constraints. The exogenous model is a simple modification of the fully endogenous one in which the DER capacities are fixed before leaving the choice of charge and discharge strategies to the model. For additional details.

- Indices and general notation:
 - EV: Electric vehicle;
 - ES: Stationary battery;
 - PV: Photovoltaic panel
 - m: Month index 1,2, 3...12;
 - h: Hour index 1, 2...24;
 - d: Day type 1,2,3;
 - k: All storage technologies ($EV \cup ES$);
 - i: Set of all technologies ($k \cup PV$);
 - s: Season winter, summer;
 - p: Tariff period on-peak, mid-peak, off-peak;

- NonCoin: Non-coincidental hours of the day;
- Coin: Coincidental hour of the day;
- Parameters
 - $load_{m,d,h}$: Client electricity demand in month m , day-type d and hour h [kW];
 - $ScArea_{PV}$: Area available for solar PV technology [m^2];
- Market data
 - $TEx_{m,d,h}$: Tariff for electricity export at time m,d,h [\$/kWh];
 - TF_m : Fixed charges for electricity access for month m [\$];
 - $TE_{m,d,h}$: Tariff for electricity consumption at time m,d,h [\$/kWh];
 - $TP_{s,p}$: Demand charges for season s and period p [\$/kW];
 - $TPNC_m$: Demand non-coincidental charges for m [\$/kW];
 - TPC_m : Demand coincidental charges for m [\$/kW];
 - P_{EV} : Electric vehicle electricity exchange price in residence [\$/kWh];
 - An_i : Annualized capital cost of DER technology i [\$];
 - IR : Interest rate on investments [%];
 - Lt_i : Lifetime of technology i [years];
 - $PBPeriod$: Payback period to integrate DER investments [years];
 - $BAUCost$: Total energy cost in the business-as-usual case without investments in DER [\$];
- Technology data
 - $SCEff_k$: Charging efficiency of storage technology k [%];
 - $SDEff_k$: Discharging efficiency of storage technology k [%];
 - $SCRate_k$: Maximum charge rate of storage technology k [%];
 - $SDCRate_k$: Maximum discharge rate of storage technology k [%];

-
- $GenU_{PV,m,d,h}$: Electricity generated to be used in the microgrid in time m,d,h [kW];
 - $GenS_{PV,m,d,h}$: Electricity generated to be exported in time m,d,h [kW];
 - $ScEff_{PV,m,h}$: Solar radiation conversion efficiency of PV technology in month m and hour h [%];
 - $ScPeakEff_{PV}$: Peak solar conversion efficiency of PV technology [%];
 - $SI_{m,d,h}$: Solar insulation at time m,d,h [kW/m²];
 - $EVCL$: Electric vehicle capacity loss per normalized Wh [dimensionless];
 - $EVFRC$: Future replacement cost of electric vehicle batteries [\$/kWh];
 - $DEROMFix_i$: DER fixed annual operation and maintenance cost per year of technology i [\$/kW or \$/kWh];
 - $CFixcost_i$: Fixed capital cost of technology i [\$];
 - $CVarcost_i$: Variable capital cost of technology i [\$/kW or \$/kWh];
 - \overline{SOC}_k : Maximum state of charge for technology k [dimensionless];
 - \underline{SOC}_k : Minimum state of charge for technology k [dimensionless];
 - φ_k : Losses due to self-discharge for technology k [%];
- Decision variables
 - $UL_{m,d,h}$: Client electricity purchased in month m, day type d and hour h [kW];
 - $SIn_{k,m,d,h}$: Energy input to storage technology k at time m,d,h [kW];
 - $SOut_{k,m,d,h}$: Energy output by storage technology k at time m,d,h [kW];
 - $E_{m,h}^{r \rightarrow c}$: Electricity flow from the residential building to the car [kWh];
 - $E_{m,h}^{c \rightarrow r}$: Electricity flow from the car to the residential building [kWh];
 - Cap_i : Installed capacity technology i [kW for PV and kWh for technologies k];
 - Psb : Binary decision of purchase or selling electricity in month m, day type d and hour h [dimensionless];

- Pur_i : Binary decision value of customer purchase of technology i [dimensionless];

Objective function:

$$Min \ c_{total} = c_{elec} + c_{DER} + c_{EV} - \sum_m \sum_d \sum_h GenS_{PV,m,d,h} \cdot Tex_{m,d,h} \quad (A.1)$$

Where:

$$\begin{aligned} c_{elec} = & \sum_m TF_m + \sum_m \sum_d \sum_h UL_{m,d,h} \cdot TE_{m,d,h} + \sum_s \sum_{m \in s} \sum_p TP_{s,p} \cdot max(UL_{m,(d,h)} \in p) \\ & + \sum_m TPN C_m \cdot max(UL_{m,d,(h)} \in NonCoin) + \sum_m TPC_m \cdot UL_{m,d,(h)} \in Coin \end{aligned} \quad (A.2)$$

$$c_{DER} = \sum_i (CFixcost_i \cdot Pur_i + CVarcost_i \cdot Cap_i) \cdot An_i + Cap_i \cdot DEROMFix_i \quad (A.3)$$

$$\begin{aligned} c_{EV} = & \sum_m \sum_h P_{EV} \cdot \left(\frac{E_{m,h}^{r \rightarrow c}}{SCEff_{k=\{EV\}}} - E_{m,h}^{c \rightarrow r} \cdot SDEff_{k=\{EV\}} \right) + \sum_m \sum_h EVCL \cdot \\ & EVFRC \cdot (SIn_{k=\{EV\}} + SOut_{k=\{EV\}} + E_{m,h}^{r \rightarrow c} + E_{m,h}^{c \rightarrow r}) \end{aligned} \quad (A.4)$$

Main constraints:

1. Energy balance

$$load_{m,d,h} + \sum_k \frac{SIn_{k,m,d,h}}{SCEff_k} = \sum_k SOut_{k,m,d,h} \cdot SDEff_k + GenU_{PV,m,d,h} + UL_{m,d,h} \quad \forall m, d, h. \quad (A.5)$$

2. PV output constraint

$$GenU_{PV,m,d,h} + GenS_{PV,m,d,h} \leq \frac{Cap_i}{ScPeakEff_{PV}} \cdot ScEff_{PV,m,h} \cdot SI_{m,d,h} \quad \forall m, d, h : i \in \{PV\} \quad (A.6)$$

$$\frac{Cap_{PV}}{ScPeakEff_{PV}} \leq ScArea_{PV} \quad (A.7)$$

3. Storage constraints

$$Cap_k \cdot \underline{SOC}_k \leq \sum_{n=0}^h (SIn_{k,m,d,n} - SOut_{k,m,d,n}) \cdot (1 - \varphi_k) \leq Cap_k \cdot \overline{SOC}_k \quad \forall k, m, d, h. \quad (A.8)$$

$$SIn_{k,m,d,n} \leq Cap_k \cdot SCRate_k \quad \forall k, m, d, h. \quad (A.9)$$

$$SOut_{k,m,d,n} \leq Cap_k \cdot SDCRate_k \quad \forall k, m, d, h. \quad (A.10)$$

4. General constraints

$$UL_{m,d,h} \leq Psb_{m,d,h} \cdot M \quad \forall m, d, h. \quad (A.11)$$

$$GenS_{PV,m,d,h} \leq (1 - Psb_{m,d,h}) \cdot M \quad \forall m, d, h. \quad (A.12)$$

$$Cap_i \leq Pur_i \cdot M \quad \forall i. \quad (A.13)$$

$$An_i = \frac{IR}{1 - \left(\frac{1}{(1+IR)^{Lt_i}} \right)} \quad \forall i. \quad (A.14)$$

$$C \leq BAUCost + \sum_i (CFixcost_i \cdot Pur_i + CVarcost_i \cdot Cap_i) \cdot \left(An - \frac{1}{PBPeriod} \right) \quad (A.15)$$

Exogenous investment DER sizing

There are several ways to size the installed solar PVs coupled with storage according to electricity needs, available space, and budget. For instance, it is possible to offset 100% of the electricity consumption and become independent of the grid. However, this method often leads to oversized solar PVs and battery storage, which is usually

not financially attractive. Another option is to size the DERs to offset a share of the non-coincidental or coincidental demand, reduce energy consumption during on-peak periods, and arbitrage electricity between different time windows or different places (commercial building and dwelling) via electric vehicle home charging. First, the portion of installed PV is expected to be large enough to offset 40% of the average annual week-day consumption; the power output required to meet 40% of the daily consumption is given by hourly adding the kWh needed along the day multiplied by the percentage offset factor¹. This is then divided by the scaled full sun equivalent obtained via the Solar Irradiation Database for the Los Angeles suburban area from the National Solar Radiation Database. Finally, this value is divided by the NREL Watts' default derate factor of 0.77, which accounts for shade, dirt, and losses².

The addition of storage can be useful to avoid excessive solar exports, reduce maximum demand, and arbitrage electricity throughout the hours of the day. To size BESSs, we simulate our average Solar PV generation to calculate the net load for each hour according to the facilities by subtracting the average annual week-day load of the facilities from the average Solar PV generation. The battery size is then the sum of the positive deviations of the net load from its mean during the most constrained hours of the system (4 - 9 PM) to flatten the peak load at this time. For the EV battery sizing, we use the equivalent capacity of the stationary battery calculated to find the trade-off between maximum charging/discharging power and available energy. Since the charging and discharging power rate and the maximum and minimum battery state of charge differ in these two DERs, we would have one scenario with the equivalent energy available and another with the equivalent power of the stationary batteries; a compromise is, therefore, necessary to avoid oversizing any of them³. The average solar PV amount for all facilities is 108.4 kWp, with a standard

¹The percentage offset factor states how much of the average annual week-day consumption will be offset by PV production. In our exogenous investment scenario, we choose 40% to avoid excessive solar exports to the grid. This factor was proved in the method not to strongly influence the qualitative results in the following sections.

²We calculate the output power for the medium office PV in the following manner: The sum of the hourly average week-day consumption is 2,063 kWh. By applying the factor of 40% we have a final value of 825 kWh; we divide this by the full sun equivalent for the region, which is 5.2h, and the NREL Watts factor 0.77, giving a final result of 206 kWp. The general formulation is given by:

$$PV_{out} = \frac{\text{Average annual week-day consumption} \cdot \% \text{ Offset factor}}{\text{Full sun equivalent} \cdot \text{NREL Watts Factor}}$$

³For example, a stationary battery of 258 kWh was sized for the medium office. To have the same

deviation of 54.89 kWp. In the case of batteries, the average is 147 kWh with 74.65 kWh of standard deviation, 278.4 kWh, and 125 kWh for EV average and standard deviation, respectively. Finally, after the amounts of DERs are calculated, we formulate three different technology scenarios: PV+BESS, PV+EV, and PV+EV+BESS⁴ under three different tariff structures (TOU-CAP, TOU-COIN, TOU-ENE) to proceed with our analysis.

