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A bilevel model for long-term studies of grid access tariffs considering behind-the-meter decentralized generation

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MADRID | January 2026

CONTENTS

CHAPTER I. INTRODUCTION 9

CHAPTER II. STATE OF THE ART 14

1. INTRODUCTION 15

2. DECENTRALIZED GENERATION EXPANSION MATHEMATICAL MODELS 15

3. ACCESS-TARIFF MATHEMATICAL MODELS 18

4. BILEVEL MODEL SOLVING ALGORITHMS 22

CHAPTER III. LOWER LEVEL I: ENERGY-ONLY EQUILIBRIUM MODEL 25

1. INTRODUCTION 27

2. THE CENTRALIZED & DECENTRALIZED ENERGY-ONLY EQUILIBRIUM MODEL 28

2.1. Hypotheses 28

2.2. Generation companies' objective functions 30

2.3. Customers' objective functions 30

2.4. Installed capacity constraint 31

2.5. Customers' constraints 31

2.6. Game set-up constraint 32

2.7. Final energy-only equilibrium formulation 32

3. RESOLUTION METHODOLOGY 32

3.1. Lagrangian functions and KKT conditions 32

3.2. Energy-only conjectural variations definition 34

3.3. Equivalent cost minimization model 34

4. DETAILED CONSTRAINTS FORMULATION 35

4.1. Generation investments constraints 35

4.2. Generation investments constraints for pre-existing units ($\boldsymbol{t} \notin \boldsymbol{I}$) 36

4.3. Thermal units model ($\boldsymbol{t} \in \boldsymbol{T}$) 36

4.4. Hydro units' constraints ($\boldsymbol{t} \in \boldsymbol{H}$) 37

4.5. Renewable plants' constraints ($\boldsymbol{t} \in \boldsymbol{R}$) 37

4.6. Energy storage facilities' constraints ($\boldsymbol{t} \in \boldsymbol{S}$) 38

4.7. System constraints 38

4.8. Transmission and distribution losses modeling 39
4.9. System net demand definition constraint 40
5. CASE STUDY AND RESULTS 40
5.1. Assumptions and input data 40
5.2. Scenarios description 43
5.3. Simulation results 45
5.4. Computational results 53
6. CONCLUSIONS 53
7. METHODOLOGICAL CONTRIBUTIONS 54
CHAPTER IV. LOWER LEVEL II: JOINT ENERGY & CAPACITY EQUILIBRIUM 55
1. INTRODUCTION 57
2. THE CENTRALIZED & DECENTRALIZED JOINT ENERGY & CAPACITY EQUILIBRIUM MODEL 58
2.1. Hypotheses 58
2.2. Generation companies' objective functions 59
2.3. Customers' objective functions 59
2.4. Installed capacity constraint 60
2.5. Customers' constraints 61
2.6. Game set-up constraints 61
2.7. Final joint energy & capacity equilibrium formulation 62
3. RESOLUTION METHODOLOGY 63
3.1. Lagrangian functions and KKT conditions 63
3.2. Joint energy & capacity conjectural variations definition 64
3.3. The equivalent cost minimization model 65
4. DETAILED CONSTRAINTS FORMULATION 66
5. CASE STUDIES AND RESULTS 66
5.1. Assumptions and input data 67
5.2. Scenarios description 70
5.3. Simulation results 71
5.4. Computational results 79

6. CONCLUSIONS 80

7. METHODOLOGICAL CONTRIBUTIONS 80

CHAPTER V. UPPER LEVEL: CENTRALIZED TARIFF OPTIMIZATION MODEL..... 83

1. INTRODUCTION 85

2. COST RECOVERY BILEVEL MODEL 87

2.1. Hypotheses.....87

2.2. Upper level: the centralized tariff optimization model.....87

2.3. Lower level: the centralized & decentralized joint energy & capacity model.....89

3. RESOLUTION METHODOLOGY 90

4. CASE STUDIES AND RESULTS..... 94

4.1. Assumptions and input data.....94

4.2. Scenarios description 95

4.3. Simulation results.....95

5. COMPUTATIONAL RESULTS 108

5.1. Model resolution 108

5.2. Convergence analysis 109

6. CONCLUSIONS 113

7. METHODOLOGICAL CONTRIBUTIONS 113

CHAPTER VI. CONTRIBUTIONS, CONCLUSIONS, AND FUTURE WORKS..... 115

1. CONCLUSIONS 117

1.1. Investment dynamics and market interactions 117

1.2. Impact of market design: energy-only versus joint energy & capacity markets 117

1.3. Tariff regulation and system incomes 118

2. METHODOLOGICAL CONTRIBUTIONS 118

2.1. Energy only equilibrium among generation companies & customers....118

2.2. Joint energy and capacity equilibrium among generation companies and customers 119

2.3. Bilevel model for regulated cost recovery 120

3. RESEARCH WORKS DEVELOPED ALONG THIS PHD THESIS 120

4. CONTRIBUTION LIMITATIONS & FUTURE WORK 123

BIBLIOGRAPHY 125

NOMENCLATURE

All items in each section are ordered alphabetically. In sections where both Greek and Latin characters are used, Latin characters are shown first, then Greek characters.

ACRONYMS

BAU	Business as Usual
CCGT	Combined Cycle Gas Turbine
CG	Centralized Generation
CP	Contracted Power
CV	Conjectural Variation
DER	Distributed Energy Resources
DG	Decentralized Generation
DSO	Distribution System Operator
EO	Energy-Only
EOE	Energy-Only Equilibrium
ET	Energy Tariff
EV	Electric Vehicle
GA	Genetic Algorithm
GENCO	Generation Company
GEP	Generation Expansion Planning
JEC	Joint Energy and Capacity
JECE	Joint Energy and Capacity Equilibrium
KKT	Karush-Kuhn-Tucker
NP-hard	Non-deterministic Polynomial-time hard
OCGT	Open Cycle Gas Turbine
PV	Photovoltaic
PT	Power Tariff
RES	Renewable Energy Sources
SO	System Operator
ToU	Time of Use
TSO	Transmission System Operator
UC	Unit Commitment
VPP	Virtual Power Plant
YoY	Year over Year

SETS

C	Set of Customer segments
E	Set of pre-existing generation units

G	Set of GENCOs
H	Hydro units
I	Set of investment candidate generation technologies
N	Consumption (or negative generation) units (such as pumping or battery charge)
P	Set of hours
P_y^M	Annual peak demand hours
R	Renewable units
S	Storage units
T	Thermal units
W	Set of weeks
Y	Set of years

INDEXES

c	Customer segment, $c \in C$
g	GENCO, $g \in G$
k	Iteration
h	Hour, $h \in P$
t, t'	Generation unit, $t \in T \cup H \cup R \cup S \cup N, t \in E \cup I$
s	Agent, $s \in C \cup G$
w	Week, $w \in W$
y	Year, $y \in Y$

PARAMETERS (UPPERCASE/GREEK LETTERS EXCEPT λ)

CI	Firm capacity security margin over demand peak [%]
$D_{c,h,y}$	Customer's base demand [MWh]
DI_t	Firmness (derating) factor[1] [MW/MW]
EF_t	Battery charge/discharge efficiency [%]
$FU_{t,h,y}$	Renewable generators utilization factor [%]
$IC_{t,s,y}$	Investment costs [€/MW]
$INCSP_y$	Total tariff incomes [€]
INC^{MAX}	Maximum tariff YoY increase for tariffs [%]
L_t	Expected lifespan of a generation asset [years]
LS	Transmission losses percentage [%]
NB_t	Battery energy-to-power capacity ratio [Wh/W]
$P_{t,s,y}^{MAX}$	Maximum investment [MW]

[1] Firm capacity factors, or firmness factors, may also be known as "de-rating factors" in the UK or as "capacity credits" in the US.

$PA^{MAX}_{t,s,y}$ Maximum cumulative investment [MW]

$PR^{Q}_{t,g,w,y}$ Maximum weekly production for hydro plants [MWh]

$Q^{MAX}_{t,g,y}$ Generation capacity of pre-existing generation units/ Average generation capacity of a thermal unit to be installed [MW]

$QB^{MAX}_{t,g}$ Maximum capacity of hydro plant in pumping mode [MW]

$Q^{MIN}_{t,g,y}$ Technical minimum (minimum stable load) of thermal plant/Minimum obligatory production of hydro plant [MW]

R Discount rate [%]

$RMU_{t,g}$ Upwards ramping capacity [MWh/h]

$RMD_{t,g}$ Downwards ramping capacity [MWh/h]

$TC_{c,y}$ Volumetric tariff term for selling energy to the grid [€/MWh]

$TE_{c,y}$ Volumetric tariff term (both buying and selling) [€/MWh]

$TP_{c,y}$ Power tariff term [€/MW]

$TV_{c,y}$ Volumetric tariff term for purchasing energy from the grid [€/MWh]

$VC_{t,g,y}$ Variable cost of CG [€/MWh]

δ Initial tariff increment [%]

ϵ Error margin for heuristic convergence [%]

$\theta^{E}_{s,h,y}$ Energy CV [€/MWh^2]

$\theta^{DQ}_{c,h,y}$ Energy CV (DG customer consumption) [€/MWh^2]

$\theta^{EQ}_{c,h,y}$ Energy CV (DG customer production) [€/MWh^2]

$\theta^{C}_{g,y}$ Capacity CV (JECE model) [€/MW^2]

μ Average for normal random distribution [p.u.]

$\rho_{t,g}$ Hydro pumping units' efficiency [%]

σ Deviation for normal random distribution [p.u.]

RELATIONSHIPS (UPPERCASE)

$HP_{t,t'}$ Relationship of each hydro production unit with its pumping unit [Binary]

$SC_{t,t'}$ Relationship of each storage generation unit with its charging unit [Binary]

PRIMAL VARIABLES (LOWERCASE)

All primal variables are positive unless explicitly stated otherwise.

$cp_{c,y}$ Customer's contracted power [MW]

$dq_{c,h,y}$ Customer's energy demand from the grid [MWh]

$e_{s,h,y}$ Battery energy level [MWh]

$eq_{c,h,y}$ Energy injected into the grid [MWh]

$d^{E}_{h,y}$ Energy market demand, free variable [MWh]

$inc^{tp|te,k}_{c,y}$ Actual incomes from demand charge (tp) or volumetric (te) tariffs [€]

$incsp_{c,y}^{tp|te,k}$ Expected incomes from demand charge (tp) or volumetric (te) tariffs [€]
$ls_{c,h,y}$ Distribution losses [MWh]
$n_{t,g,y}$ Number of invested new generation groups [Integer]
$p_{t,s,y}$ Annual commissioned capacity [MW]
$pa_{t,s,y}$ Cumulative installed capacity [MW]
$pr_{t,s,y}$ Annual decommissioned capacity [MW]
$q_{t,s,h,y}$ Energy generation [MWh]
$q'_{t,g,h,y}$ Energy over technical minimum for thermal units [MWh]
$se_{h,y}$ Energy spillages [MWh]
$tp_{c,y}^{k}$ Power tariff term as decision variable [€/MW]
$te_{c,y}^{k}$ Volumetric tariff term as decision variable [€/MWh]
$u_{t,g,h,y}$ Committed-on/off thermal unit [Integer]
$y_{t,g,h,y}$ Start-up decision for thermal units [Integer]
$z_{t,g,h,y}$ Shut-down decision for thermal units [Integer]

DUAL VARIABLES (REPRESENTED BY GREEK LETTER λ)

λ_{y}^{C} Firm capacity price [€/MW]
$\lambda_{h,y}^{C}$ Firm capacity price, hourly disaggregation [€/MWh]
$\lambda_{h,y}^{E}$ Energy price [€/MWh]
$\lambda_{c,h,y}^{CB}$ Dual variable for the customer balance constraint [€/MWh]
$\lambda_{c,h,y}^{CP}$ Dual variable for the contracted power definition constraint [€/MWh]
$\lambda_{s,h,y}^{PQ}$ Dual variable for the maximum production constraint [€/MWh]

REMARK ON NOTATION AND MATHEMATICAL CONVENTIONS

In this thesis, all mathematical formulations follow the conventions commonly adopted in operations research applied to energy systems. This practice enhances readability once the notation has been introduced. For instance, whenever an index (e.g., g, c, h, or y) appears in an expression, it is implicitly assumed that each expression applies to all elements of its corresponding set, as specified above. Therefore, the universal quantifier (∀) is omitted except when strictly necessary, for instance, to explicitly indicate that there is one objective function per agent in a Nash equilibrium. Accordingly, summations written with indexes should be interpreted as a summation throughout all members of those sets unless explicitly stated otherwise.

Chapter I. INTRODUCTION

In recent decades, the global energy sector has been undergoing a profound transformation, driven by the imperatives of decarbonization, digitalization, and decentralization. The transition toward more sustainable energy systems is motivated not only by the urgent need to mitigate climate change, but also by technological advances and evolving policy frameworks. As part of this transition, renewable energy sources (RES) are increasingly integrated into electricity grids, leading to a growing share of variable and distributed generation. At the same time, there is a notable shift in the role of the electricity grid customer, that is also transitioning from being a passive consumer to an active participant in energy markets.

The rise of this "active customer" is one of the defining trends of the current energy landscape. Enabled by the proliferation of distributed energy resources (DER), smart metering, and digital platforms, customers now have the technical and economic capacity to adjust their consumption patterns in response to price signals, participate in demand response programs, and even invest in behind-the-meter generation and storage solutions. This trend, often referred to as the "prosumer" phenomenon, is fundamentally reshaping the architecture of power systems, challenging the traditional paradigms of centralized utility-scale generation (CG) and unidirectional energy flows.

Simultaneously, the liberalization of electricity markets, initiated first in Chile during the 1980s, and continued in many other regions during the 1990s and 2000s, was intended to foster efficiency, competition, and investment in the sector. However, the design of these markets was largely based on centralized dispatch and assumed an inelastic demand side, with customers treated as passive price-takers. As decentralized generation (DG) penetrates further and customers increasingly act as active participants, the limitations of these market structures become evident, particularly in their ability to integrate distributed resources and adequately reflect their value. In parallel, the design of grid access tariffs faces additional challenges: regulated tariffs must ensure cost recovery and long-term sustainability of the grid while also guaranteeing an equitable allocation of regulated costs across heterogeneous customer segments. The combination of evolving market dynamics and tariff design constraints highlights the need for new regulatory and modeling approaches capable of addressing the dual challenge of integrating DG and maintaining fair and efficient cost recovery mechanisms.

Within this context, an emerging challenge is understanding and quantifying the economic impact of self-consumption and DG on the long-term sustainability of electricity systems. While considerable literature has addressed the modeling of liberalized electricity markets for medium- and long-term horizons ([1], [2]), most approaches either still treat customers as passive price-takers with no demand response capabilities [3], or, in some cases, model demand flexibility as the

capability to response to price signals but without considering their investment potential [4]. Only a handful of studies [5] incorporate the capability of customers to invest in behind-the-meter DG for self-consumption, thereby actively influencing their electricity bills by reducing both energy and power withdrawn from the grid, a phenomenon known as load-defection. However, decentralized investments are becoming one of the drivers of the expansion of renewable generation capacity [6].

Reference [7] defines distributed generation as a generation facility connected either to the distribution network (i.e., distributed generation, generally utility-scale, also referred to as DER) or directly to the customers' own-network (i.e., behind-the-meter decentralized generation, or DG). Throughout this thesis, aiming to study the effect of decentralized investments on consumption and tariff incomes, the term DG will refer to generation or storage resources connected behind the meter. All self-consumption in this work is considered on an individual level, collective self-consumption remaining for future work along this research line. On the other hand, CG will refer to power generated or discharged from large generation or storage facilities, either from conventional or RES, including, therefore, utility-scale RES facilities installed in higher voltages of the distribution grid. These large facilities are supposed to be operated by profit-driven traditional electricity market agents (generation companies or GENCOs).

As already discussed in [8], depending on the designs of the end-user electricity tariffs, DG investments of final customers could significantly impact the overall dynamics of the whole power sector. Under some tariff designs, the recovery of parts of the total sector costs (and therefore the economic sustainability of the sector) could be compromised. The total sector costs include (but are not limited to): (i) the cost of producing energy, related to the electricity wholesale market prices[2]; (ii) the cost of transporting that energy from the power plants to the final users, i.e., transmission and distribution network costs; (iii) other security of supply related costs, such as those associated to the provision of ancillary services or capacity remuneration mechanisms; (iv) other energy policy driven costs, such as those related to renewables support remuneration mechanisms; and (v) retail costs [10]. Costs (ii) to (iv) are often called regulated costs, as they correspond to services either provided by regulated entities (such as the system operator, SO, transmission system operator, TSO, or the distribution system operator, DSO) or dependent on regulator inputs (for instance, setting the level of security of supply or the minimum

[2] Indeed, in an energy-only market with an adequate generation mix, all costs of producing energy (both CAPEX and OPEX) are recovered provided there are a few hours of energy scarcity [9]. However, policymakers tend to avoid energy scarcity hours, as they strive to ensure security of supply. The mechanisms described in point (iii) of this list are intended to avoid this issue.

quota of renewables to be achieved). In a liberalized retail market, those regulated costs are transferred to end consumers through the so-called grid access tariffs. Since most of those regulated costs (such as (ii)) for an already existing power system are almost fixed, independently of the energy currently consumed, under a scenario of self-consumption and the corresponding expected DG expansion, the policymaker could need to increase access tariffs to compensate for the income loss caused by significant DG investments. However, an increase in access tariffs can incentivize more customers to invest in DG (additional load-defection), reducing the energy supply from the grid or even disconnecting (grid-defection), and triggering further increases in access tariffs, leading to the so-called *death spiral* [8], increasing the complexity of the tariff structure design.

This thesis aims to study the problem described by designing and developing a bilevel mathematical model for the long-term planning of the power sector. The upper level determines the optimal adjustment of electricity tariff values, while the lower level captures the optimal long-term generation expansion decisions of both CG and DG agents, in response to those tariffs.

This thesis is organized as follows:

- Chapter II performs an exhaustive literature review over the topics of (i) mathematical models that consider investments in DG, (ii) mathematical models for the numerical adjustment of tariff terms, and (iii) resolution algorithms for bilevel models.
- Chapter III presents the initial formulation of the lower-level part of the model. It includes the basic formulation of the operation & investments model, and mathematically proves that an agent-based, energy-only equilibrium between generators and active customers can be simplified as an easier to solve optimization problem using a conjectural variations (CV) approach.
- □ extends the lower-level model to include a firm capacity market, enabling the provision of two distinct prices, one for energy and another for power (installed capacity), both contributing to the final energy price paid by customers.
- □ provides a detailed description of the upper-level part of the model and proposes an iterative algorithm to solve the complete bilevel problem. It also presents case studies that explore the model results when different constraints are imposed to limit the resulting tariffs and shape their temporal evolution.
- Finally, Chapter VI presents the main conclusions and contributions of the thesis, as well as discusses the main possible future lines of research that may stem from this research.

Chapter II. STATE OF THE ART

1. INTRODUCTION

The methodological developments presented in this thesis aim to build a comprehensive modeling framework that simultaneously addresses the long-term expansion of centralized and decentralized generation, the design of grid access tariffs, and the interactions between regulators, generation companies, and customers. Achieving this goal requires drawing upon, and combining, three different strands of the literature:

1) Generation expansion models that consider DG investments, explained in section 2.
2) Models for determining grid access tariffs in the power sector, explained in section 3.
3) Resolution approaches for bilevel problems, since 2) lead typically to such type of mathematical problems, explained in section 4.

2. DECENTRALIZED GENERATION EXPANSION MATHEMATICAL MODELS

Decentralized generation (DG) expansion models are computational tools designed to determine optimal investment pathways in generation and storage technologies over a long-term planning horizon. Their primary purpose is to evaluate how different agents (some of which may be end-users) may invest in generation capacity located behind the meter, that is, installed at the customer's premises rather than at the utility scale. These models capture the interplay between technology costs, market conditions, tariff structures, demand, and regulatory frameworks, in order to project how DG adoption evolves and how it interacts with centralized generation. By simulating such investment trajectories, DG expansion models provide valuable insights into economic, technical, and policy drivers shaping the decentralization of power systems.

A summary of the main features of DG expansion mathematical models, their objectives, and their main drawbacks, as compared to the lower and bilevel models proposed in this thesis , can be found in Table 1. In particular, the models developed in this thesis are highlighted in bold at the end of the table, as well as the chapters in which they are described.

Table 1: DG expansion models, including (in bold) the models proposed in this thesis.

Ref.	Model description	Objective	Drawbacks
[11]	Comparative investment model focusing on CG and DG energy storage	Cost-minimization with network constraints	Only consider investments in CG and DG storage. No analysis of impacts on tech. mix

Ref.	Model description	Objective	Drawbacks
[12]	Socioeconomic aspects in CG and DG investments, modeling in detail the power sources used in several types of buildings in Italian cities	Cost minimization in single buildings	Small-scale model. Exogenous electricity market price
[13]	Optimization of DG energy resources in a Greek neighborhood	DG investment optimization in a neighborhood	Small-scale model. Exogenous electricity market price
[14]	Optimization of investments in before-the-meter DG by a distribution company minimizing network congestions	DG investments to minimize network congestions	Exogenous electricity market price.
[15]	Optimization of several charging strategies for electric vehicles (EVs) considering either CG or DG as power sources	EV charging strategies	Exogenous electricity market price.
[16]	CG and DG equilibrium model with only DG investments (no CG investments)	Profit maximization of CG and DG agents	Investments in CG not considered
[17], [18], [19]	Modeling of a commercial building as a microgrid considering DG installations and plug-in EV	Office building DG resources and plug-in EV	Small-scale model. Exogenous electricity market price
[5], [20]	Cost-minimization DG and CG investments model, where the CG market is represented on a per-technology basis	CG and DG cost minimization. Heating modeling for DG	CG per technology. Price flattening. Investments decided on the first simulated year
[21]	Stochastic optimization of DER subject to stochasticity in power prices, gas prices and solar irradiance	DER energy consumption minimization	Exogenous electricity market prices
[22]	Profitability of using behind-the-meter storage to reduce electricity bills	Electricity bills minimization	Exogenous electricity market prices. Single consumer model.
[23]	Multi-stage DG and distribution network expansion planning	Total net-present-value cost minimization	No market modeling
[24]	Bilevel tariff optimization subject to stochastic customer tariff selection. Lower level is stochastic with a deterministic upper level	Upper level: maximize utility profit Lower level: minimize customer energy expenses with risk aversion	Simplified electricity market model (linear electricity prices with total demand). No DG. No network losses model.
[25]	Iterative tariff optimization with a % of customers that can invest in DG. Analyzes volumetric, net-metering, capacity and fixed charges.	First step: Increase tariffs until regulated costs are covered. Second step: minimize customer energy expenses with tariffs computed in first step. Repeat the first step with new consumption data.	No electricity market model, exogenous electricity prices. No network losses model. Results highly depend on % of passive customers (that can't invest in DG), relying on cross-subsidies from passive to active customers.

Ref.	Model description	Objective	Drawbacks
[26]	Combined CG, DG and Transmission expansion planning.	Cost minimization on each subproblem	Single agent optimization, no market power.
[27]	Combined CG and DG expansion planning	Cost minimization	Single agent optimization, no market power
[28]	Genetic algorithm for private DG investments	Profit maximization for a distribution company	Single agent model.
[29]	Combined DG and distribution network expansion planning.	Upper level: minimize inv. Cost. Lower level: minimize energy to be curtailed	Small scale level (downstream from substation), exogenous centralized power prices, no market power.
[30]	Bilevel model for DSO and aggregator of DER	Upper level: minimize distribution costs Lower level: maximize profits	Small scale model, exogenous power prices.
[31]	Bilevel model for DSO and aggregator	Upper level: Adequate tariff revenue Lower level: Minimize costs	Small scale model, exogenous power prices.
Chapter III	**CG GENCOs and DG customers equilibrium converted to equivalent cost-minimization problem with CV**	**CG: profit maximization DG: energy expenses minimization**	**Not yet able to analyze death-spiral, as tariffs are inputs to the model. Energy-only equilibrium**
□	**Expands Chapter III model by adding a capacity market**	**CG: profit maximization DG: energy expenses minimization**	**Not yet able to analyze death-spiral, as tariffs are inputs to the model. Joint energy and capacity equilibrium**
□	**Builds onto □ model by including tariff decisions as upper level**	**Adjust tariff incomes to regulated costs (as inputs)**	**Able to detect & avoid death spiral with heuristic algorithm, optimality not guaranteed**

As seen in Table 1, most existing DG expansion models focus on small or medium facilities located at the distribution network, where it can be reasonable to assume exogenous market prices, since the impact of localized, small-scale, and still incipient DG on the system can still be considered negligible.

However, this assumption becomes unrealistic for large-scale or long-term DG expansion, or even for small-scale investments when their aggregated penetration becomes significant, as expected under the current trend toward energy communities and increasing energy system decentralization [30], [31].

This reveals an important gap in the literature: the lack of long-term modeling approaches that endogenously represent the interaction between DG investments, CG expansion, and electricity market prices. This thesis proposes a model that addresses this gap by explicitly linking the investment and operational decisions of final customers with those of GENCOs, while endogenously computing the electricity prices withing the model framework. In doing so, it better captures the existing relations between tariff structures, decentralized investment behavior, and centralized generation planning. Collective DG or energy community

configurations remain identified as a relevant topic for future research within this line of work.

3. ACCESS-TARIFF MATHEMATICAL MODELS

Access-tariff mathematical models are analytical models designed to represent and solve the allocation of electricity system costs among users. These costs may include not only transmission and distribution network expenditures, but also other regulated components such as generation, retailing, policy-related charges, or security-of-supply mechanisms. The central purpose of such models is to ensure that regulated revenues are recovered in a transparent and sustainable way, while simultaneously providing appropriate economic signals to different customer segments. Depending on their formulation, they may emphasize revenue adequacy for the regulated operator, profit maximization for utilities or retailers, or the assignment of marginal costs to individual consumers. By explicitly formalizing these perspectives, access-tariff models play a key role in evaluating the trade-offs between cost recovery and economic efficiency in tariff design.

Table 2 summarizes the main mathematical models found in the literature addressing these issues. As in the previous sections, the final model developed in this thesis is shown in bold, along with the chapter in which it is presented and explained.

Table 2: Access-tariff mathematical models. Bolded those which are part of this thesis.

Ref.	Model description	Objective	Drawbacks
[32]	Bilevel model: tariffs in upper level, investments in solar DG in lower level.	Upper level: recover regulated costs Lower level: minimize energy expenses	No electricity market model, exogenous electricity prices. Exogenous contracted power for customers. No network losses model.
[33]	Stochastic model of tariffs and consumer's demand considering demand elasticity.	Maximization of total welfare	No electricity market model, exogenous electricity prices. No DG. No network losses model.
[34]	Genetic algorithm for a stepwise power tariff considering demand elasticity.	Maximization of energy savings	No electricity market model, exogenous electricity prices. No DG. No network losses model.
[35]	Comparison of the UK regulator model with Yardstick competition.	Maximization of total social utility	No electricity market model, exogenous electricity prices. No demand response, no DG.
[36]	Bilevel model for setting TOU tariffs: utility in upper level, consumer's load-shifting in lower level.	Upper level: maximize utility profit Lower level: consumer cost minimization	No electricity market model, exogenous electricity prices. Inelastic annual demand. No DG. No network losses model.
[24]	Bilevel tariff optimization subject to stochastic customer tariff selection. Lower level is stochastic with a deterministic upper level	Upper level: maximize utility profit Lower level: minimize customer energy expenses with risk aversion	Simplified electricity market model (linear electricity prices with total demand). No DG. No network losses model.

Ref.	Model description	Objective	Drawbacks
[25]	Iterative tariff optimization with a % of customers that can invest in DG. Analyzes volumetric, net-metering, capacity, and fixed charges.	First step: Increase tariffs until regulated costs are covered. Second step: minimize customer energy expenses with tariffs computed in first step. Repeat the first step with new consumption data.	No electricity market model, exogenous electricity prices. No network losses model. Results highly dependent on % of passive customers (that cannot invest in DG), relying on cross-subsidies from passive to active customers.
[37]	Bilevel tariff optimization for an aggregator, simulating a day per season and a single prosumer with fixed DG capacity	Agent profit optimization. Solved with a custom heuristic algorithm.	No electricity market model, exogenous electricity prices. Small scale model.
[38]	Stochastic bilevel model for a retailer (leader) and a prosumer (follower). Stochastic upper level, scenarios in the market price & electricity demand.	Upper level: minimize conditional value at risk. Lower level: Minimize costs	Small-scale model, exogenous (but stochastic) electricity prices.
[39]	Custom algorithm for determining ToU tariffs to incentivize EV DSM	Custom prioritization of charge level of EVs	Small-scale model, exogenous electricity prices.
[31]	Bilevel model for DSO and aggregator	Upper level: Adequate tariff revenue Lower level: Minimize costs	Small scale model, exogenous power prices.
[40]	Bilevel model for aggregator and flexible consumers	Upper level: profit maximization Lower level: cost plus discomfort minimization	Small scale model, exogenous power prices
[41]	Bilevel model, market operator in upper-level, consumers as VPP in lower-level	Upper level: welfare maximization Lower level: costs minimization	Small scale model.
□	**Deterministic bilevel model for tariff design in the long-term simulating generation investment decisions in the lower level**	**Upper level: recover regulated costs. Lower level: agent profit maximization**	**Upper-level target set exogenously, optimality not guaranteed**

As can be deduced from Table 2, most models for access tariffs determination adopt bilevel approaches [42]. A bilevel model is a particular type of mathematical optimization problem in which one optimization problem is nested within the constraints of another. Typically, bilevel formulations arise when there are two interacting agents in an asymmetric relationship with conflicting objectives. The agent at the upper level (often called the *leader*) makes decisions first, while the agent at the lower level (the *follower*) adapts to those decisions in order to optimize their own objective.