Charging and discharging strategies

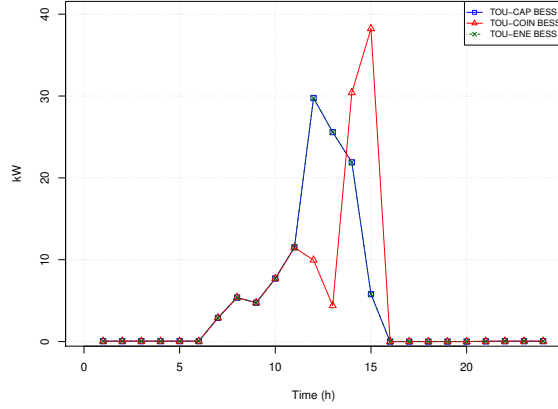
In this section, the storage charging and discharging episodes are discussed in depth according to the DER combination under the adopted tariffs. First, Figure A.1a show the charging behavior with only batteries while Figure A.1b shows the situation when vehicles are present. Then, Figure A.1c and A.1d show the charging behavior for the combination of both of them (EV+BESS).

For the BESS scenario described in Figure A.1a, under the capacity tariff (TOU-CAP), the battery is charged within the time period from 6 AM to 3 PM, but the main charging episode starts at 11 AM, lasting until 4 PM just before the beginning of the on-peak period. Under energy tariff (TOU-ENE), the charging strategies show very similar behavior to the capacity tariff to avoid the same on-peak periods. For the coincident peak tariffs, the battery is charged from 6 AM, with the main event starting at 1 PM and lasting until 4 PM, so that the battery can be charged enough when the coincident peak maximum demand charge (MDC) comes into effect.

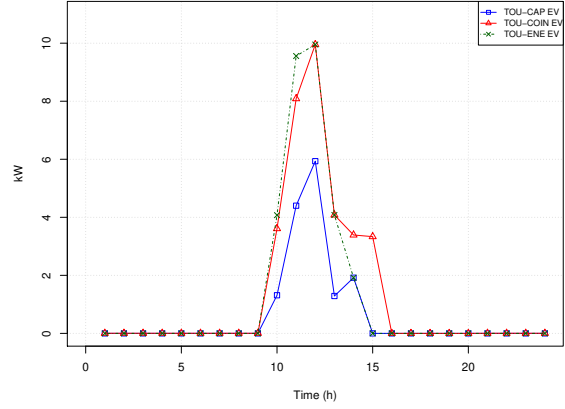
Most of the EV charging is done at owners' homes during off-peak hours with a specific tariff. However, according to Figure A.1b, a charging episode occurs when they arrive at 9 AM and lasts until 3 PM for all the tariffs when there is PV electricity excess with a peak around 12 PM to avoid profitless exports. For the coincident peak tariffs, the charging occurs from 9 AM until 4 PM, adding more energy on top of home charging. When the two forms of storage are present concomitantly (A.1c and

energy available, 6 EVs are needed. To maintain the equivalent power discharge rate, 10 EVs are required with the adopted parameters. In this case, the middle value of 8 vehicles is therefore chosen.

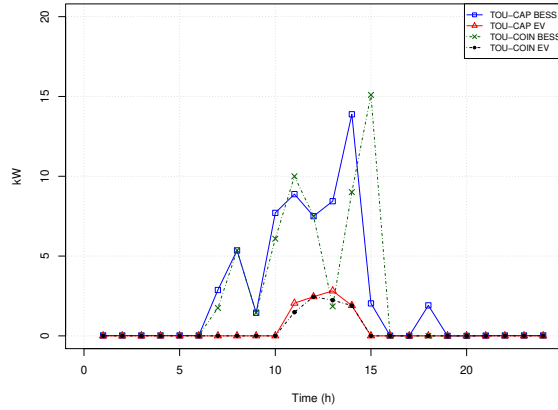
⁴The values of EV and BESS are halved in the last scenario to keep the amount of storage close to the other storage scenarios (e.g., PV+BESS and PV+EV).



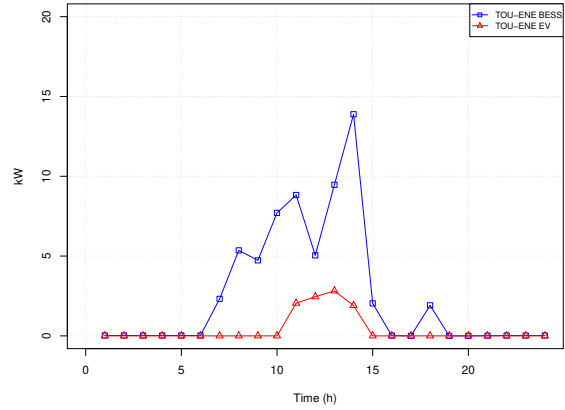
(a) BESS charging strategies under all tariffs.



(b) EV charging strategies under all tariffs.



(c) EV+BESS charging strategies under TOU-CAP and TOU-ENE.



(d) EV+BESS charging strategies under TOU-COIN.

Figure A.1: Charging strategies according to different DER scenarios and tariffs during summer (September).

Figure A.1d), the BESS charging is prioritized over EVs, while EVs are charged only when there is excess PV electricity generated from 10 AM until 3 PM for all tariffs. The charging pattern of the total charge, EV+BESS charging, is closely related to that with the BESS alone, which can be interpreted as an optimum strategy to follow. Finally, under coincident peak tariffs, the same behavior is found as under the other tariffs for the mix.

With regard to discharging strategies, there are several incentives to adopt storage, such as energy arbitrage, offset coincident peak MDC, non-coincidental MDC, and on-peak MDC. These are all summarized in Table A.1 along with the time at which each one occurs for each tariff. Since the PV generation is adequately synchronized

with the load of the facilities, it reduces a fair amount of maximum private demand, between 15% to 34% outside winter periods when the generation drops. The storage discharge strategy then focuses on offsetting the high demand periods outside the PV coverage when the fall in electricity production needs to be compensated for, which is from 4 PM. For all DER combinations, under coincident peak tariffs, the discharge occurs between 3 PM and 7 PM with different power peak rates.

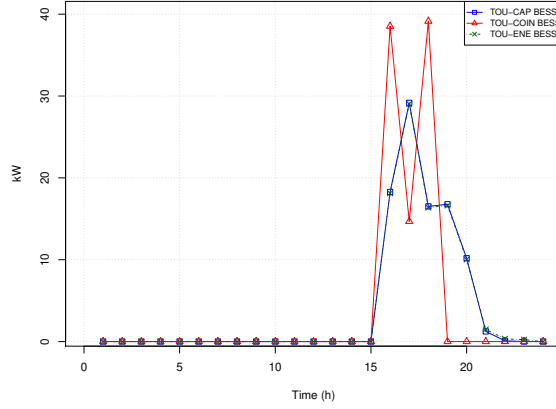
Table A.1: Discharging incentives per tariff structure

Tariff	Coin peak MDC	Non-coin MDC	On-peak MDC	Energy arbitrage
TOU-CAP	-	BESS: 3 - 8 PM (5 PM) ^a EV: 3 - 7 PM (5 PM) BESS/EV: 3 - 8 PM (7 PM) /3 - 7 PM (6 PM)	BESS: 4 - 9 PM EV: 3 - 6 PM BESS/EV: 4 - 9 PM / 4 - 7 PM	-
TOU-Coin	5 - 7 PM (6 PM)	-	-	-
TOU-ENE	-	BESS: 3 - 8 PM EV: 3 - 7 PM BESS/EV: 3 - 10 PM /3 - 7 PM	BESS: 4 - 9 PM EV: 3 - 7 PM BESS/EV: 4 - 9 PM / 4 - 7 PM	BESS: 4 - 9 PM (5 PM) EV: 4 - 7 PM (5 PM) BESS/EV: 4 - 9 PM (7 PM) / 4 - 7 PM (4 PM)

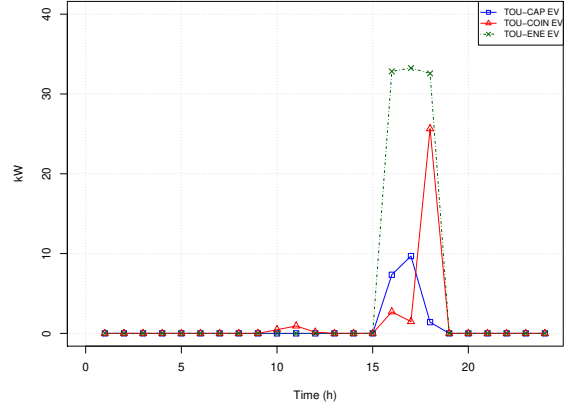
^aThe values in parentheses are the hour when the highest amount of discharging occurs.

Under the capacity tariff, the BESS starts discharging primarily to avoid its private peak demand, which is around 4–5 PM, and tries to offset the on-peak demand as much as possible until 9 PM. Under the energy-based tariff, the BESS discharge is employed to arbitrage energy between off-peak periods to on-peak. It supplies electricity from 3 PM until 9 PM with a peak at around 5 PM to offset the on-peak demand concomitantly. We note that the highest amount of energy discharge occurs, except for coincident peak tariffs, at 5 PM, as shown in Figures A.2a and A.2b when the load is still high, and the PV production is almost at its minimum level.

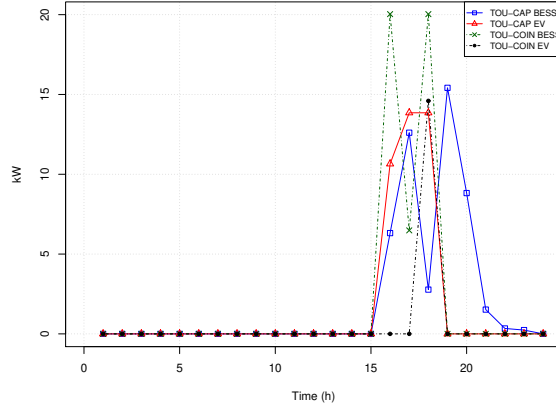
For EVs, under the capacity tariff, the EV starts discharging to primarily avoid the facility private peak demand, which is at 4-5 PM. EVs do not discharge at maximum power to offset the private peak because the battery degradation for EVs would offset the gains from private peak demand reduction. In addition, it is more useful to charge the vehicle with PV surplus to collect the narrow spread between the electricity generated at the building and that used to charge it at the owners' homes during summertime. Under the energy-based tariff, EVs discharge to arbitrage energy between off-peak and on-peak inside the facility and with the electricity consumed at their homes. This follows the strategy adopted by the BESS, but it has its constraints. EVs



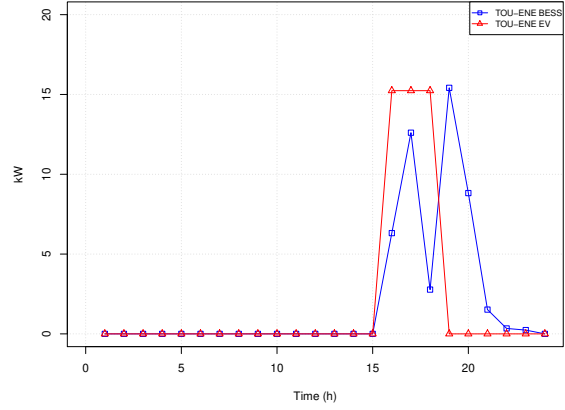
(a) BESS discharging strategies under all tariffs.



(b) EV discharging strategies under all tariffs.



(c) EV+BESS discharging strategies under TOU-CAP and TOU-ENE.



(d) EV+BESS discharging strategies under TOU-COIN.

Figure A.2: Discharging strategies according to different DER scenarios and tariffs during summer (September).

supply electricity from 3 PM to 7 PM; when the EVs depart, a higher discharge peak power rate managed by the charging station tries to compensate for the departure, proving that the EV discharging strategy is intimately connected to the arrival and departure schedules. There is no discharging episode starting around 7 AM simply because they are not yet connected at this time (A.2b, A.2c and A.2d).

For the joint combination of EV+BESS (Figures A.2c and A.2d), under the capacity tariff, it tries to replicate the same discharge strategy as in the scenario with only BESS. However, with battery support, EVs discharge nearly at their maximum average power rate (18 kW), compensating for the degradation and still trying to offset as much as possible the on-peak demand until 9 PM. Under the energy-based tariff,

EVs are the primary discharging storage form before their departure, while the BESS is just supporting them. When EVs start to leave, the BESS becomes the only storage system trying to arbitrage as much energy as possible during on-peak times.

Complementary Tables

Table A.2: SCE's General Services 2 electricity retail tariffs.

	TOU-CAP	TOU-COIN	TOU-ENE
Energy Charge (\$/kWh)			
Summer on-peak	0.11963	0.11963	0.48887
Summer mid-peak	0.11016	0.11016	0.16322
Summer off-peak	0.08055	0.08055	0.11227
Winter mid-peak	0.09781	0.09781	0.15888
Winter off-peak	0.0862	0.0862	0.08962
Winter super off-peak	0.06441	0.06441	0.07599
Non coincidental demand charges (\$/kW)	10.35	0	7.49
Coincidental demand charges (\$/kW)	0	14.37 (Winter) 30.20 (Summer)	0
Time-specific demand charges (\$/kW)			
Summer on-peak	19.85	0	4.35
Summer mid-peak	0	0	0
Winter mid-peak	4.02	0	0.85
Monthly fixed charges (\$/month)^a	129.9	129.9	129.9

^aFixed charges are the sum of customer charge, single phase service and TOU option meter charge

Table A.3: SCE's General Services 2 electricity retail tariffs time schedule.

Summer months (June 1st - September 30th):	
Summer on-peak	Weekdays: 4 PM - 9 PM
Summer mid-peak	Weekends: 4 PM - 9 PM
Summer off-peak	Weekdays and week-ends: All hours except 4 PM to 9 PM
Winter months (October 1st - May 31st):	
Winter on-peak	
Winter mid-peak	Weekdays and week-ends: 4 PM to 9 PM
Winter off-peak	Weekdays and week-ends: 9 PM to 8 AM
Winter super off-peak	Weekdays and week-ends: 8 AM to 4 PM

Table A.4: Variable coincidental hours along the months.

Month	Hour
January	7:00 PM
February	7:00 PM
March	7:00 PM
April	7:00 PM
May	7:00 PM
June	7:00 PM
July	6:00 PM
August	6:00 PM
September	6:00 PM
October	5:00 PM
November	6:00 PM
December	6:00 PM

Table A.5: Average % change in demand during system peak times for PV+BESS and PV+EV.

	PV+BESS			PV+EV		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
January	-30.8	-35.9	-33.7	-9.0	-2.0	-8.1
february	-34.0	-42.4	-37.3	-11.5	-5.2	-9.9
March	-37.8	-51.0	-42.7	-14.9	-11.0	-14.9
April	-34.9	-59.9	-56.2	-20.0	-19.7	-20.0
May	-58.3	-70.5	-63.3	-23.6	-23.3	-23.6
June	-57.4	-70.6	-65.9	-27.4	-27.0	-58.5
July	-43.9	-43.0	-43.6	-12.6	-29.5	-46.7
August	-42.7	-41.7	-42.5	-10.6	-28.6	-45.5
September	-38.3	-37.0	-38.0	-7.8	-25.8	-42.9
October	-32.5	-29.7	-32.6	-4.8	-19.0	-4.8
November	-26.8	-25.1	-27.9	-10.0	-16.6	-10.0
December	-27.3	-27.2	-30.1	-9.4	-17.5	-9.4

Table A.6: Average % change in maximum private demand for PV+BESS and PV+EV.

	PV+BESS			PV+EV		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
January	-39.6	9.7	-36.8	-16.6	-2.7	-16.6
february	-42.7	-5.4	-39.6	-18.7	-4.8	-18.7
March	-49.4	-16.8	-45.5	-24.0	-15.0	-24.0
April	-64.8	-35.9	-61.2	-36.6	-35.5	-36.6
May	-63.2	-35.7	-60.1	-34.9	-30.6	-34.9
June	-59.1	-37.5	-55.2	-38.4	-34.6	-38.4
July	-46.8	-14.7	-47.1	-33.2	-20.2	-33.2
August	-45.1	-12.9	-45.0	-29.4	-19.1	-29.4
September	-43.4	-9.9	-43.8	-27.8	-16.6	-27.8
October	-44.7	11.2	-44.7	-25.9	-16.4	-25.9
November	-35.7	19.6	-34.5	-21.4	-6.7	-21.4
December	-34.9	28.8	-31.7	-19.3	-4.9	-19.3

Table A.7: Average % change in demand for PV+EV+BESS.

	System peak demand			Private peak demand		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
January	-25.0	-17.8	-25.7	-33.7	-3.6	-32.3
february	-28.8	-22.3	-30.0	-38.2	-6.4	-36.5
March	-31.0	-28.4	-33.3	-43.7	-18.0	-41.8
April	-40.6	-37.6	-47.2	-57.9	-39.1	-56.6
May	-44.9	-44.1	-49.1	-56.9	-34.1	-56.2
June	-49.8	-49.7	-60.7	-55.7	-37.5	-52.8
July	-37.5	-34.2	-45.5	-46.8	-27.0	-46.7
August	-36.2	-32.6	-43.3	-44.3	-25.1	-43.8
September	-32.3	-29.8	-38.7	-43.1	-22.2	-43.1
October	-28.1	-23.6	-28.4	-43.4	-18.0	-43.6
November	-25.8	-20.1	-25.1	-35.2	-7.3	-34.6
December	-21.6	-21.1	-23.1	-30.2	-4.9	-29.2

Table A.8: Total building electric costs per technology scenario.

Total building electric costs (\$)			
	TOU-CAP	TOU-COIN	TOU-ENE
Basecase	50,144	43,729	57,517
(St. Dev.)	(23,538)	(20,931)	(27,012)
PV+BESS	24,640	18,557	27,774
(St. Dev.)	(10,359)	(8,659)	(12,432)
PV+EV	31,104	25,882	33,079
(St. Dev.)	(13,110)	(12,470)	(14,742)
PV+EV+BESS	26,304	22,243	29,620
(St. Dev.)	(10,881)	(10,467)	(13,093)

Table A.9: Average avoided costs - Case 2. (\$)

Avoided costs of solar PV+BESS - Case 2.			
	TOU-CAP	TOU-COIN	TOU-ENE
Total mean	17,501	17,589	17,201
(St. Dev.)	(8,503)	(8,431)	(8,400)
Energy	9,042	8,644	8,767
(St. Dev.)	(4,447)	(4,348)	(4,332)
Capacity	8,459	8,684	8,434
(St. Dev.)	(4,090)	(4,177)	(4,108)
Avoided costs of solar PV+EV - Case 2			
	TOU-CAP	TOU-COIN	TOU-ENE
Total mean	10,521	12,770	15,051
(St. Dev.)	(6,057)	(6,150)	(7,669)
Energy	6,596	6,811	7,332
(St. Dev.)	(3,480)	(3,344)	(3,741)
Capacity	3,926	5,959	7,719
(St. Dev.)	(2,584)	(2,856)	(3,968)
Avoided costs of solar PV+EV+BESS - Case 2			
	TOU-CAP	TOU-COIN	TOU-ENE
Total mean	15,290	15,142	16,327
(St. Dev.)	(8,114)	(7,553)	(8,471)
Energy	8,132	7,740	8,370
(St. Dev.)	(4,198)	(3,952)	(4,272)
Capacity	7,157	7,402	7,957
(St. Dev.)	(3,932)	(3,659)	(4,209)

Table A.10: Average cost-shifting measures by technologies and tariffs - Case 2. (\$)

	TOU-CAP	TOU-COIN	TOU-ENE
PV+BESS	8,095	7,829	12,668
(St. Dev.)	(5,312)	(4,141)	(6,329)
% of savings	31.7	31.1	42.6
PV+EV	8,519	5,077	9,386
(St. Dev.)	(5,150)	(2,390)	(5,045)
% of savings	44.7	28.4	38.4
PV+EV+BESS	8,550	6,345	11,569
(St. Dev.)	(5,174)	(3,058)	(5,657)
% of savings	35.9	29.5	41.5

Table A.11: Average DER installed capacity - TOU-COIN Endogenous case.

	Conservative scenario		Optimistic scenario	
	5 - 8 PM	6 PM	5 - 8 PM	6 PM
PV (kW)	0.0	0.0	83.8	84.0
(St. Dev.)	(0.0)	(0.0)	(38.2)	(37.7)
#> 0 ^a	0.0	0.0	5.0	5.0
BESS (kWh)	183.2	2.2	258.8	261.0
(St.Dev.)	(103.6)	(-)	(152.4)	(149.2)
#> 0	5.0	1.0	5.0	5.0
EV (kWh)	72.3	475.4	0.0	0.0
(St. Dev.)	(29.2)	(269.8)	(0.0)	(0.0)
#> 0	4.0	5.0	0.0	0.0

^a#>0 values count the facilities with positive DER capacity installed.