In the context of access tariffs, upper-level decisions typically consist in setting tariff structures and values, while lower-level responses include demand-side behaviors such as demand elasticity or load-shifting. However, the literature reveals a significant gap concerning DG, particularly for the medium and long term, as final consumers are generally not modeled as active agents responding to tariffs or

wholesale electricity prices. Furthermore, few models incorporate the impact of transmission or distribution losses.

The last row of Table 2 outlines the main features of the model proposed in this thesis, comparing it with existing access tariff models in literature. The main distinguishing feature is the treatment of tariffs as decision variables at the upper level, allowing the model to capture both CG and DG expansion decisions in response to these tariffs by modeling the power market at the lower level, with a simplified representation of the distribution network. Moreover, to overcome the gaps found in the literature, particularly regarding the integration of DG expansion and access tariff design in long-term planning models, this thesis' bilevel model has been designed to assess critical aspects such as the recovering of regulated costs, the impact of the tariffs structure design and the potential emergence of the so-called death spiral. The model consists of two levels:

1) An upper level where the policymaker or regulator set tariff values with the objective of ensuring regulated cost-recovery; and
2) A lower level where CG and DG agents make operation and investment decisions, aiming to maximize profits or minimize costs in the Nash sense [43], respectively.

The basic structure of the bilevel model is shown in Figure 1:

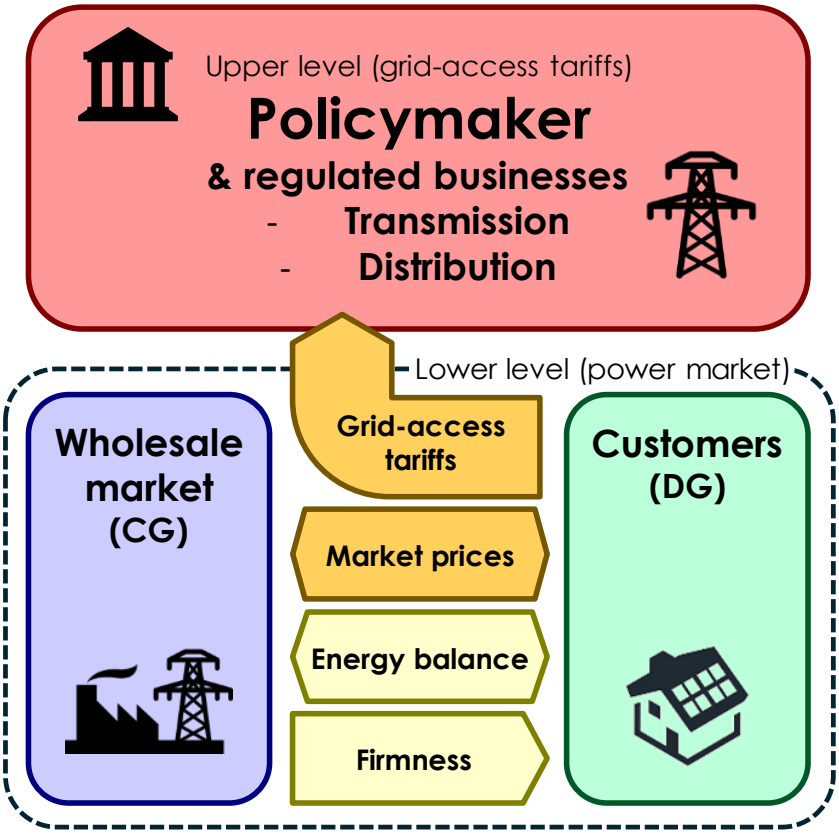

Figure 1: Proposed bilevel model structure.

A similar but more simplified approach was already proposed in [32], considering only DG decisions in the lower level, exogenous tariff capacity charges, exogenous electricity market and homogenous customers. The conceptual model of [44] (previous work that sets up some of the basic points of this thesis) overcomes the drawback of [32] and, at the same time, addresses several of the gaps found in earlier DG investment models that treat electricity prices as exogenous parameters (see Table 1), ignoring the impact of CG and DG investments on the electricity prices, and therefore, on the tariffs. In [44], the leader's objective (in the upper level) is the design of an adequate and cost-effective tariff system to recover regulated costs, while considering other relevant constraints such as constraining the year-over-year change on tariff terms. Each follower's objective (in the lower level) is an individual agent profit maximization, subject to the inputs coming from the policy decisions of the first level. However no detailed mathematical formulation was proposed in [44], which was a preliminary conceptual approach.

This thesis advances the state of the art by fully developing that formulation and overcoming the drawbacks of most access-tariff models found in the literature. These models typically fail to consider behind-the-meter DG expansion as a rational strategy for consumers to reduce their tariff and energy expenses. This aspect is essential in the long term. Unlike other approaches (see Table 1) the access-tariffs are therefore decision variables taken at the upper level by the policy maker or the

regulator (the leader in the bilevel model). In addition, the proposed approach can account for transmission and distribution losses using a simplified network model, improving the realism and policy relevance of the results.

4. BILEVEL MODEL SOLVING ALGORITHMS

As shown in [42], bilevel models are non-convex, and solving them is a NP-hard problem. NP-hard means that they cannot be solved in polynomial time, which makes problematic to solve real life-scale problems. Table 3 presents a summary of several algorithms found in the literature to solve bi-level models. The algorithm presented as part of this thesis to solve the bilevel problem shown in section 3 is shown in bold in this table.

Table 3: Resolution algorithms for bilevel models. Bolded those that are part of this thesis.

Ref.	Algorithm description	Lower-level treatment	Optimality and adaptability
[45]	Transformed into MILP after replacing follower problem with KKT cond.	Replaced by its KKT conditions	Optimal but specific to a single problem, solution not unique
[46]	Trust-region methodology after replacing follower problem with KKT cond.	Replaced by its KKT conditions	Optimal if upper-level constraints are independent from lower-level variables
[47]	KKT conditions solved by applying strong duality theorem	Replaced by its KKT conditions	Optimal but specific to a single problem
[48]	Trust-region derivative-free methodology for an inexact solution of the lower-level	Inexact solution of the lower level, reutilizes previous solutions	Optimal if upper-level constraints are independent from lower-level variables
[49]	Iterative algorithm until all fuzzy satisfactory degrees are satisfied for all levels	Fuzzy solution, checks satisfaction degree	Sub-optimal. Approaches optimality as satisfaction degrees become stricter each iteration.
[50]	Hybrid gradient-descent and taboo optimization	LP solve per each candidate solution	Upper-level optimality not guaranteed
[51]	Genetic algorithm to solve the resulting MILP from lower-level's KKT conditions	Substituted by its KKT conditions	Upper-level optimality not guaranteed
[52]	Genetic algorithm that iterates through the inducible region vertexes	LP solve per each candidate solution	Upper-level optimality not guaranteed
[53]	Genetic algorithm for upper level	LP solve per each candidate solution	Upper-level optimality not guaranteed

Ref.	Algorithm description	Lower-level treatment	Optimality and adaptability
[54]	Particle swarm optimization for upper level	LP solve per each candidate solution	Upper-level global optimality not guaranteed (locally optimal)
[55]	Cutting plane solution algorithm	LP solve per each candidate solution	Optimality proven for this exact problem structure
[30]	Different metaheuristics: GA, PSO, Red Deer Algorithm, Evolve class topper optimization (ECTO)	Metaheuristic	Sub-optimal. ECTO shows a better response.
[40]	Reformulation of lower level into primal and dual	Strong duality theorem	Optimality proven for this exact problem structure
[56]	Column and constraint generation algorithm to solve parts of the main problem	Added into the master problem iteratively using optimality cuts	Optimal but specific to this problem
□	**Heuristic iterative search for the upper level**	**LP solve per each lower-level candidate solution**	**Upper-level optimality not guaranteed**

As seen in Table 3, many of the resolution algorithms of bilevel models are based on metaheuristic strategies in the upper level to reduce the problem complexity at the expense of being unable to prove the optimality of the solution. In addition, most approaches use traditional optimization algorithms, such as simplex, to solve the lower-level problem for each candidate solution. The search algorithm proposed in this thesis, based on [57], adopts a similar approach: each candidate solution has its lower-level solved optimally using the equivalent optimization problem proposed in □ and the Gurobi solver [58]. As it will be explained in □, finding this equivalent problem enables the use of commercial solvers and allows the resolution of large-scale, realistic problems, representing a novel contribution compared to existing literature, where such scalability is often limited. The final solution for the upper level will be obtained based on a searching strategy until a stop condition is met. Since each lower-level problem is independent from each other, parallelization techniques could enhance computational efficiency, although they have not been implemented in this thesis.

Chapter III. LOWER LEVEL I: ENERGY-ONLY EQUILIBRIUM MODEL

1. INTRODUCTION

This chapter proposes a new hourly conjectural Nash equilibrium problem corresponding to an energy-only equilibrium (EOE) problem that considers, in the same level, both CG and DG operation and capacity expansion, with endogenous marginal prices (i.e., prices are outputs of the operation and expansion problems) and price-response conjectural variations [43]. Both the model and the case studies presented herein were already published in EPSR, a high-impact JCR-indexed journal [59].

Figure 2 illustrates the structure of the equilibrium model developed in Chapter III, corresponding to the energy-only equilibrium formulation. In this version, both the upper-level policymaker (responsible for setting grid-access tariffs) and the firm capacity market are disabled. The model therefore represents an energy-only version of the lower level of the framework, focused exclusively on the interactions between CG GENCOs and DG customers in an energy-only market.

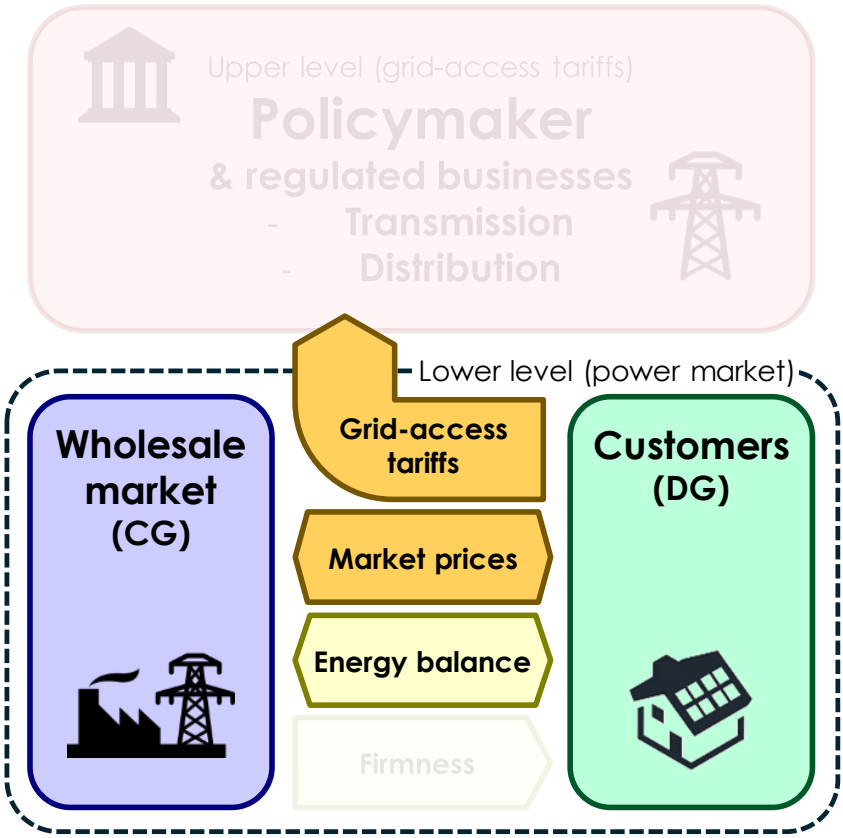

Figure 2: Energy-only equilibrium model structure.

The chapter is structured as follows: sections 2 and 3 formulate the proposed equilibrium model and present an equivalent and easier-to-solve minimization problem. Section 4 presents the detailed GEP-UC (Generation expansion planning with unit commitment) formulation. Section 5 presents a case study to validate

some of the main contributions of the proposed model, section 6 presents the main contributions of this chapter, and finally section 6 draws the main conclusions.

2. THE CENTRALIZED & DECENTRALIZED ENERGY-ONLY EQUILIBRIUM MODEL

The proposed equilibrium problem consists of two different types of interconnected optimization problems:

- The first problem addresses GENCO's operation and investment decision making on CG, under a profit-maximization scheme.
- The second problem represents the customers' operating and investing decision making on DG to minimize their total energy expenses. Thus, customers may decide either to invest and produce for self-consumption or to purchase energy from the grid, or any intermediate arrangement, to minimize their energy costs.

For simplicity, a reduced version of the model is presented in this section, although the complete model considers thermal constraints such as start-ups, shut-downs or ramps, as described in section 4.

In this model, the investments and operation for all agents are solved in the same level [60] instead of considering them in two different levels [61], which would correspond to modeling investments in the upper level, and solving the operation in the lower level. This approximation was adopted since, as proven in [60], it provides accurate enough investment results while considerably reducing the computational complexity required to solve the problem.

2.1. Hypotheses

The model presented in this chapter assumes that:

- Access tariffs are treated as exogenous inputs in this chapter. Consequently, how load or grid defections might endogenously influence these tariffs is not yet addressed, but will be analyzed in Chapter V[3].
- Each customer has the capability of installing DG facilities (at a given investment cost) to self-consume and sell the surplus to the grid (electricity buying and selling prices are explained below).
- DG investments considered are Solar PV and storage batteries, both of which with zero production (variable) costs. Only upfront investment costs are considered.

[3] In fact, □ incorporates tariff terms in the objective function as decision variables that multiply customers' absolute net consumption (also a decision variable). As a result, the model developed in □ requires optimization techniques beyond the linear or quadratic approaches applied in the present chapter. The methods used to solve that problem will be discussed in detail in □.

- No demand response or load-shifting mechanisms on the customer side have been considered, aside from their capacity to invest in DG[4] and the operational flexibility of the newly installed batteries.
- Each DG customer has an hourly fixed final electricity consumption (denoted throughout this work as the customer's base demand $D_{c,h,y}$), which they may cover either by buying power from the grid or by consuming their own self-production from their DG assets.
- DG customers are categorized into different segments c according to:
    - Firstly, their type (residential, industrial or commercial customers)
    - Secondly, their economic activity (metallurgy, chemistry, mining, wood/paper, food, hotels and restaurants, services, etc.) or household type (block, single-family, etc.).