Table A.12: Average avoided costs and cost-shifting - Endogenous case 2. (\$)

Avoided costs - Endogenous case 2						
	Conservative scenario			Optimistic scenario		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
Total Mean	6,932	9,625	22,189	27,879	16,506	28,446
(St. Dev.)	(4,510)	(5,577)	(9,931)	(22,632)	(13,581)	(23,219)
Energy	2,672	2,581	8,658	15,598	9,310	16,132
(St. Dev.)	(1,753)	(1,578)	(3,491)	(7,508)	(4,403)	(7,882)
Capacity	4,260	7,043	13,531	18,318	11,123	18,275
(St. Dev.)	(2,805)	(4,006)	(7,039)	(9,065)	(5,577)	(9,266)
Cost-shifting - Endogenous case 2						
	Conservative scenario			Optimistic scenario		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
Total Mean	5,658	3,217	7,642	9,245	10,296	16,897
(St. Dev.)	(3,918)	(2,054)	(2,023)	(13,018)	(9,641)	(13,132)
% from savings	44.9	25.1	25.6	24.9	38.4	37.3

Table A.13: EV financial flow breakdown - Endogenous case. (\$)

	Conservative scenario			Optimistic scenario		
	TOU-CAP	TOU-COIN	TOU-ENE	TOU-CAP	TOU-COIN	TOU-ENE
Home charging energy	205.7	72.1	334.9	133.4	0.0	0.0
(St. Dev.)	(22.4)	(37.1)	(16.5)	(71.6)	(0.0)	(0.0)
Battery Degradation	111.3	20.5	194.6	83.1	0.0	0.0
(St. Dev.)	(14.5)	(9.8)	(10.8)	(24.3)	(0.0)	(0.0)
Energy service	436.4	303.5	114.5	51.7	0.0	0.0
(St. Dev.)	(129.2)	(232.3)	(46.6)	(18.9)	(0.0)	(0.0)
Total Mean	753.4	396.2	644.0	198.3	0.0	0.0
(St. Dev.)	(128.1)	(273.9)	(73.8)	(7.6)	(0.0)	(0.0)
#> 0 ^a	3.0	4.0	3.0	3.0	0.0	0.0

^a#>0 values count the facilities with EVs.

Table A.14: Average EV financial flow breakdown - TOU-COIN Endogenous case. (\$)

	Conservative scenario		Optimistic scenario	
	5 - 8 PM	6 PM	5 - 8 PM	6 PM
Home charging energy (St. Dev.)	72.1 (37.1)	229.1 (23.7)	0.0 (0.0)	0.0 (0.0)
Battery Degradation (St. Dev.)	20.5 (9.8)	126.7 (15.3)	0.0 (0.0)	0.0 (0.0)
Energy service (St. Dev.)	303.5 (232.3)	852.0 (221.1)	0.0 (0.0)	0.0 (0.0)
Total Mean (St. Dev.)	396.2 (273.9)	1,207 (250.1)	0.0 (0.0)	0.0 (0.0)
# > 0 ^a	4.0	5.0	0.0	0.0

^a#>0 values count the facilities with EVs.

Chapter B

Appendix to Chapter 4

The detailed mathematical model

An overview of the bi-level model and associated sets, variables, and parameters will be described alongside the framework to solve it.

Nomenclature

- Indices:
 - c : Customers
 - h : Time period (hours)
- Sets:
 - C : Set of all customers
 - C_{EV} : Subset of customers set containing consumers with EV submetered ($\subset C$)
 - $C_{EV/DER}$: Subset of customers set containing prosumers with EV submetered ($\subset C$)
 - H : Set of hours
- Upper level parameters:

- egc : Existing grid capacity [kW]
- I^{DSO} : Annualized investment cost for grid capacity [€/kW/year]
- n : number of agents [-]
- NM : Net metering coeficient [-]
- $PBE_{c,h}^P$: Price of buying energy for agent c at hour h [€/kWh]
- $PSE_{c,h}^P$: Price of selling energy for agent c at hour h [€/kWh]
- $SunkCosts$: Sunk annualized grid costs, scaled per average consumer [€]
- W : Weigh of hour h [h/h]
- Lower-level parameters
 - $D_{c,h}^{\Delta EV-}$: EV driving needs of agent c in hour h [kWh/h]
 - $D_{c,h}$: Electricity demand of agent c in hour h [kWh/h]
 - $\overline{E}_{c,h}^{EV}$: Maximum EV state of charge of agent c in hour h [kWh]
 - $\underline{E}_{c,h}^{EV}$: Minimum EV state of charge of agent c in hour h [kWh]
 - $G_{c,h}^{PV}$: Solar ressource availability [kW/kWp]
 - I^S, I^{PV} : Annualized DER investment costs for agent c [\$/kW/Year]
 - L^S, L^{EV} : Battery and EV converter losses [%]
 - $P_{c,h}^{EVdis}$: EV discharging power of agent c in hour h [kW]
 - $P_{c,h}^{EVch}$: EV charging power of agent c in hour h [kW]
 - P_c^{ch} :Power capacity ratio for battery charging for agent c [kW/kWh]
 - P_c^{dis} :Power capacity ratio for battery discharging for agent c [kW/kWh]
 - $R; R^{EV}$: Battery and EV battery self-discharge [%]
 - $S^{\%max}, S^{\%min}$: Maximum and minimum battery allowed state of charge level [%]
 - U_c^S, U_c^{PV} : Ressource limits of storage and PV for agent c [kWh,kW]
- Upper-level variables

- agc : Additional grid capacity investment in interconnection [€/kWh]
- cnt : Capacity network charge [€/kW]
- e_h^{GE} : EV fleet exports in hour h [kWh/h]
- e_h^G : Total net load [kWh/h]
- e_h^{GI} : Total imports in hour h [kWh/h]
- fnt : Fixed network charge [€/customer]
- vnt : Volumetric network charge [€/kWh]
- Lower-level Variables
 - $d_{c,h}^{\Delta EV+}, d_{c,h}^{\Delta EV-}$: EV battery charge/discharge in hour h [kWh/h]
 - $d_{c,h}^{\Delta+}, d_{c,h}^{\Delta-}$: Stationary battery charge/discharge in hour h [kWh/h]
 - $exp_{c,h}^P$: Energy exported to grid by agent c in hour h [kWh/h]
 - $exp_{c,h}^L$: Energy exported to agent behind the meter [kWh/h]
 - $g_{c,h}^{PV}$: Solar PV electricity generation by agent c in hour h [kWh/h]
 - ic_c^{PV} : Solar PV installed capacity for agent c [kW]
 - ic_c^S : Battery storage capacity for agent c [kWh]
 - ic_c^S : Battery storage capacity for agent c [kWh]
 - $imp_{c,h}^P$: Energy imported from grid by agent c in hour h [kWh/h]
 - $imp_{c,h}^L$: Energy imported from agent behind the meter [kWh/h]
 - p_c : Measured peak power of agent c [kW]
 - $s_{c,h}^{EV}$: EV battery state of charge in hour h [kWh]
 - $s_{c,h}$: Stationary battery state of charge in hour h [kWh]

Upper-level objective function:

$$Min Cost^{NRA} = Cost^{DER} + Cost^P + Cost^N \quad (B.1)$$

Where:

$$Cost^{DER} = \sum_{c \in C} (I_c^S * ic_c^S + I_c^{PV} * ic_c^{PV}) \quad (B.2)$$

$$Cost^P = \sum_{c \in C} \sum_{h \in H} W_h * (imp_{c,h}^P * PBE_{c,h}^P - exp_{c,h}^P * PSE_{c,h}^P) \quad (B.3)$$

$$Cost^N = SunkCosts + I^{DSO} * agc \quad (B.4)$$

Subject to:

1. Coincidental peak : To maintain the linearity of the problem, Equation 4.5) will calculate the hourly sum of net imports and net exports in Equations B.5 B.6 as just one term of those equation will be nonzero, then the sum of both Equation B.7 will measure the aggregated hourly demand as stated below:

$$e_h^{GI} \geq \sum_{c \in C} (imp_{c,h}^P - exp_{c,h}^P), \forall h \in H \quad (B.5)$$

$$e_h^{GE} \geq \sum_{c \in C} (exp_{c,h}^P - imp_{c,h}^P), \forall h \in H \quad (B.6)$$

$$e_h^G = e_h^{GI} + e_h^{GE}, \forall h \in H \quad (B.7)$$

2. Grid capacity

$$egc + agc \geq e_h^G, \forall h \in H \quad (B.8)$$

3. DSO cost recovery

$$Cost^N = \sum_{c \in C} \sum_{h \in H} W * (imp_{c,h}^P - NM * exp_{c,h}^P) * vnt + \sum_{c \in C} p_c * cnt + n * fnt \quad (B.9)$$

Lower-level objective function:

$$Min Cost = Cost_c^{DER} + Cost_c^P + Cost_c^N \quad (B.10)$$

Where:

$$Cost_c^{DER} = I^S * ic_c^S + I^{PV} * ic_c^{PV} \quad (B.11)$$

$$Cost_c^P = \sum_{h \in H} W * \left(imp_{c,h}^P * PBE_{c,h}^P - exp_{c,h}^P * PSE_{c,h}^P \right) \quad (B.12)$$

$$Cost_c^N = \sum_{h \in H} W * \left(imp_{c,h}^P - NM * exp_{c,h}^P \right) * vnt + p_c * cnt + fnt \quad (B.13)$$

Subject to:

1. Energy balance

$$\begin{aligned} & -D_{c,h} - d_{c,h}^{\Delta EV+} + d_{c,h}^{\Delta EV-} - d_{c,h}^{\Delta+} + d_{c,h}^{\Delta-} + ic_c^{PV} * G_{c,h}^{PV} \\ & + imp_{c,h}^P - exp_{c,h}^P + \alpha_c * (imp_{c,h}^L - exp_{c,h}^L) = 0 \quad \forall c \in C, h \in H : \left(\lambda_{c,h}^{EB} \right) \end{aligned} \quad (B.14)$$

2. Peak power measurement

$$-p_c + imp_{c,h}^P + exp_{c,h}^P \leq 0 \quad \forall c \in C, h \in H : \left(\mu_{c,h}^G \right); \quad (B.15)$$

3. EV storage constraints

$$\begin{aligned} & s_{c,h}^{EV} - s_{c,h-1}^{EV} * (1 - R^{EV}) - d_{c,h}^{\Delta EV+} * (1 - L^{EV}) + d_{c,h}^{\Delta EV-} * (1 + L^{EV}) + D_{c,h}^{\Delta EV-} = 0, \\ & \forall c \in C, h \in H \setminus \{1\} : \left(\lambda_{c,h}^{EV1} \right) \end{aligned} \quad (B.16)$$

$$s_{c,1}^{EV} - SOC_0^{EV} - d_{c,1}^{\Delta EV+} * (1 - L^{EV}) + d_{c,1}^{\Delta EV-} * (1 + L^{EV}) + D_{c,1}^{\Delta EV-} = 0 \quad (B.17)$$

$$\forall c \in C : \left(\lambda_{c,1}^{EV1} \right) \quad (B.18)$$

$$s_{c,H}^{EV} - SOC_0^{EV} = 0, \quad \forall c \in C, h \in H : \left(\lambda_c^{EV2} \right) \quad (B.19)$$

$$s_{c,h}^{EV} - \bar{E}_{c,h}^{EV} \leq 0, \quad \forall c \in C, h \in H : \left(\mu_{c,h}^{EV2} \right) \quad (B.20)$$

$$\underline{E}_{c,h}^{EV} - s_{c,h}^{EV} \leq 0, \quad \forall c \in C, h \in H : \left(\mu_{c,h}^{EV3} \right) \quad (B.21)$$

$$d_{c,h}^{\Delta EV+} - P_{c,h}^{EVch} \leq 0, \quad \forall c \in C, h \in H : \left(\mu_{c,h}^{EV4} \right) \quad (B.22)$$

$$d_{c,h}^{\Delta EV-} - P_{c,h}^{EVdis} \leq 0, \quad \forall c \in C, h \in H : \left(\mu_{c,h}^{EV5} \right) \quad (B.23)$$

4. Battery storage constraints

$$s_{c,h} - s_{c,h-1} * (1 - R^S) - d_{c,h}^{\Delta+} * (1 - L^S) + d_{c,h}^{\Delta-} * (1 + L^S) = 0, \\ \forall c \in C, h \in H \setminus \{1\} : (\lambda_{c,h}^{S1}) \quad (\text{B.24})$$

$$s_{c,1} - s_{c,H} * (1 - R^S) - d_1^{\Delta+} * (1 - L^S) + d_1^{\Delta-} * (1 + L^S) = 0, \\ \forall c \in C : (\lambda_{c,1}^{S1}) \quad (\text{B.25})$$

$$ic_c^s - U_c^S \leq 0, \forall c \in C : (\mu_c^{S1}) \quad (\text{B.26})$$

$$s_{c,h} - ic_c^s * S^{\%max} \leq 0 \forall c \in C, h \in H : (\mu_{c,h}^{S2}) \quad (\text{B.27})$$

$$S^{\%min} * ic_c^s - s_{c,h} \leq 0 \forall c \in C, h \in H : (\mu_{c,h}^{S3}) \quad (\text{B.28})$$

$$d_{c,h}^{\Delta+} - ic_c^s * P_c^{ch} \leq 0 \forall c \in C, h \in H : (\mu_{c,h}^{S4}) \quad (\text{B.29})$$

$$d_{c,h}^{\Delta-} - ic_c^s * P_c^{dis} \leq 0 \forall c \in C, h \in H : (\mu_{c,h}^{S5}) \quad (\text{B.30})$$

5. Solar PV constraints

$$ic_c^{PV} - U_c^{PV} \leq 0 \forall c \in C : (\mu_c^{PV1}) \quad (\text{B.31})$$

6. Submetering constraints

$$\sum_{c \in C_{EV}} (imp_{c,h}^L - exp_{c,h}^L) = 0, \forall h \in H : (\lambda_h^{LEV}) \quad (B.32)$$

$$\sum_{c \in C_{EV/DER}} (imp_{c,h}^L - exp_{c,h}^L) = 0, \forall h \in H : (\lambda_h^{LEV/DER}) \quad (B.33)$$

$$imp_{EV,h}^L - d_{c,h}^{\Delta-} - ic_c^{PV} * G_{c,h}^{PV} \leq 0 \quad \forall c \in (C_{EV} \cup C_{EV/DER}), \forall h \in H : (\mu_{c,h}^{impL}) \quad (B.34)$$

$$imp_{c,h}^L - d_{EV,h}^{\Delta EV-} \leq 0 \quad \forall c \in C_{EV}, \forall c \in (C_{EV} \cup C_{EV/DER}), \forall h \in H : (\mu_{c,h}^{impL2}) \quad (B.35)$$

7. Non-negativity constraints

$$- imp_{c,h}^P \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^{imp}) \quad (B.36)$$

$$- exp_{c,h}^P \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^{exp}) \quad (B.37)$$

$$- d_{c,h}^{\Delta-} \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^{dminb}) \quad (B.38)$$

$$- d_{c,h}^{\Delta+} \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^{dplusb}) \quad (B.39)$$

$$- d_{c,h}^{\Delta EV+} \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^{dEV+}) \quad (B.40)$$

$$- d_{c,h}^{\Delta EV-} \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^{dEV-}) \quad (B.41)$$

$$- ic_c^{PV} \leq 0 \quad \forall c \in C, h \in H : (\mu_c^{icpv}) \quad (B.42)$$

$$- ic_c^S \leq 0 \quad \forall c \in C, h \in H : (\mu_c^{ics}) \quad (B.43)$$

$$- s_{c,h}^{EV} \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^{sEV}) \quad (B.44)$$

$$- s_{c,h} \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^s) \quad (B.45)$$

$$- imp_{c,h}^L \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^{Limp}) \quad (B.46)$$

$$- exp_{c,h}^L \leq 0 \quad \forall c \in C, h \in H : (\mu_{c,h}^{Lexp}) \quad (B.47)$$

Transforming the Bi-level problem into a solvable MPEC

The lower level conditions are changed by their KKT optimality conditions. This step allows the transformation of the bi-level problem into a MPEC which has now

a single objective function. We derive the KKT necessary optimality conditions from the primal feasibility restrictions of the lower problem:

$$W * (PBE_{c,h}^P + vnt) + \lambda_{c,h}^{EB} + \mu_{c,h}^G - \mu_{c,h}^{imp} = 0, \forall c \in C, h \in H \quad (B.48)$$

$$-W * (PSE_{c,h}^P + NM * vnt) - \lambda_{c,h}^{EB} + \mu_{c,h}^G - \mu_{c,h}^{exp} = 0, \forall c \in C, h \in H \quad (B.49)$$

$$I^{PV} + \sum_{h \in H} \lambda_{c,h}^{EB} * G_{c,h}^{PV} + \mu_c^{PV1} - \mu_c^{icpv} = 0, \forall c \in C \quad (B.50)$$

$$-\lambda_{c,h}^{EB} - (1 - L^{EV}) * \lambda_{c,h}^{EV1} + \mu_{c,h}^{EV4} - \mu_{c,h}^{dEV+} = 0, \forall c \in C, h \in H \quad (B.51)$$

$$\lambda_{c,h}^{EB} + (1 + L^{EV}) * \lambda_{c,h}^{EV1} + \mu_{c,h}^{EV5} - \mu_{c,h}^{dEV-} = 0, \forall c \in C, h \in H \quad (B.52)$$

$$\lambda_{c,h}^{EV1} - (1 - R^{EV}) * \lambda_{c,h+1}^{EV1} + \mu_{c,h}^{EV2} - \mu_{c,h}^{EV3} - \mu_{c,h}^{sEV} = 0, \forall c \in C, h \in H \setminus \{48\} \quad (B.53)$$

$$\lambda_{c,H}^{EV1} + \lambda_c^{EV2} + \mu_{c,H}^{EV2} - \mu_{c,H}^{EV3} - \mu_{c,H}^{sEV} = 0 \forall c \in C, h = H \quad (B.54)$$

$$-\lambda_{c,h}^{EB} - (1 - L^S) * \lambda_{c,h}^{S1} + \mu_{c,h}^{S4} - \mu_{c,h}^{d+} = 0, \forall c \in C, h \in H \quad (B.55)$$

$$\lambda_{c,h}^{EB} + (1 + L^S) * \lambda_{c,h}^{S1} + \mu_{c,h}^{S5} - \mu_{c,h}^{d-} = 0, \forall c \in C, h \in H \quad (B.56)$$

$$\lambda_{c,h}^{S1} - (1 - R^S) * \lambda_{c,h+1}^{S1} + \mu_{c,h}^{S2} - \mu_{c,h}^{S3} - \mu_{c,h}^s = 0, \forall c \in C, h \in H \setminus \{48\} \quad (B.57)$$

$$\lambda_{c,H}^{S1} - (1 - R^S) * \lambda_{c,1}^{S1} + \mu_{c,H}^{S2} - \mu_{c,H}^{S3} - \mu_{c,H}^s = 0, \forall c \in C \quad (B.58)$$

$$cnt - \sum_{h \in H} \mu_{c,h}^G = 0, \forall c \in C \quad (B.59)$$

$$\lambda_{c,h}^{EB} + \lambda_h^{LEV} - \mu_{c,h}^{impL} = 0, \forall c \in C, h \in H \quad (B.60)$$

$$-\lambda_{c,h}^{EB} - \lambda_h^{LEV} - \mu_{c,h}^{expL} = 0, \forall c \in C, h \in H \quad (B.61)$$

$$0 \leq imp_{c,h}^P \perp \mu_{c,h}^{imp} \geq 0, \forall c \in C, h \in H \quad (B.62)$$

$$0 \leq exp_{c,h}^P \perp \mu_{c,h}^{exp} \geq 0, \forall c \in C, h \in H \quad (B.63)$$

$$0 \leq ic_c^{PV} \perp \mu_{c,h}^{icpv} \geq 0, \forall c \in C \quad (B.64)$$

$$0 \leq U_c^{PV} - ic_c^{PV} \perp \mu_c^{PV1} \geq 0, \forall c \in C \quad (B.65)$$

$$0 \leq d_{c,h}^{\Delta EV+} \perp \mu_{c,h}^{dEV+} \geq 0, \forall c \in C, h \in H \quad (B.66)$$

$$0 \leq d_{c,h}^{\Delta EV-} \perp \mu_{c,h}^{dEV-} \geq 0, \forall c \in C, h \in H \quad (B.67)$$

$$0 \leq s_{c,h}^{EV} \perp \mu_{c,h}^{sEV} \geq 0, \forall c \in C, h \in H \quad (B.68)$$

$$0 \leq \overline{E}_{c,h}^{EV} - s_{c,h}^{EV} \perp \mu_{c,h}^{EV2} \geq 0, \forall c \in C, h \in H \quad (B.69)$$

$$0 \leq s_{c,h}^{EV} - \underline{E}_{c,h}^{EV} \perp \mu_{c,h}^{EV3} \geq 0, \forall c \in C, h \in H \quad (B.70)$$

$$0 \leq P_{c,h}^{EVch} - d_{c,h}^{\Delta EV+} \perp \mu_{c,h}^{EV4} \geq 0, \forall c \in C, h \in H \quad (B.71)$$

$$0 \leq P_{c,h}^{EVdis} - d_{c,h}^{\Delta EV-} \perp \mu_{c,h}^{EV5} \geq 0, \forall c \in C, h \in H \quad (B.72)$$