  It is assumed that all customers belonging to the same segment c behave similarly within them, allowing the model to consider each segment as a single agent.

To simplify the model, the following assumptions are made regarding the consumer's incomes and payments to and from the grid:

- Purchases from and sales of electricity surpluses to the grid are valued at the hourly market price, based on an hourly energy net metering scheme.
- A regulated grid access tariff is paid by the customers according to the following structure:
    - a power-related term, which is applied to the power contracted by the customer and paid annually (also known as demand charge) and
    - an energy-related term (volumetric term), which is applied hourly to the energy both withdrawn from and injected into the grid, which can be different when importing to or exporting from the grid.
- The annual power contracted with the grid by each customer is given by its annual peak net demand. For simplicity, time-differentiated tariff periods are not considered, and the contracted power is therefore defined on an annual basis rather than by tariff period.

In addition, regarding investment decisions and their economic assessment in GEP models:

- For simplicity, planned and random outages of generation units are not explicitly modeled in the formulation. However, their effects are implicitly captured by multiplying the installed capacity of each generator by one

[4] Indeed, after-the-meter batteries can load-shift, but subject to the investment cost required to use them. Adding other load-shifting capabilities would compromise the investment results of the model.

minus their expected outage factors, resulting in their effectively available installed capacity. This approach allows to represent average availability conditions, while avoiding the complexity of explicitly modeling unit-level outage events.

- All terms in the objective functions hereinafter should have the discount rate R applied by multiplying them by $(1-R)^{ord(y)}$ to optimize their net present value. However, for the sake of clarity, these multiplying factors have been omitted but are considered in the model implementation.
- When assets have lifetimes longer than the simulation horizon, the so-called end-of-horizon effect distorts prices and investment decisions toward the final years of the simulation period ([62]). Two main approaches can be applied to mitigate this problem. The first one consists in adjusting the investment costs, for example according to the methodology described in [62]. The second one consists in extending the simulation horizon by repeating the last simulated year and reducing the investment costs of each candidate investment asset to the fraction that can be amortized within the effective simulation period. In this thesis, the second approach has been adopted, applying linear amortization to adjust the investment costs $IC_{t,c,y}$ accordingly.

2.2. Generation companies' objective functions

Omitting, for simplicity, the discount rate R, it is assumed that each GENCO *g* seeks to maximize its profits when making investments and operating decisions for a set of available generation units *t* throughout the set of years *y* under study. Profits for a GENCO are expressed, see (1), as its market incomes (energy market price $\lambda^{E}_{h,y}$ times power production, $q_{t,g,h,y}$), minus its generation units' variable operation costs ($VC_{t,g,y}$ times $q_{t,g,h,y}$) and its investment costs in new generation capacity ($IC_{t,g,y}$ times installed power $p_{t,g,y}$):

$$\text{Max}\left\{\sum_{t,h,y}\left(\lambda^{E}_{h,y}\cdot q_{t,g,h,y} - VC_{t,g,y}\cdot q_{t,g,h,y}\right) - \sum_{t,y} IC_{t,g,y}\cdot p_{t,g,y}\right\}, \forall g \qquad (1)$$

2.3. Customers' objective functions

DG customers, as GENCOs do, also buy and sell energy on an hourly basis at the energy market price $\lambda_{h,y}$. It is also assumed that DG customers are subject to a grid access tariff with the following generic structure:

- An energy related *buying* term, or volumetric *buying* term, $TV_{c,y}$ [€/MWh], proportional to the customer segment's energy consumed from the grid, $dq_{c,h,y}$.

- An energy related *selling* term, or volumetric *selling* term, $TC_{c,y}$ [€/MWh], applied as a payment from the customer to the SO in case the customer sells energy $eq_{c,h,y}$ back to the grid (when its DG production surpasses its own consumption in an hourly basis)[5].
- A power related term, or demand charge, $TP_{c,y}$ [€/MW], that customers pay for their contracted power $cp_{c,y}$. This is a simplification of actual demand charge terms, which generally have several different periods (and therefore several different contracted powers for each customer) throughout both the day and the year.

Therefore, the objective function of each customer segment c is defined in (2):

$$\text{Min}\left\{\sum_{y} TP_{c,y}\cdot cp_{c,y} + \sum_{t,y} IC_{t,c,y}\cdot p_{t,c,y} + \right. \\ \left. + \sum_{h,y}\left[\left(\lambda^{E}_{h,y} + TV_{c,y}\right)\cdot dq_{c,h,y} - \left(\lambda^{E}_{h,y} - TC_{c,y}\right)\cdot eq_{c,h,y}\right]\right\}, \forall c \tag{2}$$

The first term is the consumer peak consumption related costs [63] due to the power related term of the grid access tariff. The second one represents the investment costs of installing its own DG capacity. The third one adds up the hourly costs of purchasing and selling energy from or to the grid associated with the hourly energy market price and the volumetric terms of the grid access tariff.

2.4. Installed capacity constraint

The production $q_{t,s,h,y}$ for either DG or CG generation units could never exceed the installed capacity, as in (3):

$$q_{t,s,h,y} \leq p_{t,s,y} : \lambda^{PQ}_{t,c,h,y}, s \in C \cup G \tag{3}$$

2.5. Customers' constraints

In the customer's subproblem, the electricity demand $D_{c,h,y}$ of each segment c must be supplied either by the energy $dq_{c,h,y}$ bought from the grid, or by the energy $q_{t,c,h,y}$ produced with their own installed DG capacity. In case the customer production is larger than its demand, it is assumed that the excess $eq_{c,h,y}$ is injected to the grid. Mathematically, this is represented as in (4):

[5] This tariff scheme may effectively allow for net metering by setting $TC_{c,y} = -TV_{c,y}$. However, it is not the expected use-case of the model, as net metering is not widely applied anymore.

$$\sum_{t} q_{t,c,h,y} + dq_{c,h,y} = D_{c,h,y} + eq_{c,h,y} : \lambda^{CB}_{c,h,y} \quad (4)$$

As mentioned, the annual customer contracted power, for which he will be charged with the power term of the grid access tariff that year *y*, is set to the maximum power ever demanded from or sold to (not simultaneously) the grid during that year, as in (5):

$$dq_{c,h,y} + eq_{c,h,y} \leq cp_{c,y} : \lambda^{CP}_{c,h,y} \quad (5)$$

Note that the cost-minimization nature of the customer's subproblem (see details on section 4.8) will force $eq_{c,h,y}$ and $dq_{c,h,y}$ to not be non-null simultaneously.

2.6. Game set-up constraint

All subproblems are linked by the hourly total energy balance of the whole system, (6):

$$\sum_{t,g} q_{t,g,h,y} + \sum_{c} eq_{c,h,y} = \sum_{c} dq_{c,h,y} : \lambda^{E}_{h,y} \quad (6)$$

2.7. Final energy-only equilibrium formulation

The final mathematical formulation of the EOE is defined through the equilibrium, in the sense of Nash, of (1) subject to (3) (for $s \in G$) and (2) subject to (4)-(5) (for $s \in C$), with (6) as the game-defining linking constraint.

3. RESOLUTION METHODOLOGY

This section proves that the EOE can be solved with an equivalent minimization problem using a CV approach.

3.1. Lagrangian functions and KKT conditions

The Lagrangian functions of the objective functions in (1) and (2) subject to (3) (for $s \in G$), (4)-(5) (for $s \in C$) and (6) are:

$$
\begin{aligned}
&\ell_g(q,p,\lambda^{PQ},\lambda^{E}) = \\
&\quad = -\sum_{t,h,y}\left(\lambda^{E}_{h,y}\cdot q_{t,g,h,y} - VC_{t,g,y}\cdot q_{t,g,h,y}\right) + \sum_{t,y} IC_{t,g,y}\cdot p_{t,g,y} + \\
&\quad + \sum_{t,h,y} \lambda^{PQ}_{t,g,h,y}\cdot\left(q_{t,g,h,y} - p_{t,g,y}\right)
\end{aligned}
$$

$$
\begin{aligned}
&\ell_c(q,p,cp,dq,eq,\lambda^{PQ},\lambda^{CB},\lambda^{CP},\lambda^{E}) = \\
&\quad = \sum_{y} TP_{c,y}\cdot cp_{c,y} + \sum_{t,y} IC_{t,c,y}\cdot p_{t,c,y} + \\
&\quad + \sum_{h,y}\left[\left(\lambda^{E}_{h,y} + TV_{c,y}\right)\cdot dq_{c,h,y} - \left(\lambda^{E}_{h,y} - TC_{c,y}\right)\cdot eq_{c,h,y}\right] + \\
&\quad + \sum_{t,h,y} \lambda^{PQ}_{t,c,h,y}\cdot\left(q_{t,c,h,y} - p_{t,c,y}\right) + \\
&\quad + \sum_{h,y} \lambda^{CB}_{c,h,y}\cdot\left[\sum_{t} q_{t,c,h,y} + dq_{c,h,y} - eq_{c,h,y} - D_{c,h,y}\right] + \\
&\quad + \sum_{h,y} \lambda^{CP}_{c,h,y}\cdot\left(dq_{c,h,y} + eq_{c,h,y} - cp_{c,y}\right)
\end{aligned}
\tag{7}
$$

Their Karush-Kuhn-Tucker (KKT) first order optimality conditions are computed in (8):

$$
\begin{aligned}
&\frac{\partial \ell_g}{\partial q_{t,g,h,y}} = VC_{t,g,y} - \frac{\partial \lambda_{h,y}}{\partial q_{t,g,h,y}}\cdot q_{t,g,h,y} - \lambda^{E}_{h,y} + \lambda^{PQ}_{t,g,h,y} = 0 \\
&\frac{\partial \ell_c}{\partial q_{t,c,h,y}} = \lambda^{PQ}_{t,c,h,y} + \lambda^{CB}_{c,h,y} = 0 \\
&\frac{\partial \ell_c}{\partial cp_{c,y}} = TP_{c,y} - \sum_{h} \lambda^{CP}_{(c,h,y)} = 0 \\
&\frac{\partial \ell_c}{\partial dq_{c,h,y}} = -\frac{\partial \lambda^{E}_{h,y}}{\partial dq_{c,h,y}}\cdot\left(eq_{c,h,y} - dq_{c,h,y}\right) + \left(\lambda_{h,y} + TV_{c,y}\right) + \lambda^{CB}_{c,h,y} + \lambda^{CP}_{c,h,y} = 0 \\
&\frac{\partial \ell_c}{\partial eq_{c,h,y}} = -\frac{\partial \lambda^{E}_{h,y}}{\partial eq_{c,h,y}}\cdot\left(eq_{c,h,y} - dq_{c,h,y}\right) - \left(\lambda_{h,y} - TV_{c,y}\right) - \lambda^{CB}_{c,h,y} + \lambda^{CP}_{c,h,y} = 0 \\
&\frac{\partial \ell_s}{\partial p_{t,s,y}} = IC_{t,s,y} - \sum_{h} \lambda^{PQ}_{t,s,h,y} = 0, s \in C \cup G \\
&\qquad \lambda^{CB}_{c,h,y} \perp \sum_{t} q_{t,c,g,y} - eq_{c,h,y} + dq_{c,h,y} - D_{c,h,y} = 0 \\
&0 \le \lambda^{PQ}_{t,s,h,y} \perp q_{t,s,h,y} - p_{t,s,y} = 0 \\
&0 \le \lambda^{CP}_{c,h,y} \perp dq_{c,h,y} + eq_{c,h,y} - cp_{c,y} \le 0 \\
&\qquad \lambda^{E}_{h,y} \perp \sum_{t,g} q_{t,g,h,y} + \sum_{c}\left(eq_{c,h,y} - dq_{c,h,y}\right) = 0
\end{aligned}
\tag{8}
$$

3.2. Energy-only conjectural variations definition

Then, by taking a CV approach [64] we can define the following price-response conjectures as in (9):

$$\frac{\partial \lambda^{E}_{h,y}}{\partial\left(\sum_t q_{t,g,h,y}\right)} = -\theta^{E}_{g,h,y};\ \frac{\partial \lambda^{E}_{h,y}}{\partial dq_{c,h,y}} = -\theta^{DQ}_{c,h,y};\ \frac{\partial \lambda^{E}_{h,y}}{\partial eq_{c,h,y}} = -\theta^{EQ}_{c,h,y} \tag{9}$$

It has also been assumed that the reaction to the price is the same, for hour *h*, whether the customer is purchasing energy from the grid and this energy increases ($\Delta dq_{c,h,y} > 0$), or whether the customer is injecting energy to the grid and this energy decreases ($\Delta eq_{c,h,y} > 0$), allowing us to perform substitution (10):

$$-\theta^{DQ}_{c,h,y} = \theta^{EQ}_{c,h,y} = \theta^{E}_{c,h,y} \tag{10}$$

That is to say, the residual demand slope of a customer as consumer equals the residual generation slope as producer (see [65] for definitions of residual slopes for producers, retailers and consumers). This is a reasonable assumption, since both a unitary increase in generation by a customer and a unitary decrease in consumption by the same customer would result in the same effect for the other participants in the generation pool, provided that the residual slopes near the equilibrium point are continuous and derivable.

3.3. Equivalent cost minimization model

By considering the CVs defined in (9) & (10) and substituting them into (8), we can propose the minimization problem defined by (11) subject to (3)-(6):

$$\begin{aligned}\text{Min}\Bigg(&\sum_g\Bigg\{\sum_{h,y}\Bigg(\sum_t VC_{t,g,y}\cdot q_{t,g,h,y} + \theta^{E}_{g,h,y}\cdot 0.5\cdot\Bigg(\sum_t q_{t,g,h,y}\Bigg)^2\Bigg) + \sum_{t,y} IC_{t,g,y}\cdot p_{t,g,y}\Bigg\} + \\ &+\sum_c\Bigg\{\sum_y TP_{c,y}\cdot cp_{c,y} + \sum_{t,y} IC_{t,c,y}\cdot p_{t,c,y} + \\ &+\sum_{h,y}\left[TV_{c,y}\cdot dq_{c,h,y} + TC_{c,y}\cdot eq_{c,h,y} + \theta^{E}_{c,h,y}\cdot 0.5\cdot\left(eq_{c,h,y} - dq_{c,h,y}\right)^2\right]\Bigg\}\Bigg)\end{aligned} \tag{11}$$

Indeed, it can be easily checked that the KKT conditions of the EOE problem shown in (8) coincides with the KKT conditions of (11) by performing the corresponding substitutions in (9) & (10). Moreover, the electricity price is the dual variable $\lambda^{E}_{h,y}$ of the energy balance (6) in the above optimization problem.

4. DETAILED CONSTRAINTS FORMULATION

For the sake of clarity sections 2 & 3 have ignored several detailed constraints included in the final model that deal with a better and more realistic representation of the GENCO's and DG consumer's generation units' behavior, as well as the impact of network losses. These new constraints extend (3)-(6) to better represent a real large-scale system. Most of these constraints have been previously described and formulated in works like [66] and [67]. For the sake of completeness and to ensure that this document is self-contained, they are also presented in this section. It is important to note that the inclusion of these constraints does not affect the equivalence proved in the previous section, as they are not agent-linking constraints [68].