$$0 \leq d_{c,h}^{\Delta+} \perp \mu_{c,h}^{d+} \geq 0, \forall c \in C, h \in H \quad (B.73)$$

$$0 \leq d_{c,h}^{\Delta-} \perp \mu_{c,h}^{d-} \geq 0, \forall c \in C, h \in H \quad (B.74)$$

$$0 \leq s_{c,h} \perp \mu_{c,h}^s \geq 0, \forall c \in C, h \in H \quad (B.75)$$

$$0 \leq ic_c^s * S^{\%max} - s_{c,h} \perp \mu_{c,h}^{S2} \geq 0, \forall c \in C, h \in H \quad (B.76)$$

$$0 \leq s_{c,h} - S^{\%min} * ic_c^s \perp \mu_{c,h}^{S3} \geq 0, \forall c \in C, h \in H \quad (B.77)$$

$$0 \leq ic_c^s * P_c^{ch} - d_{c,h}^{\Delta+} \perp \mu_{c,h}^{S4} \geq 0, \forall c \in C, h \in H \quad (B.78)$$

$$0 \leq ic_c^s * P_c^{dis} - d_{c,h}^{\Delta-} \perp \mu_{c,h}^{S5} \geq 0, \forall c \in C, h \in H \quad (B.79)$$

$$0 \leq p_c - imp_{c,h}^P - exp_{c,h}^P \perp \mu_{c,h}^G \geq 0, \forall c \in C, h \in H \quad (B.80)$$

$$0 \leq imp_{c,h}^L \perp \mu_{c,h}^{impL} \geq 0, \forall c \in C, h \in H \quad (B.81)$$

$$0 \leq exp_{c,h}^L \perp \mu_{c,h}^{expL} \geq 0, \forall c \in C, h \in H \quad (B.82)$$

$$0 \leq -imp_{c,h}^L + d_{EV,h}^{\Delta EV-} \perp \mu_{c,h}^{impL2} \geq 0 \quad \forall c \in (C_{EV} \cup C_{EV/DER}), \forall h \in H \quad (B.83)$$

$$\begin{aligned}
 0 \leq -imp_{EV,h}^L + d_{c,h}^{\Delta EV-} + d_{c,h}^{\Delta-} + ic_c^{PV} * G_{c,h}^{PV} \perp \mu_{c,h}^{impL1} \geq 0 \\
 , \forall c \in (C_{EV} \cup C_{EV/DER}), \forall h \in H \quad (B.84)
 \end{aligned}$$

$$\begin{aligned}
 -D_{c,h} - d_{c,h}^{\Delta EV+} + d_{c,h}^{\Delta EV-} - d_{c,h}^{\Delta+} + d_{c,h}^{\Delta-} + ic_c^{PV} * G_{c,h}^{PV} \\
 imp_{c,h}^P - exp_{c,h}^P + \alpha_c * (imp_{c,h}^L - exp_{c,h}^L) = 0 : (\lambda_{c,h}^{EB}, free), \forall c \in C, h \in H \\
 (B.85)
 \end{aligned}$$

$$\begin{aligned}
 s_{c,h}^{EV} - s_{c,h-1}^{EV} * (1 - R^{EV}) - d_{c,h}^{\Delta EV+} * (1 - L^{EV}) + d_{c,h}^{\Delta EV-} * (1 + L^{EV}) + D_{c,h}^{\Delta EV-} = 0 \\
 : (\lambda_{c,h}^{EV1}, free), \forall c \in C, h \in H \setminus \{1\} \quad (B.86)
 \end{aligned}$$

$$\begin{aligned}
 s_{c,1}^{EV} - SOC_0^{EV} - d_{c,1}^{\Delta EV+} * (1 - L^{EV}) \\
 + d_{c,1}^{\Delta EV-} * (1 + L^{EV}) + D_{c,1}^{\Delta EV-} = 0 : \\
 (\lambda_{c,1}^{EV1}, free), \forall c \in C \quad (B.87)
 \end{aligned}$$

$$s_{c,H}^{EV} - SOC_0^{EV} = 0 : (\lambda_c^{EV2}, free), \forall c \in C \quad (B.88)$$

$$\begin{aligned}
 s_{c,h} - s_{c,h-1} * (1 - R^S) - d_{c,h}^{\Delta+} * (1 - L^S) + d_{c,h}^{\Delta-} * (1 + L^S) = 0 : \\
 (\lambda_{c,h}^{S1}, free), \forall c \in C, h \in H \setminus \{1\} \quad (B.89)
 \end{aligned}$$

$$s_{c,1} - s_{c,H} * (1 - R^S) - d_{c,1}^{\Delta+} * (1 - L^S) + d_{c,1}^{\Delta-} * (1 + L^S) = 0 : (\lambda_{c,1}^{S1}, free), \forall c \in C \quad (B.90)$$

$$\sum_{c \in C_{EV}} (imp_{c,h}^L - exp_{c,h}^L) = 0 : (\lambda_h^{LEV}, free), \forall h \in H \quad (B.91)$$

$$\sum_{c \in C_{EV/DER}} (imp_{c,h}^L - exp_{c,h}^L) = 0 : (\lambda_h^{LEV/DER}, free), h \in H \quad (B.92)$$

Before treating the non-linearities of the model, a adjustment regarding the cost recovery equality is needed to facilitate convergence. The total network charges costs collected should be within a band (calibrated as $\delta = 0.1\%$):

$$(Cost^N) * (1 - \delta) - \sum_{c \in C} \sum_{h \in H} W * (imp_{c,h}^P - NM * exp_{c,h}^P) * vnt + \sum_{c \in C} p_c * cnt + n * fnt \leq 0 \quad (B.93)$$

$$-(Cost^N) * (1 + \delta) + \sum_{c \in C} \sum_{h \in H} W * (imp_{c,h}^P - NM * exp_{c,h}^P) * vnt + \sum_{c \in C} p_c * cnt + n * fnt \leq 0 \quad (B.94)$$

To fully transform the MPEC into a MILP, two non-linearities must be taken into account: the bilinear terms and the complementarity constraints in the KKT conditions. First, the bilinear products in the equality constraint of the upper-level ($imp_{c,h}^P * vnt$, $exp_{c,h}^P * vnt$ and $p_c * cnt$) are already taken into account internally by the solver Gurobi 9.1. Instead of discretizing the terms by using binary expansion beforehand, the solver deals with this type of non-convexity by applying cutting planes and special branching techniques. Finally, the complementarity constraints are linearized using Fotuny-Amat method in which they are reformulated using additional binary variables and large enough constants (Big-Ms). Another solution to deal with the complementarity constraints in the MPEC framework could be the SOS1 variables.

At this point, the bi-level problem turned into a mixed-integer linear program that can be solved using the prior Gurobi 9.1 solver:

$$imp_{c,h}^P \leq M^{imp} * (1 - r_{c,h}^a) \quad , \forall c \in C, h \in H \quad (B.95)$$

$$W * (PBE_{c,h}^P + vnt) + \lambda_{c,h}^{EB} + \mu_{c,h}^G \leq M^{imp} * r_{c,h}^a \quad \forall c \in C, h \in H \quad (B.96)$$

$$exp_{c,h}^P \leq M^{exp} * (1 - r_{c,h}^b) \quad , \forall c \in C, h \in H \quad (B.97)$$

$$-W * (PSE_{c,h}^P + NM * vnt) - \lambda_{c,h}^{EB} + \mu_{c,h}^G \leq M^{exp} * r_{c,h}^b \quad , \forall c \in C, h \in H \quad (B.98)$$

$$ic_c^{PV} \leq M^{icpv} * (1 - r_c^c) \quad , \forall c \in C \quad (B.99)$$

$$I^{PV} + \sum_{h \in H} \lambda_{c,h}^{EB} * G_{c,h}^{PV} + \mu_c^{PV1} \leq M^{icpv} * r_c^c \quad \forall c \in C \quad (B.100)$$

$$U_c^{PV} - ic_c^{PV} \leq M^{PV1} * (1 - r_c^d) \quad , \forall c \in C \quad (B.101)$$

$$\mu_c^{PV1} \leq M^{PV1} * r_c^d \quad , \forall c \in C \quad (B.102)$$

$$d_{c,h}^{\Delta EV+} \leq M^{dEV+} * (1 - r_{c,h}^e) \quad , \forall c \in C, h \in H \quad (B.103)$$

$$-\lambda_{c,h}^{EB} - (1 - L^{EV}) * \lambda_{c,h}^{EV1} + \mu_{c,h}^{EV4} \leq M^{dEV+} * r_{c,h}^e \quad , \forall c \in C, h \in H \quad (B.104)$$

$$d_{c,h}^{\Delta EV-} \leq M^{dEV-} * (1 - r_{c,h}^f) \quad , \forall c \in C, h \in H \quad (B.105)$$

$$\lambda_{c,h}^{EB} + (1 + L^{EV}) * \lambda_{c,h}^{EV1} + \mu_{c,h}^{EV5} \leq M^{dEV-} * r_{c,h}^f \quad , \forall c \in C, h \in H \quad (B.106)$$

$$s_{c,h}^{EV} \leq M^{sEV} * (1 - r_{c,h}^g) \quad , \forall c \in C, h \in H \quad (B.107)$$

$$\mu_{c,h}^{sEV} \leq M^{sEV} * r_{c,h}^g \quad , \forall c \in C, h \in H \quad (B.108)$$

$$\bar{E}_{c,h}^{EV} - s_{c,h}^{EV} \leq M^{uEV2} * (1 - r_{c,h}^h) \quad , \forall c \in C, h \in H \quad (B.109)$$

$$\mu_{c,h}^{EV2} \leq M^{uEV2} * r_{c,h}^h \quad , \forall c \in C, h \in H \quad (B.110)$$

$$s_{c,h}^{EV} - \underline{E}_{c,h}^{EV} \leq M^{uEV3} * (1 - r_{c,h}^i) \quad , \forall c \in C, h \in H \quad (B.111)$$

$$\mu_{c,h}^{EV3} \leq M^{uEV3} * r_{c,h}^i \quad , \forall c \in C, h \in H \quad (B.112)$$

$$P_{c,h}^{EVch} - d_{c,h}^{\Delta EV+} \leq M^{uEV4} * (1 - r_{c,h}^j) \quad , \forall c \in C, h \in H \quad (B.113)$$

$$\mu_{c,h}^{EV4} \leq M^{uEV4} * r_{c,h}^j \quad , \forall c \in C, h \in H \quad (B.114)$$

$$P_{c,h}^{EVdis} - d_{c,h}^{\Delta EV-} \leq M^{uEV5} * (1 - r_{c,h}^k) \quad , \forall c \in C, h \in H \quad (B.115)$$