4.1. Generation investments constraints

For the sake of simplicity, installed capacities in section 2.4 are shown in a very simplified manner by only considering the annual investment in generation capacity $p_{t,s,y}$ as the upper bound for generation. This is acceptable only if the lifetime L_t is equal to one year. The present section addresses this limitation by introducing the cumulative installed capacity $pa_{t,s,y}$, which represents the actual upper bound for generation capacity. Accordingly, constraint (12) replaces constraint (3):

$$q_{t,s,y} \leq pa_{t,s,y} \tag{12}$$

Then the cumulative installed capacity $pa_{t,s,y}$ considering the decommissioned capacity $pr_{t,s,y}$ due to a lifetime L_t higher than one is expressed as in (13):

$$pa_{t,s,y} = pa_{t,s,y-1} + p_{t,s,y} - pr_{t,s,y} \tag{13}$$

where (14) ensures that all investments are decommissioned after their lifetime L_t.

$$pr_{t,s,y} = p_{t,s,y-L_t} \tag{14}$$

Upper bounds are set on both the cumulative and annual installed capacity, with constraints (15) & (16), respectively:

$$pa_{t,s,y} \leq PA_{t,s,y}^{MAX} \tag{15}$$

$$p_{t,s,y} \leq P_{t,s,y}^{MAX} \tag{16}$$

It should be noted that, by setting either of these upper bounds to zero for a given investment technology and agent, investments can be disabled for that specific agent–technology pair. For instance, setting the parameter to zero for thermal technologies in DG effectively prevents investments in those units.

The new installed capacity must be equal to the amount of new groups times the capacity of an average candidate group $Q_{t,g,y}^{MAX}$:

$$p_{t,g,y} = n_{t,g,y} \cdot Q_{t,g,y}^{MAX} \quad (17)$$

Finally, the number of units committed in the dispatch must be lower than or equal to the number of new groups (investment decision by the model).

$$u_{t,g,h,y} \leq n_{t,g,y} \quad (18)$$

4.2. Generation investments constraints for pre-existing units ($t \notin I$)

For pre-existing units (i.e., already existing thermal generators) the number of new groups installed is one, i.e., $n_{t,g,y} = 1$, and the cumulative installed capacity $pa_{t,g,y}$ is set equal to $Q_{t,g,y}^{MAX}$ during the lifetime L_t of the unit, i.e.:

$$pa_{t,g,y} = Q_{t,g,y}^{MAX} \quad (19)$$

setting $Q_{t,g,y}^{MAX} = 0$ for all years after its planned closure year, which is known for pre-existing thermal units.

4.3. Thermal units model ($t \in T$)

Constraints (20) and (21) limit the minimum and maximum production per committed thermal unit:

$$q_{t,g,h,y} = u_{t,g,h,y} \cdot Q_{t,g,y}^{MIN} + q'_{t,g,h,y}, t \in T \quad (20)$$

$$q'_{t,g,h,y} \leq u_{t,g,h,y} \cdot \left(Q_{t,g,y}^{MAX} - Q_{t,g,y}^{MIN}\right), t \in T \quad (21)$$

Constraints (22) to (25) guarantee complying with the thermal units' ramping constraints:

$$q'_{t,g,h,y} - q'_{t,g,h-1,y} \leq RMU_{t,g}, t \in T \quad (22)$$

$$q'_{t,g,h-1,y} - q'_{t,g,h,y} \leq RMD_{t,g}, t \in T \quad (23)$$

$$q_{t,g,h,y} + ru_{t,g,h,y} \leq u_{t,g,h,y} \cdot Q_{t,g,y}^{MAX}, t \in T \quad (24)$$

$$rd_{t,g,h,y} + u_{t,g,h,y} \cdot Q_{t,g,y}^{MIN} \leq q_{t,g,h,y}, t \in T \quad (25)$$

Finally, constraint (26) manages the start-up and shut-down decisions. For pre-installed units (i.e., units already present in the generation mix in the first year of the

simulation, whose investment is not decided by the investments model), $u_{t,g,h,y}$, $y_{t,g,h,y}$ and $z_{t,g,h,y}$ are binary variables, whereas for investments they are integer variables.

$$u_{t,g,h,y} - u_{t,g,h-1,y} = y_{t,g,h,y} - z_{t,g,h,y}, t \in T \quad (26)$$

4.4. Hydro units' constraints ($t \in H$)

Hydro units are modeled each as two sub-units, for generating ($t \in H \setminus N$) or pumping ($t \in H \cap N$, whenever they have this capability), each related with the other using binary parameter $HP_{t,t}$. They are managed on a weekly schedule, based on historical data. Temporal coupling is partly considered with the maximum weekly production constraint, albeit no temporal coupling between weeks is considered. Also, no spatial coupling has been modelled. Indeed, spatial coupling, more relevant in short-term models, is usually neglected in medium and long-term approaches (see [69] for an example). Further details can be found in [67].

Hydro plants have a minimum and maximum production and a maximum pumping capacity set by constraints (27) to (29):

$$q_{t,g,h,y} \geq Q^{MIN}_{t,g,y}, t \in H \setminus N \quad (27)$$

$$q_{t,g,h,y} \leq Q^{MAX}_{t,g,y}, t \in H \setminus N \quad (28)$$

$$q_{t,g,h,y} \leq QB^{MAX}_{t,g}, t \in H \cap N \quad (29)$$

A total weekly production limit, which can be increased with pumping, is enforced by constraint (30).

$$\sum_{h \in w} q_{t,g,h,y} \leq PR^{Q}_{t,g,w,y} + \rho_{t',g} \cdot \sum_{h \in w} q_{t',g,h,y}, t \in H \setminus N, t' \in H \cap N, HP_{t,t'} = 1 \quad (30)$$

4.5. Renewable plants' constraints ($t \in R$)

In the case of renewable generation plants (solar PV and wind technologies), power output is lower than or equal to the installed capacity times the historical utilization factor $FU_{t,h,y}$ with constraint (31):

$$q_{s,t,h,y} \leq pa_{s,t,y} \cdot FU_{t,h,y} \quad (31)$$

Note that constraint (31) effectively replaces constraint (12) for renewable generators, since, if $FU_{t,h,y} < 1$ for all hours, constraint (12) can never be active before constraint (31).

4.6. Energy storage facilities' constraints ($t \in S$)

Energy storage facilities are modeled by using two sub-units, in a manner analogous to hydro generators: one for charging ($t \in S \cap N$) and another for discharging ($t \in S \setminus N$), both related to the other using binary parameter $SC_{t,t'}$. The power capacity of each energy storage facility installed, either in CG plants (for $s \in G$) or at the customer's site (for $s \in C$), sets both the maximum charge and discharge rates:

$$pa_{s,t',y} = pa_{s,t,y} \; \forall t \in S \setminus N, t' \in S \cap N, SC_{t,t'} = 1 \tag{32}$$

$$q_{s,t,h,y} \leq pa_{s,t,y} \; \forall t \in S \tag{33}$$

The hourly energy balance of the storage facility is represented in (34), linking the hourly change of the energy level of the storage facility ($e_{s,h,y}$) with its hourly use (charge or discharge rates), considering both charging and discharging efficiency factors, EF_t.

$$q_{s,t',h,y} \cdot EF_{ch'} - \frac{q_{s,t,h,y}}{EF_{dc'}} = e_{s,h,y} - e_{s,h-1,y}, s \in C \cup G, t \in S \setminus N, t' \in S \cap N, SC_{t,t'} = 1 \tag{34}$$

The power-to-energy-capacity ratio NB_t of each storage facility is the ratio between its power capacity (maximum charge and discharge rates) and the total amount of energy that it can store. This parameter was set to 2 hours, in accordance with [70]. For a given installed capacity, the actual energy stored in a storage facility will be therefore limited to the maximum energy storable at this facility, as shown in (35):

$$e_{s,y} \leq NB_t \cdot pa_{s,t,y}, \forall t \in S, s \in C \cup G \tag{35}$$

4.7. System constraints

The total hourly energy balance described in (6) is extended in (36) to consider negative generators, such as pumping and battery charging:

$$\sum_{g,t \notin N} q_{g,t,h,y} = d^E_{h,y} + \sum_{g,t \in N} q_{g,t,h,y} \quad : \lambda_{h,y} \tag{36}$$

where $\lambda_{h,y}$ is the dual variable of (36), assumed to be the energy market price. Note that consumption technologies *N* with negative generation, such as hydro units when pumping or battery storage when charging, are added in the demand side of the constraint. CG demand $d^E_{h,y}$ is defined in the next subsection and includes transmission and distribution losses in a simplified approach, leading to a more detailed formulation of (6).

In this model, demand is always satisfied due to being able to invest in sufficient generation capacity, and therefore, scarcity is not considered. Any scenario with a

priori insufficient generation capacity results in higher investments until there is enough generation capacity to supply the demand peak. However, as it is common in many other similar approaches ([71]), investment costs recovery is not guaranteed (see [72] for a study where investment cost recovery has been guaranteed as an explicit mathematical constraint in a cost minimization model), since investments in this model are driven by generation capacity requirements and not by market players' profit maximization.

4.8. Transmission and distribution losses modeling

Transmission and distribution network losses are modeled (similarly to [5]) using a simplified DC network, as illustrated in Figure 3.

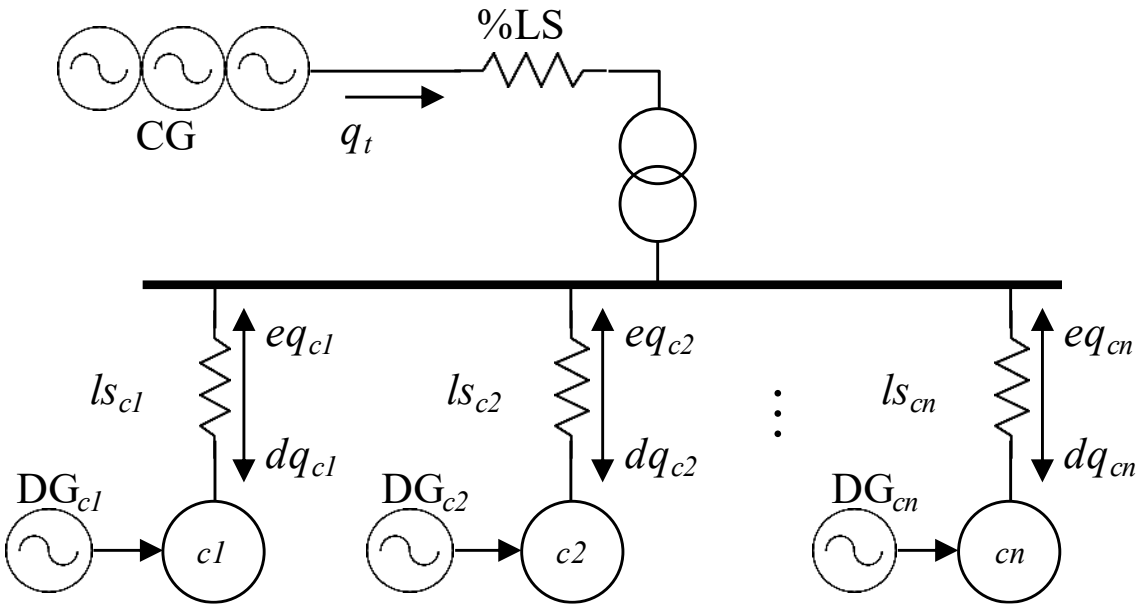

Figure 3: Schema of the transmission and distribution losses model.

As shown, all energy generated from CG power plants flows through a single resistor (that models transmission network losses) to reach a busbar that represents an ideal transmission network. Customer segments are also connected to the ideal transmission network through a resistor that models the distribution losses, while they are directly connected to their DG generation, with no internal losses. In case a customer segment is producing more than its demand ($eq_{c,h,y} > 0$), this surplus of energy flows through the distribution network to reach the ideal transmission network, so that other different customer segments may make use of it. Note that in this case distribution losses are doubled (since this surplus is first going to and then coming from the ideal transmission network).

To avoid additional computational complexity, Kirchhoff laws were not considered in this model used to estimate the grid losses. Therefore, line capacities or bus voltages are not represented. However, the model still captures key long-term effects, such as the lower efficiency of DG generation injected into the transmission

grid under high DG penetration, and it provides a simplified representation of transmission and distribution losses.

Losses are represented as a quadratic function $ls()$ of the energy flows as shown in (37), although this expression has been linearized with an outer piecewise linear approximation, see the standard approach described in [73] for more details:

$$ls_{c,h,y} = ls\left(\left(dq_{c,h,y} + eq_{c,h,y}\right)^2\right) \quad (37)$$

4.9. System net demand definition constraint

System net demand $d^E_{h,y}$ to be supplied by CG generators is defined as the aggregation of the net DG demand including distribution losses of each customer c, embiggened by a percentage *LS*, which represents transmission losses:

$$d^E_{h,y} = (1 + LS) \cdot \sum_c \left(dq_{c,h,y} + ls_{c,h,y} - eq_{c,h,y}\right) \quad (38)$$

5. CASE STUDY AND RESULTS

The case study shown herein was already published in [59], a JCR paper published in 2020 but produced in 2018. Therefore, input data for these cases is in accordance with data available in 2018. Where relevant, a comparison with more recent data is also presented.

The proposed model has been applied to a large-scale case study representing a Spain-like power system over the 2019–2037 horizon. The objective was not to carry out a long-term forecasting exercise, but rather to demonstrate the model's capabilities and to gain insight into how the design of access tariffs and the market power of large industrial consumers may influence the interaction between CG and DG. These two factors are particularly relevant, as they can significantly impact the deployment balance between CG and DG technologies.

Input data, assumptions and scenarios' description are explained in section 5.1 while the results and the analysis are shown from sub-section 5.2 onwards.

5.1. Assumptions and input data

5.1.1. Temporal horizon

The simulation period has been set to 19 years (from 2019 to 2037), using a single representative week of 168 hours per year to reduce the computational load. The methodology to build the representative week is described in detail in [74] and was developed by the student during the development of this thesis. In brief, the representative week is constructed by selecting the set of historical days that

minimizes the distance between its load-duration curves and the load-duration curves of the historical period for several key variables such as demand, net demand, renewable generation, and hourly ramps. Due to the nature of the problem, minimization is performed by applying a genetic algorithm. This approach preserves the main chronological and operational features of the original data while strongly reducing the model size, thus yielding investment outcomes close to those obtained with full-year simulations but at a fraction of the computational cost.

5.1.2. Demand

Demand profiles of customer segments have been extracted from [75] and [76]. Demand growth has been set to 0.5% per year, resulting, for the last year of the simulation horizon, 2037, in an hourly average demand of 33.8 GW and a peak demand of 47.0 GW (excluding losses). By contrast, the Spanish National Energy and Climate Plan (NECP, [77]) forecasts for 2030 an average hourly demand of 31.3 GW and a peak demand of 43.5 GW, which is in line with the growth estimations performed here.

The hourly demand profiles of the 12 customer segments have been extracted from [75] and [76], and are represented in Figure 4.

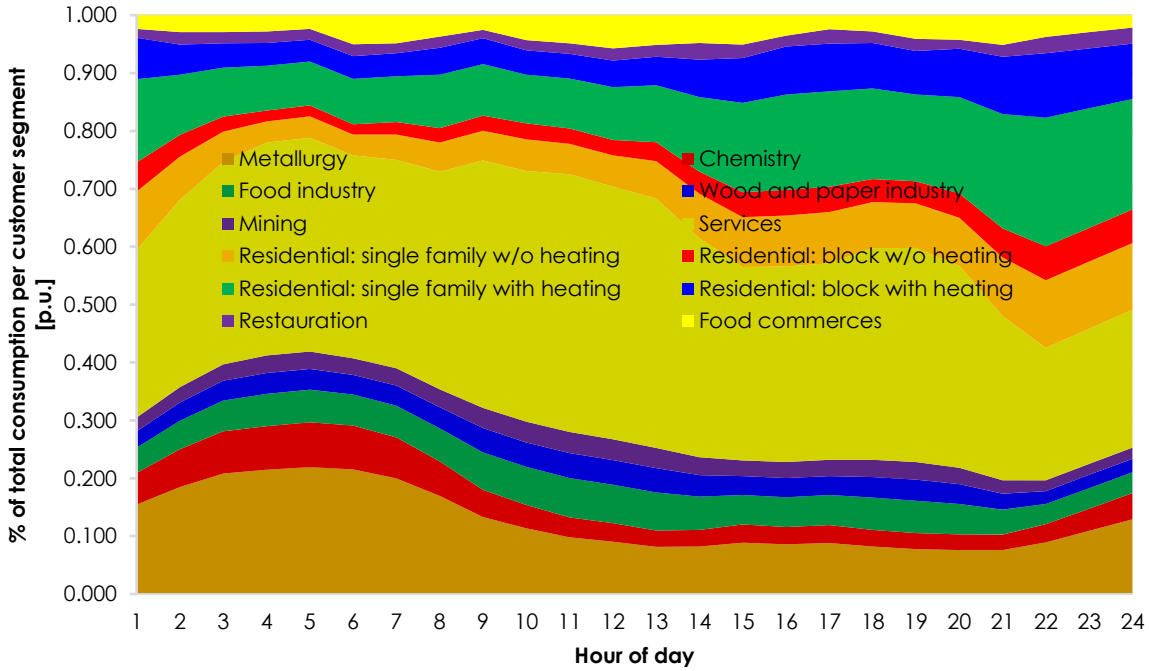

Figure 4: % of total consumption per customer segment.

5.1.3. Transmission & distribution network

Transmission and distribution network losses are considered in a simplified manner as explained in section 4.8. The piecewise linear approximation for distribution losses was calibrated to achieve 6% distribution losses, and the transmission losses were set

to a 3% of the total system demand. These values are in accordance with the Spanish system as described in [78].

5.1.4. Technologies

Each thermal generation plant is modeled individually, including their start-up, shut-down and ramping constraints. Their expected lifespan is assumed to be 30 years for combined cycle gas turbines (CCGT) and open cycle gas turbines (OCGT) units, 45 years for coal-fired units, and 60 years for nuclear power plants.

5.1.5. Investment costs

The technologies to invest in in this case study are CCGT, OCGT, wind, solar PV and storage (batteries) facilities for CG, and solar PV and storage (batteries) facilities for DG. Investment costs for all CG and DG technologies have been estimated from [79], [80], and are equal across all scenarios. Their values and evolution can be seen in Figure 5, in real 2018 costs[6]. For reference, actual costs observed in 2025 from [81] have also been added to Figure 5, allowing a direct comparison between the projections made in 2018 and the current cost levels.

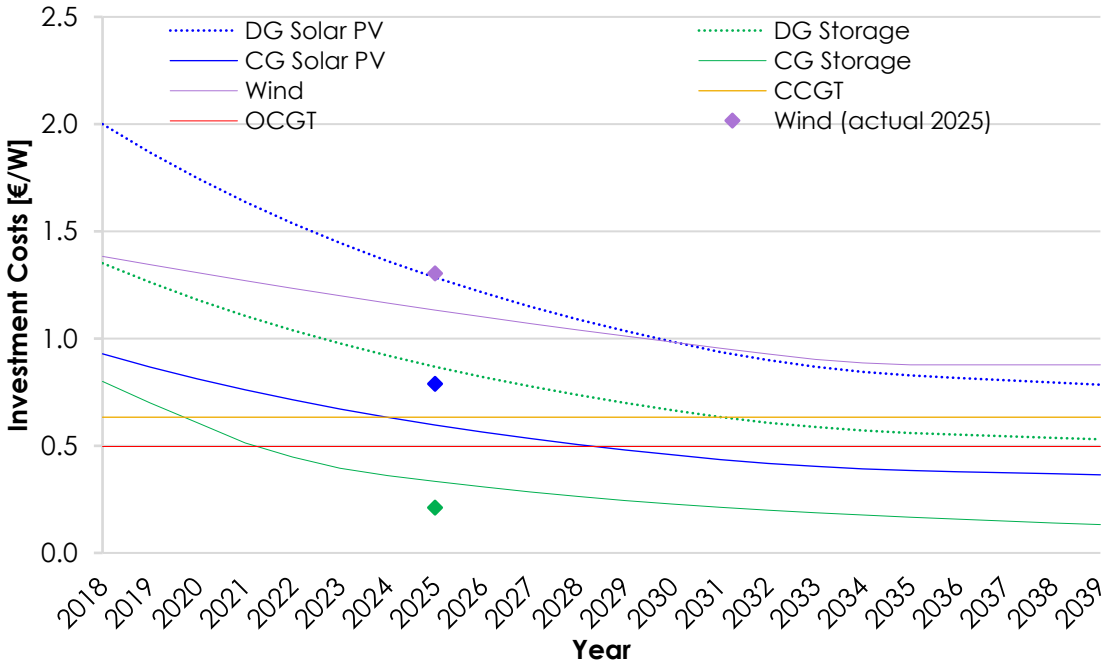

Figure 5: Investment costs evolution.

Two main factors explain the shape of these curves: first, a steady decrement accounts for technological advancements in the production of less mature technologies, as can be observed in [82]. However, this decrement is expected to

[6] All costs and prices are expressed in constant 2018 euros, adjusted for inflation to ensure comparability across the temporal horizon. While cost information from 2025 is also included for benchmarking purposes, these values have also been deflated to 2018 euros. The optimization model itself minimizes the net present value of system costs, consistently formulated in real 2018 terms, applying a 6% discount rate.

slow down as some technologies become mature. More mature technologies' costs such as CCGT or OCGT remain constant. For the sake of clarity, regarding DG technologies, only the costs for industrial consumers are displayed. Storage investment costs refer to those of a 2-hour battery (i.e., the investment cost shown for storage corresponds to the installation of a 1 kW facility able to store up to 2 kWh of energy). Comparing 2025 values of these curves with actual data from [81] reveals that solar PV and wind costs have remained higher than originally projected, whereas storage costs were significantly overestimated in this study. The unexpected acceleration in cost reductions for storage can be largely attributed to the rapid expansion of the EV market and its associated industrial ecosystem, which has driven technological innovation, large-scale manufacturing, and economies of scale in battery technologies.

5.1.6. Conjectural variations

GENCOs' CVs ($\theta_{s,h,y}$) were estimated from historical data for the period 2010–2015 through the analysis of the residual demand curve around the equilibrium point (see more details of this methodology in [83][7]). Although these values vary by hour of the day, they were averaged over the entire year. Customers' CVs were assumed to be equal to those of GENCOs of comparable size. The resulting values are reported in Table 4:

Table 4: Energy CV for all agents.

Agent	Energy CV [€/MWh²]
Large GENCOs	5
Mid-sized GENCOs	3
Small-sized GENCOs	0
Industry	3
Commercial	1
Residential	0

5.2. Scenarios description

To analyze the impact that the format of the grid access tariff and the market power of industrial customers' (modeled assuming CVs) have on the evolution of CG and DG investment decisions, a set of 24 scenarios have been built and

[7] Indeed, optimal CVs for all agents can also be estimated endogenously by applying a fixed-point algorithm, [68]. However, due to the size of the current problem, this approach is too computationally intensive to be considered for this work.

simulated. These scenarios result from 12 different compositions of the format of the access-tariff, crossed with two CV scenarios, as detailed below.

Regarding the grid access tariff, the case studies, originally designed in 2018, consider a set of alternative grid-access tariff structures by varying the relative weight of the variable ($TV_{c,y}$, $TC_{c,y}$) and demand charge ($TP_{c,y}$) components. The share of total grid-access tariff income recovered through the demand charge term is gradually increased from 0% (a fully variable grid-access tariff) to 100% (a fully demand charge grid-access tariff) in increments of 10%. In each scenario, grid-access tariff levels are calibrated so that total tariff revenues match the amount of regulated system costs reported in [84] for the first simulation year (2019), under the assumption that no DG is installed at that point. A special scenario was also simulated corresponding of the approximate prevailing Spanish grid-access tariff design at the time of the study, comprising approximately 67% demand charge and 33% volumetric revenues, is also included as an additional scenario. Values for this scenario (67%) and both extreme scenarios (0%, 100%) scenarios are shown in Table 5, where the other scenarios have been omitted for simplicity. Moreover, in all cases the buying and selling volumetric terms are assumed to be equal ($TV_{c,y} = TC_{c,y}$). To isolate the effects of grid-access tariff structure, annual grid-access tariff increases are not considered.

Table 5: Tariff terms for 0%, 67% and 100% scenarios.

Scenario	Tariff term	Industrial	Commercial	Residential
0% demand charge	$TP_{c,y}$[€/kW-y]	0	0	0
	$TV_{c,y}, TC_{c,y}$[€/MWh]	42.56	31.91	85.24
67% demand charge	$TP_{c,y}$[€/kW-y]	50.03	52.07	56.82
	$TV_{c,y}, TC_{c,y}$[€/MWh]	14.05	10.53	28.13
100% demand charge	$TP_{c,y}$[€/kW-y]	74.68	77.71	84.80
	$TV_{c,y}, TC_{c,y}$[€/MWh]	0	0	0

Regarding customers' CV, two options are considered: either customers have no market power ($\theta_{c,h,y} = 0$ for all c), or industrial customers (which are the biggest consumers, around 28% of total demand) have a market power like mid-sized GENCOs (see values presented in Table 4). In all cases, GENCOs are assumed to have some market power with their CV values deduced heuristically with the methodology described in [83].

The following subsections present and analyze the results obtained for this case study. The results cover DG and CG investment decisions, energy market prices, contracted power by consumers, and the shape of demand across all 24 considered scenarios. For clarity, only the last simulation year (2037) is shown and analyzed, as it captures the outcome of the investment trajectory without the need to represent the full temporal evolution.

5.3. Simulation results

5.3.1. DG investments results

Figure 6 shows the cumulative DG capacity investments as a function of the % of demand charge tariffs incomes (marker types refer to "with CV" (W CV) or "without CV" (W/O CV) for customers, while green and blue lines correspond respectively to PV solar and battery storage facilities):

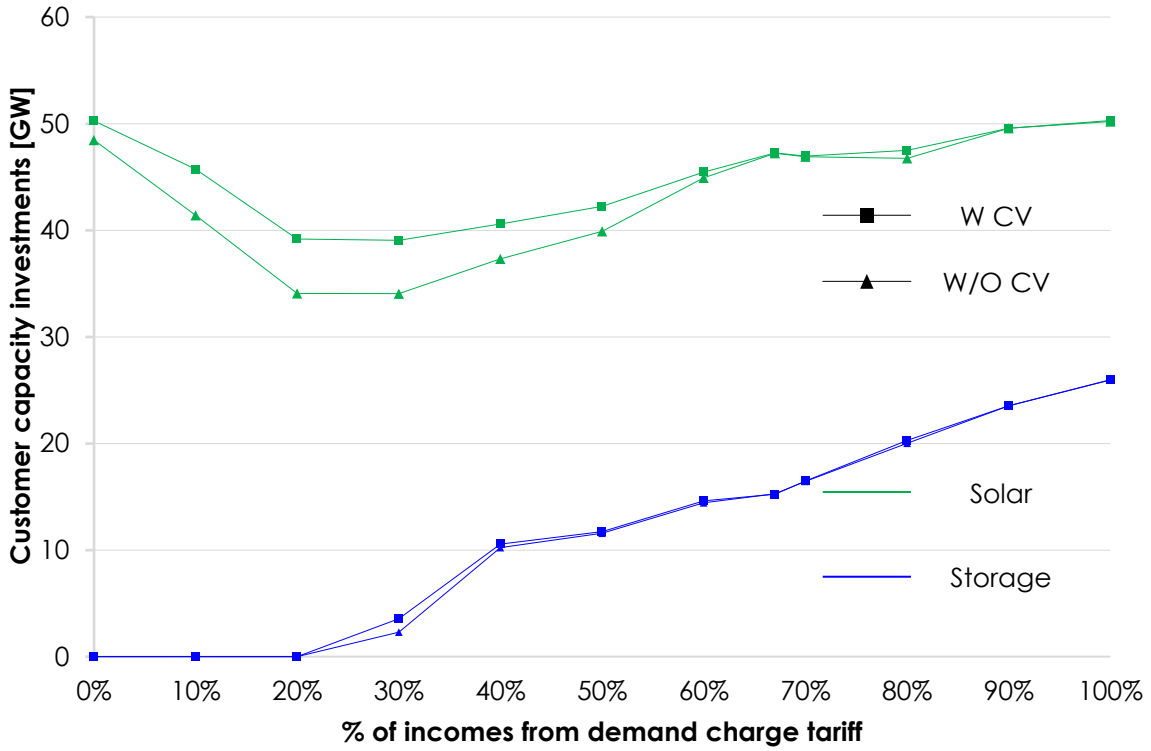

Figure 6: Cumulative DG investments in 2037 per tariff levels.

Several interesting conclusions can be drawn from Figure 6:

- As can be seen, for % of demand charge tariff incomes greater than 20%, customers' DG storage investments increase almost linearly at an average rate of 3.2 GW per each 10%. This indicates that, for this case study, and with the tariff hypothesis taken, the main driver for customers' storage investments is the demand charge tariff term. Indeed, the DG battery cost is still too high for the battery to be used only for energy purposes. Only savings in peak net demand consumption from the grid (thus, reducing the contracted power),

when the demand charge (contracted power-based) tariff term is high enough, makes battery attractive enough for consumers.