$$\mu_{c,h}^{EV5} \leq M^{uEV5} * r_{c,h}^k \quad , \forall c \in C, h \in H \quad (B.116)$$

$$d_{c,h}^{\Delta+} \leq M^{d+} * (1 - r_{c,h}^l), \forall c \in C, h \in H \quad (\text{B.117})$$

$$-\lambda_{c,h}^{EB} - (1 - L^S) * \lambda_{c,h}^{S1} + \mu_{c,h}^{S4} \leq M^{d+} * r_{c,h}^l, \forall c \in C, h \in H \quad (\text{B.118})$$

$$d_{c,h}^{\Delta-} \leq M^{d-} * (1 - r_{c,h}^m), \forall c \in C, h \in H \quad (\text{B.119})$$

$$\lambda_{c,h}^{EB} + (1 + L^S) * \lambda_{c,h}^{S1} + \mu_{c,h}^{S5} \leq M^{d-} * r_{c,h}^m, \forall c \in C, h \in H \quad (\text{B.120})$$

$$s_{c,h} \leq M^s * (1 - r_{c,h}^n), \forall c \in C, h \in H \quad (\text{B.121})$$

$$\mu_{c,h}^s \leq M^s * r_{c,h}^n, \forall c \in C, h \in H \quad (\text{B.122})$$

$$ic_c^s * S^{\%max} - s_{c,h} \leq M^{uS2} * (1 - r_{c,h}^o), \forall c \in C, h \in H \quad (\text{B.123})$$

$$\mu_{c,h}^{S2} \leq M^{uS2} * r_{c,h}^o, \forall c \in C, h \in H \quad (\text{B.124})$$

$$s_{c,h} - S^{\%min} * ic_c^s \leq M^{uS3} * (1 - r_{c,h}^p), \forall c \in C, h \in H \quad (\text{B.125})$$

$$\mu_{c,h}^{S3} \leq M^{uS3} * r_{c,h}^p, \forall c \in C, h \in H \quad (\text{B.126})$$

$$ic_c^s * P_c^{ch} - d_{c,h}^{\Delta+} \leq M^{uS4} * (1 - r_{c,h}^q), \forall c \in C, h \in H \quad (\text{B.127})$$

$$\mu_{c,h}^{S4} \leq M^{uS4} * r_{c,h}^q, \forall c \in C, h \in H \quad (\text{B.128})$$

$$ic_c^s * P_c^{dis} - d_{c,h}^{\Delta-} \leq M^{uS5} * (1 - r_{c,h}^r), \forall c \in C, h \in H \quad (\text{B.129})$$

$$\mu_{c,h}^{S5} \leq M^{uS5} * r_{c,h}^r, \forall c \in C, h \in H \quad (\text{B.130})$$

$$\mu_{c,h}^G \leq M^P * r_{c,h}^t, \forall c \in C \quad (\text{B.131})$$

$$p_c - imp_{c,h}^P - exp_{c,h}^P \leq M^P * (1 - r_{c,h}^t), \forall c \in C \quad (\text{B.132})$$

$$imp_{c,h}^L \leq M^{impL} * (1 - r_{c,h}^u), \forall c \in C, h \in H \quad (\text{B.133})$$

$$\lambda_{c,h}^{EB} + \lambda_h^{LEV} \leq M^{impL} * r_{c,h}^u, \forall c \in C, h \in H \quad (\text{B.134})$$

$$exp_{c,h}^L \leq M^{expL} * (1 - r_{c,h}^v), \forall c \in C, h \in H \quad (\text{B.135})$$

$$-\lambda_{c,h}^{EB} - \lambda_h^{LEV} \leq M^{expL} * r_{c,h}^v, \forall c \in C, h \in H \quad (\text{B.136})$$

$$\mu_{c,h}^{impL1} \leq M^{impL1} * r_{c,h}^w, \forall c \in C, h \in H \quad (\text{B.137})$$

$$-imp_{EV,h}^L + d_{c,h}^{\Delta EV-} + d_{c,h}^{\Delta-} + ic_c^{PV} * G_{c,h}^{PV} \leq M^{impL1} * (1 - r_{c,h}^w), \forall c \in C, h \in H \quad (\text{B.138})$$

$$\mu_{c,h}^{impL2} \leq M^{impL2} * r_{c,h}^x, \forall c \in (C_{EV} \cup C_{EV/DER}), \forall h \in H \quad (\text{B.139})$$

$$-imp_{c,h}^L + d_{EV,h}^{\Delta EV-} \leq M^{impL2} * (1 - r_{c,h}^x), \forall c \in (C_{EV} \cup C_{EV/DER}), \forall h \in H \quad (\text{B.140})$$

Electric Nation Customer Trial: Insights from the pilot

The Electric Nation pilot was conducted in the U.K by the electricity distribution network operator for the Midlands, South Wales and the South West called Western Power Distribution. The aim of the project was to better understand the impact of charging at home on electricity distribution networks. The trials happened between January 2017 and 2018 with a total of 673 smart chargers installed at participants' homes.

From the final database containing more than 157,520 rows of charging episodes and various columns with detailed parameters such as start and stop charging time, consumed kWh, the power level of the EVSE, battery capacity, etc. We derive some important parameters to be used in our study case, as for example the connection hours. We calculated the disconnection hour based on two observations: the hour in which the amount of energy needed before leaving home is the highest and the greatest difference of available power between two consecutive hours. We calculate the average daily profile of energy consumption per hour before disconnection and the average available power of the fleet.

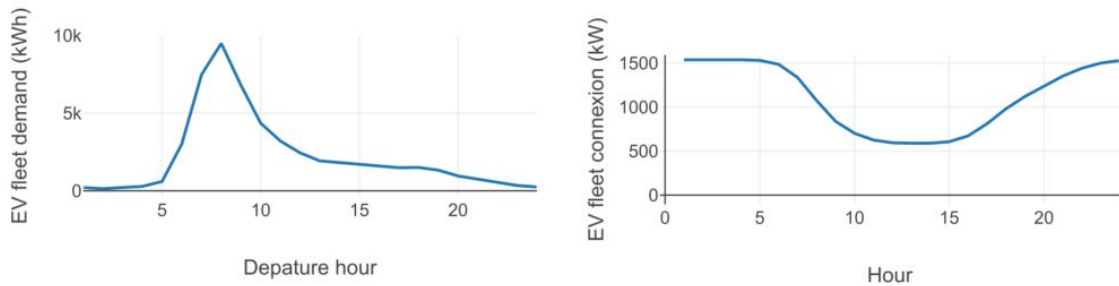


Figure B.1: Electric Nation Trial data.

First, it is observed that the EVs need more energy before leaving at 7 A.M as shown by Figure B.1. Then, the greatest steepness of the curve is between 7 A.M and 8 A.M, meaning that most vehicles left their homes at the former hour. The same analysis is done regarding reconnection hour, in which the highest difference of power between two consecutive hours is 5 P.M and 6 P.M. As a result the second hour is

defined as 5 P.M.

Complementary Tables

Table B.1: Total cost and DER for different energy profiles (MILP analysis)

Passive consumers with EV (No V2G)					
	One Meter			Submetering	
	Flat	TOU1	TOU2	Flat/TOU1	Flat/TOU2
Total costs (\$)	1175	1050	1090	1039	1079
Coincident peak (kW)	8,4	3,2	3,2	3,2	3,2
Active consumers with EV (V2G allowed)					
	One Meter			Submetering	
	Flat	TOU1	TOU2	Flat/TOU1	Flat/TOU2
Total costs (\$)	1704	1323	1506	1425	1533
Coincident peak (kW)	4,8	0	0	0	0
PV investments (kW)	0,77	0,44	1,04	0,63	0,77
Battery investments (kWh)	0	0	3,51	1,37	0
Active consumers with EV (No V2G)					
	One Meter			Submetering	
	Flat	TOU1	TOU2	Flat/TOU1	Flat/TOU2
Total costs (\$)	1704	1476	1583	1568	1608
Coincident peak (kW)	3,1	0	0	3,1	3,1
PV investments (kW)	0,77	2,96	2,96	0,77	0,77
Battery investments (kWh)	0	13,6	13,6	0	0

Table B.2: Total cost and DER for different energy profiles (PV cost = 1,500\$/kWp)

Passive consumers with EV (No V2G)					
	One Meter			Submetering	
	Flat	TOU1	TOU2	Flat/TOU1	Flat/TOU2
Total costs (\$)	1175	1050	1090	1039	1079
Coincident peak (kW)	8,4	3,2	3,2	3,2	3,2
Active consumers with EV (V2G allowed)					
	One Meter			Submetering	
	Flat	TOU1	TOU2	Flat/TOU1	Flat/TOU2
Total costs (\$)	1722	1340	1529	1442	1551
Coincident peak (kW)	9,5	0	2,5	0	4,5
PV investments (kW)	0,45	0,36	0,45	0,38	0,45
Battery investments (kWh)	0	0	0	0	0
Active consumers with EV (No V2G)					
	One Meter			Submetering	
	Flat	TOU1	TOU2	Flat/TOU1	Flat/TOU2
Total costs (\$)	1722	1598	1648	1586	1627
Coincident peak (kW)	4,7	4,3	4,7	4,7	4,7
PV investments (kW)	0,45	2,5	0,77	0,45	0,45
Battery investments (kWh)	0	11	0	0	0

Table B.3: Total network costs for all scenarios according to grid cost structure

	Sunk	50/50	Prospective
Volumetric	2040	1538	817
Three-part tariff	2020	1533	848
Volumetric (V2G and Submetering)	2039	1618	1103
Three-part tariff (V2G and Submetering)	2035	1639	1041

Chapter C

Research outcome

- Peer-reviewed publication:
 - Freitas Gomes, I. S., Perez, Y., & Suomalainen, E. (2020). “Coupling small batteries and PV generation: A review”. **Renewable and Sustainable Energy Reviews**, 126 (March), 109835.
 - Freitas Gomes, I. S., Perez, Y., & Suomalainen, E. (2021). “Rate design with distributed energy resources and electric vehicles: A Californian case study.” FSR RSCAS Working Paper 2020/2021. Accepted: **Energy Economics**.
- Working Paper:
 - Freitas Gomes, I. S., Abdin, A. F., Puchinger, J. & Perez, Y. (2021). “New EV rate design: An MPEC assessment.”
- Technical report:
 - Freitas Gomes, I. S (2021). “Positive energy territories and electromobility: Highlights from EVER Monaco 2020”. **Energy Forum**, IAEE First Quarter 2021, pag 32.
- Academic conferences:
 - 42nd International Association for Energy Economics (IAEE) Annual Conference: Local Energy, Global Markets - Montréal, May 2019 - Presented:

“Coupling between distributed battery systems and photovoltaic generation: A Techno-socio-economic review.”