- No discernible differences can be seen in storage investments with the CV scenario. Indeed, as storage is unable to produce energy on its own, it cannot reduce market prices by reducing total demand[8]. Therefore, having storage does not affect whether a customer has market power in an energy-only market. Market power, thus, does not seem an issue regarding the DG storage investment decisions.
- Regarding DG solar PV investments, it is interesting to notice the bathtub curve as a function of the % of demand charge tariff incomes. DG solar PV decreases steadily, up to the 20% fixed demand charge incomes case. Indeed, a high volumetric grid-access tariff term is a powerful incentive to reduce energy consumption by installing energy production such as DG solar PV. Thus, decreasing the volumetric (energy) weight of the tariff leads to installing lower amounts of DG solar PV. Note that the uncontrollable profile production of solar PV facilities does not help significantly to reduce the contracted power, even increasing its installed capacity. But from 30% on, an interesting secondary effect incentivizes investments in DG solar PV. Indeed, it should be noticed that this is exactly the point upon which customers' investments in storage start to happen. Once storage is in place, investing in solar PV does allow to reduce the contracted power from the grid, since storage can be used to shift the energy produced by the solar PV facility to consumer's peak load hours. So, therefore, higher DG solar PV investments take place both with high volumetric and high demand charge tariffs.
- On average, the presence of customers' CVs increases DG solar PV investments by about 1.9 GW. This is because customers with market power can strategically reduce their purchases from the grid to lower market prices, and investing in DG solar PV provides them with a direct way to achieve this reduction in demand. In other words, PV allows them both to cut their exposure to the energy market and to influence prices downward. However, when the share of the demand charge tariff is high, this effect becomes negligible. Under such tariff structures, the volumetric component of the bill is relatively small, so the economic savings from reducing grid consumption (or the income from selling surpluses) are limited, making additional PV investments less attractive and weakening the role of customers' CVs in driving them.

[8] Although in strict terms an agent could use storage to move their generation/demand to hours where it could exert higher market power, this behavior was not observed in the results of the model. This may be a limitation of this study, due to averaging CV values across all hours.

Next subsection proves that customer storage investments are mainly driven by the reduction in the contracted power, and customer solar PV investments are mainly driven by the reduction in energy demand.

5.3.2. Contracted power and demand

Figure 7 shows the total contracted power ($cp_{c,y}$, left hand side axis) and net grid customer demand (i.e., the annual sum of the whole net customers demand from the grid $dq_{c,h,y} - eq_{c,h,y}$ for all customer segments c, without including transmission or distribution losses, right hand side axis), per tariff scenario.

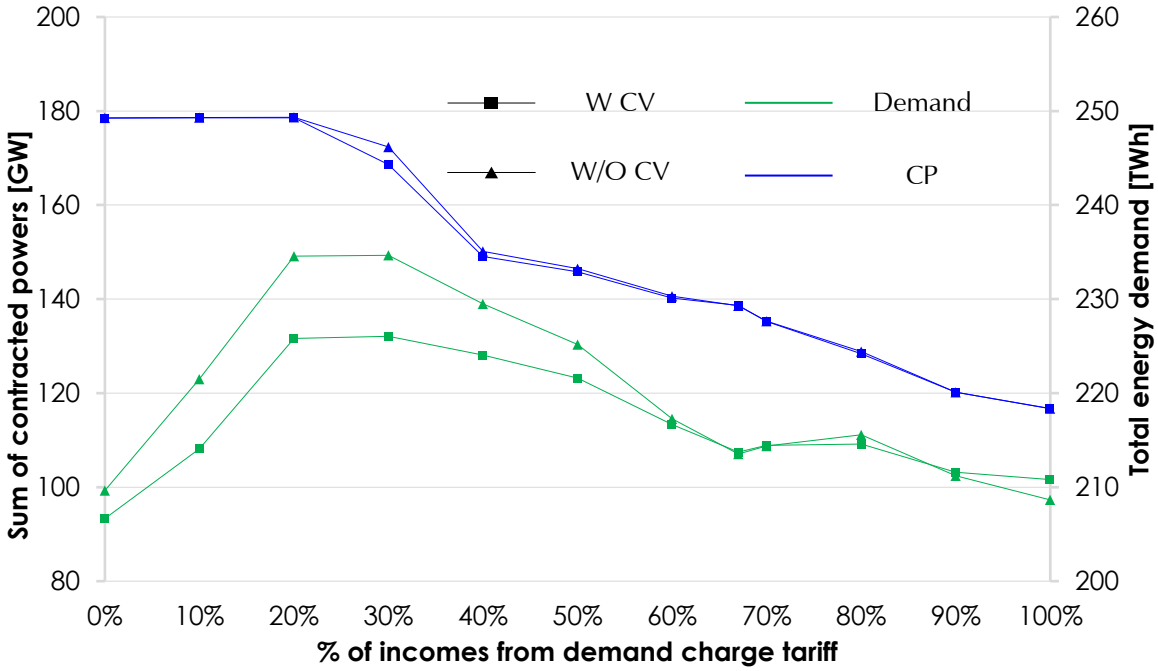

Figure 7: Total contracted power and net grid demand per tariff scenario.

Figure 7 shows:

- Each 10% increase in the demand charge (contracted power-based) tariff weight above 20% triggers a reduction of around 7.8 GW of consumers' contracted power, which is around 2.4 times higher than the 3.2 GW investment in storage we observed previously from Figure 6. This result shows that the customers are using both storage and solar PV to reduce their contracted powers[9].
- A pure demand charge tariff (contracted power-based) format leads to a very large decrease (62 GW, i.e., 34.7%) in the contracted power of consumers. By contrast, the system's actual peak demand only falls

[9] Interestingly, the current demand peak in the Spanish system occurs at 9 pm in the evening, with little to no solar PV production. However, most of the consumption at that time of the day comes from residential customers. Industrial and commercial customers, on the other hand, have their consumption peak closer to noon, near solar PV's peak production.

moderately (by about 17% across the same scenarios, see Figure 11), which shows that customers mainly use behind-the-meter investments to reduce their individual contracted power rather than to lower the system's overall peak. In other words, the power-based tariff provides incentives for minimizing individual billing exposure but does not necessarily translate into an equivalent reduction of the system peak.

- Industrial customers' market power (CVs) does not have a discernible impact on the total contracted power in the system. The reason is analogous to that previously discussed when analyzing the customers' storage investments results shown in Figure 6.
- However, the customers' CVs reduce the total energy net grid demand on average by 3.0 TWh (1.4%). This is caused by the difference of 1.9 GW (in average) of DG solar PV investments mentioned in previous subsection. Indeed, considering an average PV utilization factor of 21%, these investments would have produced 3.5 TWh, which coincides with the 3.0 TWh of reduced net grid demand including losses in the storage cycle and in the transmission and distribution networks.
- Whether these reductions in customers' contracted power and grid consumption may trigger a death spiral scenario remains an open question, since the model, at this stage, does not consider the foreseen reaction of the regulator to maintain the system regulated incomes. This will be analyzed in □.

As will be seen in the next two subsections, the reduction in contracted power also reduces peak technologies (like CG) investments and market prices.

5.3.3. CG investments results

Although the model allows for CG investments in CCGT[10], OCGT, wind, CG solar PV and storage technologies, results show that for the evolution of technologies costs assumed in the study, only investments in OCGT, CG solar PV and storage technologies take place. Total CG capacity investments at the last simulation year, 2037, for the different tariff and CV scenarios, are shown in Figure 8.

[10] The Spanish system currently has overcapacity in CCGT, and many units of this technology remain idle for most of the year. However, most of these units will reach the end of their operational lifespan at the beginning of the 30s, so in this case study investments in CCGT are enabled to allow for replacement for these units.

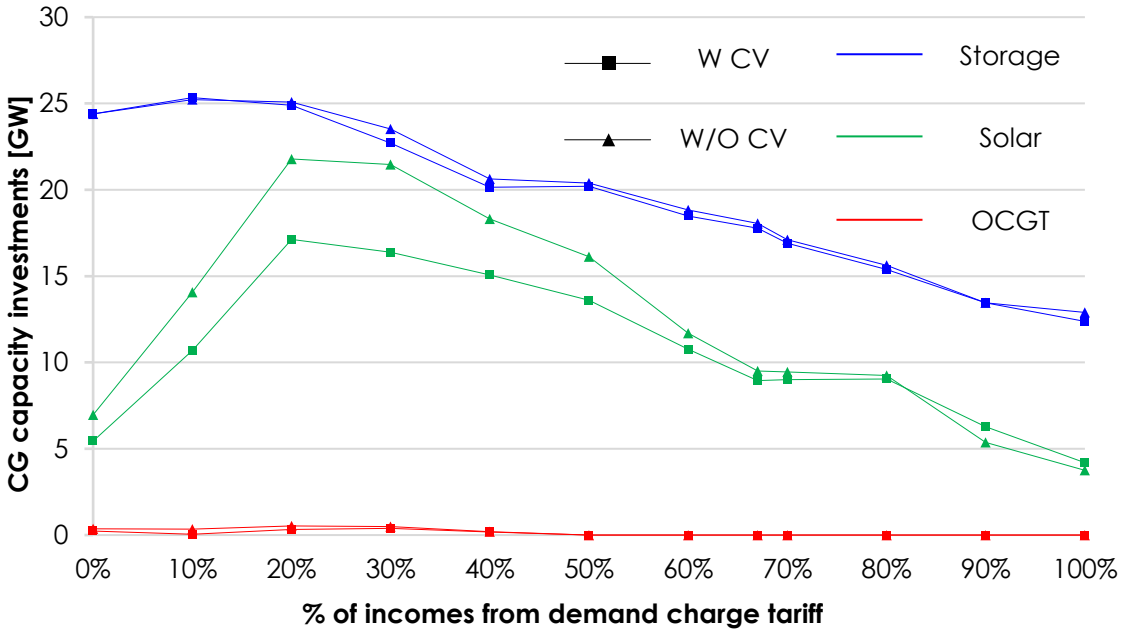

Figure 8: Cumulative CG investments in 2037 per tariff levels.

It can be observed that:

- OCGT provides some supporting capacity for peak hours[11], although its maximum capacity across all scenarios accounts for only 0.5 GW. This maximum is at the 20% and 30% scenarios, which coincide with the highest CG solar PV investments, indicating that OCGT is used as a backup for solar PV generation.
- CG solar PV investments are complementary to DG solar PV investments (see Figure 6), i.e., the former increase for all scenarios in which the later decrease. Specifically, the system requires around 55 GW of additional solar PV, while heavily favoring investments in DG (see Figure 6).
- The model results show no new investments in wind capacity. This outcome stems from the use of a single representative week, which tends to overvalue short-term storage relative to variable renewable generation. Under average conditions, the combination of solar PV and short-cycle storage (with daily or sub-daily cycles) appears more cost-efficient than wind. However, the model does not capture seasonal effects, such as prolonged winter periods with low solar output, when the solar & storage combination alone would be insufficient to meet demand and wind generation would play a critical role.

CG storage investments are also complementary to DG storage investments, and the system requires around 25 GW of storage across all scenarios (see Figure 6).

[11] A peak technology is a thermal technology with low investment costs but high variable costs, and thus normally used only at peak, high-price, hours.

5.3.4. Energy market prices

Figure 9 displays the average energy market price for 2037 for different tariff levels.

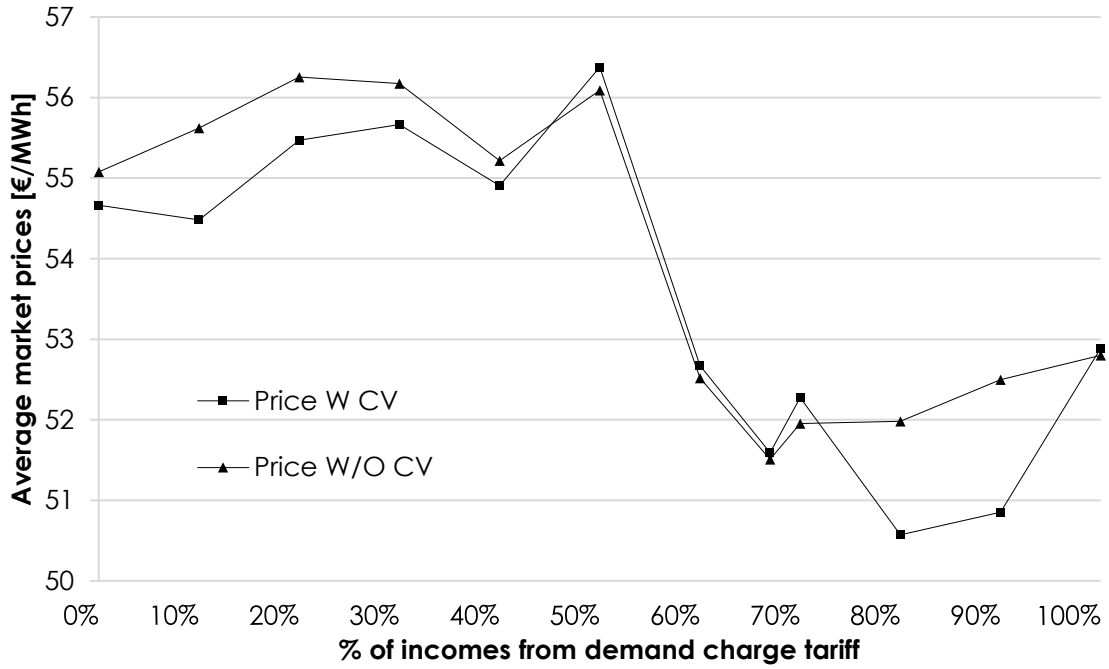

Figure 9: Hourly average energy market price in 2037 per tariff levels.

As can be seen:

- If industrial customers have market power (scenario with CV), market price tends to decrease, up to 1 €/MWh in scenarios with low demand charge tariffs (high volumetric tariffs) and up to 1.5 €/MWh in scenarios with high demand charge tariffs. This is reasonable since customers would use their market power to reduce market prices, thus reducing their costs of purchasing energy.
- In addition, demand charge demand charge tariffs (high volumetric tariffs) cause generally higher market prices, and vice versa. The average difference between lower and higher demand charge tariffs is 3.5 €/MWh. This is due to two factors:

    i) Lower demand charge tariff scenarios have lower investments in DG but higher investments in CG. Lower DG investments increase demand from the market (See Figures 10 and 11), and therefore market prices.

    ii) A high demand charge tariff is an incentive to flatten the demand shape, which entails lower market prices (due to less peak hours, start-ups and shut-downs, See Figures 10 and 11). Therefore, high demand charge tariffs entail lower market prices.

These variations in market prices are explained by analyzing the hourly demand profiles, as seen in Figures 10 and 11.

5.3.5. Hourly demand distribution

Figure 10 depicts the resulting hourly net grid demand (to be purchased from the market) of the representative week in 2037. Darker tones represent scenarios with higher demand charge tariff and lower volumetric one, and lighter tones the opposite (being 100% demand charge tariffs darkest, and 100% volumetric ones lightest). Only the scenarios without CVs are represented for simplicity[12].