- Electric Vehicles and global urban adoption conferece - Berkeley, June 2019
- Presented: “Rate design with distributed energy resources and electric vehicles: A Californian case study.”
- International Conference on Mobility Changes of the Armand Peugeot Chair
- Paris, December 2019 - Presented: “Rate design with distributed energy resources and electric vehicles.”
- Financing Long-Term Investment in Hybrid Electricity Markets - CEEM Paris-Dauphine research conference - February 2021 - Presented: “Rate design with distributed energy resources and electric vehicles: A Californian case study.”
- First International Association of Energy Economics (IAEE) online conference - June 2021 - Presented: “Is one meter enough? Assessing the impacts of domestic electric vehicle-only rate adoption via submetering.”
- Other presentations:
 - Ecologic Vehicle Renewables Energies (EVER) Monaco - May 2019 - Presentation about socio-economic and technical barriers for vehicle-to-grid adoption.
 - Smart Mobility and Intelligent Vehicle (SMIV) - Paris, November 2019
- Presentation about Rate design with distributed energy resources and electric vehicles.
 - IAEE electromobility webinar: Technical solution for systems coupling - May 2020 - Presentation about electric vehicle-grid integration through adapted rate design.
 - HEV-TCP Task 39 Interoperability & Task 43 Vehicle-Grid-Integration Joint Workshop (only for IEA task members) - June 2020 - Presentation about electric vehicle-grid integration through adapted rate design.

- Ecologic Vehicle Renewables Energies (EVER) Monaco - September 2020 - Presentation about electricity vehicles charging rates.
- FiME (Laboratoire de Finance des Marchés de l'Energie) Seminar - Online seminar, 12 February 2021: Presentation about network tariffs with DERs and EVs.
- Ecologic Vehicle Renewables Energies (EVER) Monaco - May 2021 - Presentation about electric vehicles and DERs added value to power systems in an energy transition framework.
- Teaching:
 - Instructor: Vedecom training for companies: “Electric vehicles for those who design it: Batteries, Charging and Networks” (Three sessions for Stellantis and two for ENEDIS: 7.5 hours).
 - Teaching Assistant: Responsible for exercise classes of “General Economics” at M1 CentraleSupélec (English and French classes: 42 hours).
 - Teaching Assistant: “Energy Economics” at M1 INSTN/CEA (15 hours).
- Reviewer
 - Revue d'économie Industrielle, Solar Energy, Journal of Cleaner Production.
- Organizer:
 - First International Association of Energy Economics (IAEE) online conference - CentraleSupélec, Paris, 7th - 9th June 2021.
- European Projects:
 - Participation in the consortium PEERS (Promoting European Energy communities) for H2020 project calls.

Chapter D

Résumé en français

Les interactions entre les véhicules électrique (VE) et les ressources énergétiques distribuées (RED) peuvent apporter des avantages aux secteurs de la mobilité et de l'électricité. Toutefois, pour parvenir à une synergie optimale, il faut comprendre les aspects technico-économiques sous-jacents qui déterminent l'adoption des VE et des RED. La conception des tarifs est considérée comme un point critique qui influence le choix et la rentabilité des investissements. Les changements dans le scénario de l'électricité, avec l'adoption de technologies innovantes, affectent directement la façon dont les services publics facturent à leurs clients un tarif de détail équitable et reflétant les coûts. Par conséquent, les nouveaux tarifs et les tarifs ajustés ont un impact sur l'adoption de l'innovation, mettant en évidence une boucle de rétroaction claire. L'objectif de ce manuscrit est (i) de mettre en lumière les relations technico-économiques fondamentales du couplage des VE et des RED et (ii) de mieux comprendre la boucle de rétroaction entre la conception des tarifs et l'investissement dans les RED. Cette thèse étudie différents aspects de la transition vers la mobilité électrique. Elle contient trois chapitres qui sont liés les uns aux autres et sont organisés comme suit : Le chapitre 2 explore les aspects technico-économiques de l'évolution du système électrique dans lequel les VE et les RED deviennent des technologies essentielles ; Les chapitres 3 et 4 proposent des solutions potentielles aux problèmes de conception des tarifs dans le secteur électrique en évolution.

Chapitre 2

Dans notre cadre analytique, le couplage entre PV–VE–batterie est lié à différentes couches d’analyse. Les synergies du couplage entre les ressources de batteries distribuées et la production d’électricité photovoltaïque contribueront à décarboniser les secteurs de l’électricité et de la mobilité tout en étant rentables - si elles sont bien gérées - pour la plupart des agents impliqués : opérateurs de systèmes, régulateurs, consommateurs ordinaires, etc. Les technologies émergentes (par exemple, les micro-réseaux, le vehicle-to-grid et la blockchain) vont remodeler la synergie PV-VE-batterie, obligeant les opérateurs de réseaux électriques à ajuster la gestion du réseau. Ensuite, des réglementations économiques inappropriées (par exemple, des conceptions obsolètes des tarifs et du marché des services auxiliaires) et des stratégies dépassées formulées par le secteur automobile pourraient mettre en péril tous les avantages potentiels du couplage VE/PV. Ensuite, l’acceptation des utilisateurs semble être une variable décisive pour savoir si les gens sont prêts à investir dans les systèmes énergétiques distribués.

Chapitre 3

Suite aux lacunes de la littérature trouvées dans le deuxième chapitre, cette étude se concentre sur les investissements en ressources énergétiques distribuées (RED) dans les installations privées. Nous évaluons l’impact des tarifs de l’électricité sur les investissements en RED du point de vue des installations privées et sur le recouvrement des coûts du point de vue des services publics. Nous avons simulé différentes combinaisons technologiques d’énergie photovoltaïque (PV), de systèmes de stockage électrique (BESS) et de véhicules électriques (EV) pour évaluer la partie investissement privé et le modèle de coût évité pour tenir compte de l’impact du côté des services publics. Le passage d’une tarification basée sur l’énergie à une tarification basée sur la demande de pointe et la capacité peut atténuer les valeurs de transfert de coûts causées par une forte pénétration des RED. En ce qui concerne les VE, les revenus nets varient entre 57 et 218 dollars, les revenus les plus élevés étant obtenus avec les tarifs de capacité.

Chapitre 4

L'adoption d'un tarif d'électricité explicitement conçu pour charger les véhicules électriques (VE) à domicile permet de réduire les coûts de charge pour de nombreux logements. En supposant que la demande des ménages sans charges flexibles est quasi-inélastique, la séparation des factures de recharge des VE constitue une incitation équitable à adopter des tarifs domestiques réservés aux VE. Nous développons un modèle de théorie des jeux, exprimé et traité comme un programme mathématique avec des contraintes d'équilibre (MPEC), pour modéliser l'interaction entre une autorité de régulation nationale (NRA) et les logements. Le concept de sous-comptage peut apporter des gains annuels variant de 64 à 110 dollars sous ce type de tarif. Nous avons confirmé l'effet positif du sous-comptage sur les valeurs de recharge des VE par une évaluation intégrée explorant la variation de l'énergie et des frais de réseau.

Titre : Au-delà de la mobilité : Economie des multiples rôles du véhicule électrique dans la transition énergétique.

Mots clés : Vehicle-to-Grid, Photovoltaïque, Batterie stationnaire, Voiture électrique, Optimisation énergétique, Conception tarifaire

Résumé :

L'adoption rapide des véhicules électriques soutenue par des objectifs de réduction des émissions de gaz à effet de serre peut créer des défis pour le système électrique. Néanmoins, ils peuvent contribuer à la décarbonation des secteurs de l'électricité et de la mobilité simultanément si des réglementations économiques appropriées sont présentes. Des signaux économiques appropriés couplés à des technologies essentielles telles que la recharge intelligente et le « Vehicle-to-Grid » (V2G) faciliteront l'intégration des véhicules électriques dans le secteur de l'électricité. À leur tour, ces technologies permettront l'utilisation de milliers de GWh de capacité de batterie par les gestionnaires du système électrique à moyen terme. Cette thèse étudie plusieurs aspects économiques sur la façon de libérer tout le potentiel des véhicules électriques, non seulement en tant que moyen de transport mais aussi en tant que ressource énergétique dans un scénario de transition énergétique.

Premièrement, elle étudie la synergie entre les véhicules électriques et les ressources énergétiques distribuées telles que le solaire photovoltaïque et les batteries stationnaires. Un cadre analytique identifiant les principaux domaines de recherche et les relations entre eux est fourni. Ensuite, elle analyse l'impact de différentes conceptions de tarifs de détail sur les incitations à l'investissement privé et le transfert des coûts. Dans ce contexte, sont présents dans les installations commerciales à la fois des véhicules électriques et des ressources énergétiques distribuées. Par ailleurs, elle évalue également la rémunération des véhicules électriques obtenue après la fourniture des services de gestion de factures selon la conception tarifaire. Enfin, passant au secteur résidentiel, la thèse aborde l'avenir des tarifs de recharge des véhicules électriques domestiques. Plusieurs plans tarifaires et solutions adoptant le sous-comptage sont proposés aux usagers et aux autorités réglementaires nationales. Elles ont comme objectif d'encourager la mobilité électrique tout en garantissant un maximum de bien-être social.

Title: Beyond mobility: On the economics of electric vehicle multiple roles in the energy transition.

Keywords : Vehicle-to-Grid, Photovoltaic, Stationary battery, Electric Vehicle, Energy optimization, Tariff design

Abstract:

The rapid uptake of electric vehicles supported by greenhouse gas emission reduction targets may create challenges to the electricity system. Nevertheless, they can contribute to the decarbonization of both power and mobility sectors simultaneously if appropriate economic regulations are present. Appropriate economic signals coupled with essential technologies like smart charging and Vehicle-to-Grid (V2G) will facilitate the integration of electric vehicles in the power sector. In turn, these technologies will allow the utilization of thousands of GWh of battery capacity by system operators in a mid-term horizon. This dissertation investigates several economic aspects on how to unlock the full potential of electric vehicles, not only as a means of transportation but also as an energy resource in an energy transition scenario.

First, it investigates the synergy between electric vehicles and distributed energy resources such as solar PV and stationary batteries. An analytical framework identifying the main research areas and underlying relationships between them is provided. Then, it analyses the impact of different retail tariff designs on private investment incentives and cost-shifting. The context of commercial facilities with both electric vehicles and distributed energy resources is considered. Moreover, it also assesses electric vehicle remuneration obtained from bill management services according to the tariff design. Finally, moving to the residential sector, it discusses the future of domestic electric vehicle rates. Several rate plans and solutions adopting submetering are proposed to users and national regulatory authorities. These proposals have the goal to incentivize electric mobility while ensuring maximum social welfare.