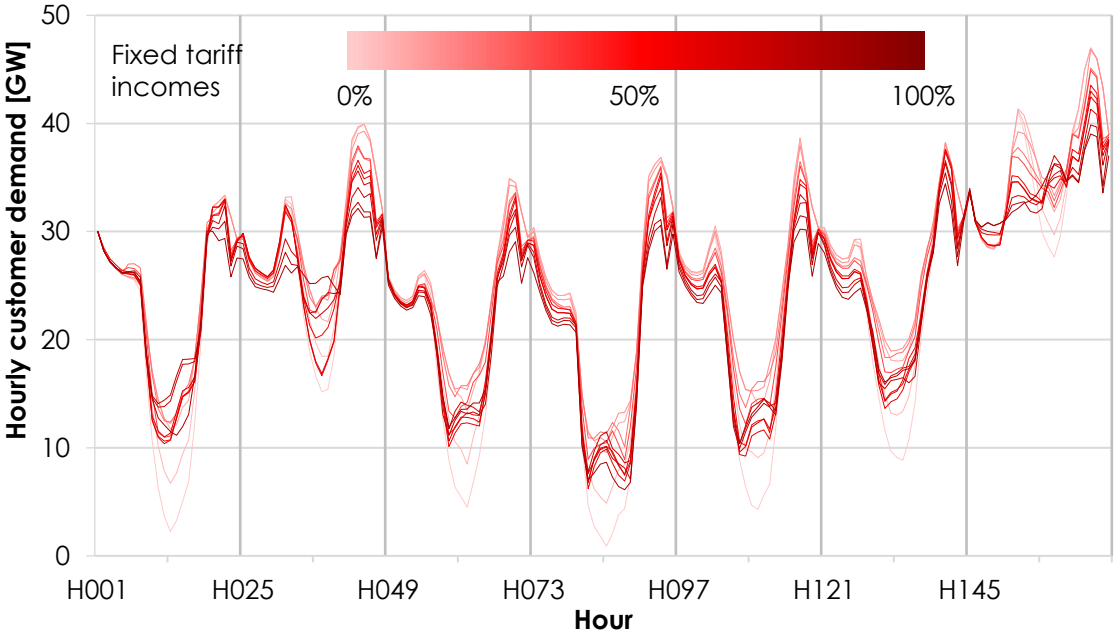

Figure 10: Hourly net grid demand purchased from the market in 2037 W/O CV per tariff scenario.

In addition, Figure 11 represents some statistics of the curves shown in Figure 10: their average, maximum and standard deviation.

[12] The effect of CVs in these curves is mainly a lower overall demand, which hides the effect of the shape of the demand in Figure 10. Showing only the scenario W/O CVs allows to focus on the shape of the demand effect.

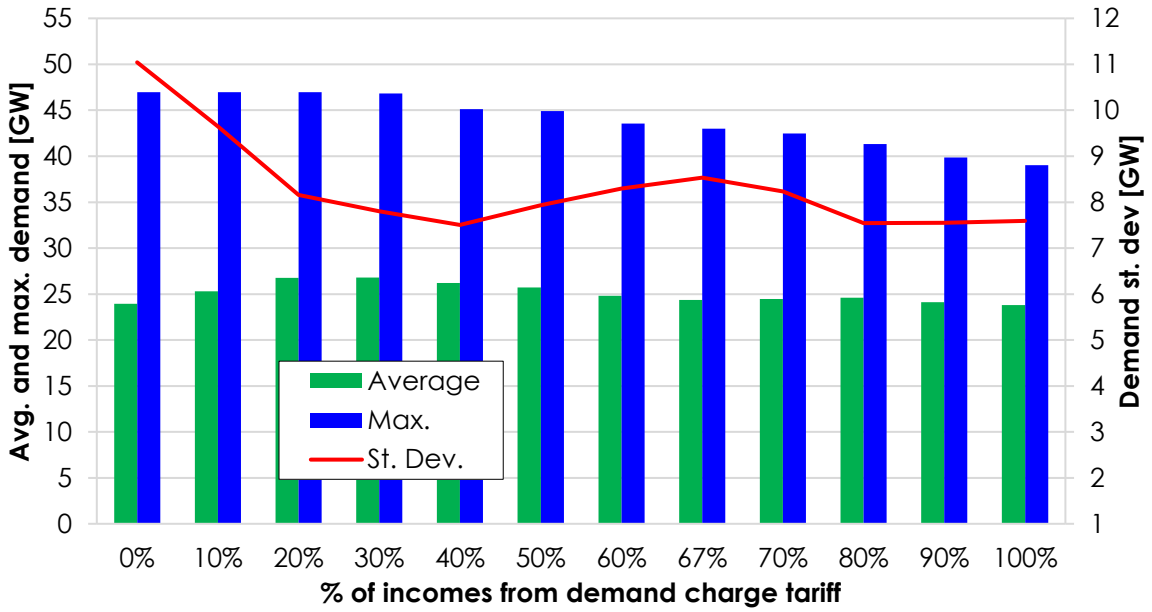

Figure 11: Statistics of the 2037 market demand W/O CV per tariff scenario.

Figures 10 and 11 show:

- Extreme duck-shaped demand curves (very pronounced valleys during noon, [85]) for low demand charge tariffs, caused by the high investments in DG solar PV. Indeed, these investments generate their peak power at noon, causing the mentioned reduction in net demand.
- Scenarios with higher demand charge tariffs are flatter, i.e., they show both lower peak-valley difference, lower overall peaks, and a lower standard deviation. This is caused by the higher incentive for the customers to reduce their peak consumption (contracted power), and a higher capacity for peak-shaving by investing in decentralized storage.
- Comparing Figure 11 with Figure 9, higher average or peak demand entails higher average market prices. In addition, a higher standard deviation of the demand also entails higher market prices. The reason for this is that a system with a more variable demand would have higher ramping and start-up costs.
- The peak market demand is 47 GW in the 0% demand charge tariff incomes scenario (100% volumetric tariffs), and 39 GW in the 100% demand charge tariff incomes scenario, showing a reduction of 8 GW (17.0%). However, the reduction in the sum of the customers' contracted powers $cp_{c,y}$ is much higher than that: from 179 GW in the pure volumetric tariff scenario to 117 GW in the pure demand charge scenario (62GW, or 34.7%, of reduction, see Figure 7). Therefore, the demand charge term $TP_{c,y}$ may not be sending the optimal incentives to customers for decreasing the peak demand of the system, as it is rather an incentive to reduce their own peak in consumption, and not to reduce the system peak. This is a feature of the equilibrium model: customers are modeled as rational agents that optimize their own expenses rather than the overall system cost. Consequently, they minimize their individual

contracted power even if this does not translate into a reduction of the system peak. To better align individual incentives with system efficiency, alternative schemes such as critical peak pricing can be proposed. E.g., a firm capacity market whose price signal is reflected in peak demand hours is introduced in □.

5.4. Computational results

To solve the proposed model, the first step was to transform it into an equivalent cost minimization model as described in section 3.3. Solving through an optimization approach facilitates the inclusion of technical and economic constraints, avoiding the complexity entailed by equilibrium problems with the need of deriving the KKT conditions. The equivalent optimization problem was programmed with GAMS v24.7 and solved using CPLEX's barrier algorithm [86], on an Intel i7-4790 CPU at 3,6 GHz with 32 GB of RAM. Each case study amounts to approximately 3.5 million constraints and 3 million variables, 1.3 million of which are discrete, such as those for start-ups and shutdowns modeling. However, for these case studies, all integer variables were relaxed. The resolution in the above-mentioned computer takes up around 15 minutes of execution time for the time horizon 2019-2037.

6. CONCLUSIONS

The application of the proposed model to a Spain-like system shows that:

1) DG investments are driven by two main factors: high volumetric or demand charge access-tariffs, or high customer market power. More balanced (demand charge/volumetric) access-tariff scenarios result in lower DG investments.
2) CG investments appear to be complementary to DG investments: depending on the tariff scenario, if DG investments increase, CG investments decrease.
3) Wholesale market prices seem to be directly related to the shape of the demand: higher peak values, higher average values or higher deviation of the demand curve can cause higher market prices.
4) Comparing high volumetric tariff and high demand charge tariff scenarios, the reduction in total contracted power is much larger (around 35%) than the reduction in the system's peak demand (around 17%). This divergence highlights a case of misaligned incentives in the demand charge term of the grid-access tariff: customers are driven to minimize their individual contracted power to reduce their bills, but this behavior does not necessarily contribute to lowering the overall system peak. As a result, it fails to provide an efficient economic signal for system-wide peak demand reduction. The next chapter addresses this issue by introducing a firm capacity market into the equilibrium model (□).

5) The inclusion of conjectural variations in the model allows to represent situations in which large consumers or generators exert market power and strategically influence wholesale prices through their consumption or production decisions. When conjectural variations are disabled, the model reduces to a perfectly competitive equilibrium, which may be appropriate for systems dominated by small, price-taking agents, or for very long-term decisions where the markets participants structure is unknown. However, when significant market concentration exists, or when large industrial consumers can affect prices through load-defection or self-generation decisions, neglecting conjectural variations may lead to an underestimation of price effects and investment results. From a regulatory perspective, the use of conjectural variations is therefore relevant when designing tariffs for systems where large agents play a significant role, whereas a competitive assumption may be enough in contexts with highly fragmented demand and supply.

7. METHODOLOGICAL CONTRIBUTIONS

The main contributions of this chapter are:

- The formulation of an investment model for market equilibrium among GENCOs and DG customers, with an explicit modeling of different decision-making drivers for both, and considering distribution network losses, tariffs, contracted power, UC constraints, different types of technologies (such as storage and solar photovoltaic, PV), etc.
- A model that represents the long-term evolution of a large-scale power system, with endogenous market prices, exogenous tariffs, and that can represent load- and grid-defection scenarios, including a simplified representation of the transportation and distribution network losses.
- The mathematical deduction of a novel equivalent quadratic optimization model from the original equilibrium model KKT conditions, which allows a simpler implementation for computing the simulations.
- The electricity price, being an output of the equivalent optimization model, depends simultaneously on both CG and DG investments.
- The analysis of a Spain-like case study for the period 2019-2037 with different tariffs and CVs scenarios.

Chapter IV. LOWER LEVEL II: JOINT ENERGY & CAPACITY EQUILIBRIUM

1. INTRODUCTION

This chapter proposes a new hourly conjectural Nash equilibrium problem based on the EOE model of Chapter III. This problem, as the one in the previous chapter, models both CG and DG operation and capacity expansion, with endogenous marginal prices (i.e., prices are outputs of the operation and expansion problem) with price-response conjectural variations [43]. In addition, it introduces a firm capacity market, following [87], in equilibrium with the energy market. Both the model and the case studies presented herein were already published in IJEPES, a high-impact JCR-indexed journal [88].

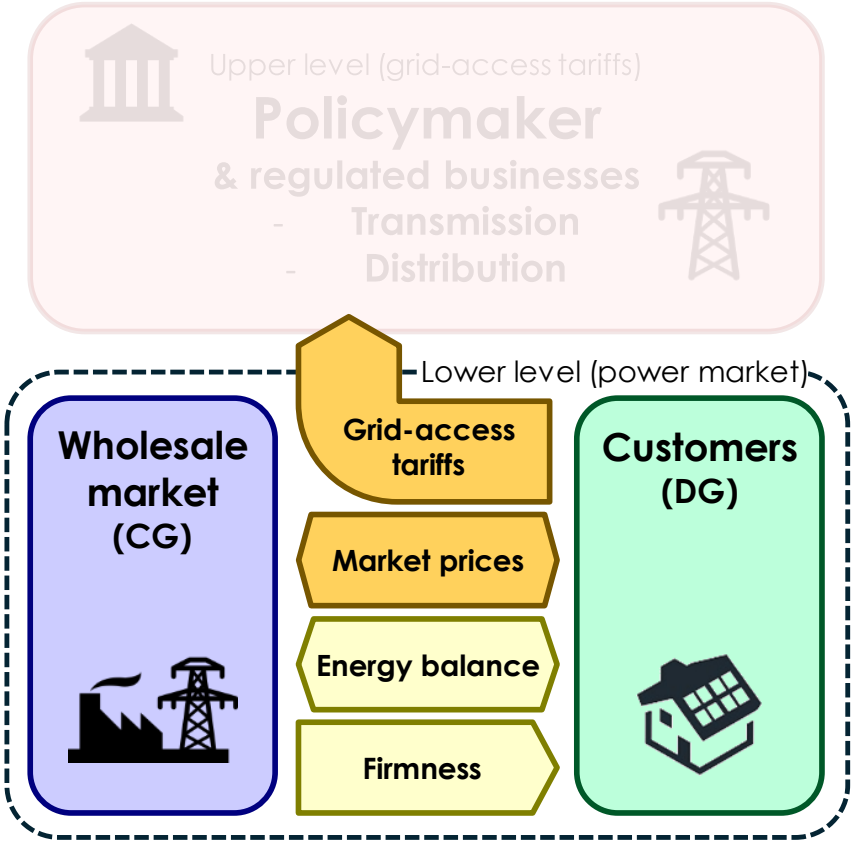

Figure 12: joint energy & capacity equilibrium model structure.

Following the scheme adopted in Chapter III, and as shown in Figure 12, two different kinds of optimization problems are linked together to build the proposed joint energy and capacity conjectural Nash equilibrium (JECE) model: The first kind of optimization problems addresses the maximization of the GENCOs' profits. The second one addresses the minimization of the expenses of DG customers. Investment costs in new generation capacity are considered in the optimization problems. Therefore, the joint model represents the individual decision-making rationality of each market agent, including both GENCOS and DG customers, taking also into account the reaction of the competitors by employing price-response CVs, leading altogether to the JECE model proposed.

The detailed hourly operation and investment constraints for CG and DG are those described in Chapter III which, for the sake of clarity, are not repeated here. Only the two linking constraints that set the game, that is, the generation and demand balance constraint in the energy market, and the maximum firm capacity constraint, are described in this chapter for the sake of charity.

This chapter is structured as follows. Sections 2 and 3 formulate the proposed JECE model and the equivalent quadratic optimization model to solve the equilibrium conditions, respectively. Section 4 presents the final formulation on the problem. Section 5 presents a case study that compares the results of the JECE with the EOE, and finally sections 6 & 6 enumerate the main contributions & draw the main conclusions, respectively.

2. THE CENTRALIZED & DECENTRALIZED JOINT ENERGY & CAPACITY EQUILIBRIUM MODEL

2.1. Hypotheses

This model, in addition to the hypotheses presented in Chapter III section 2.1, assumes the following new hypotheses:

- It is assumed that the payment for firm generation capacity is distributed across all peak hours of the year. Consequently, the total price of energy in those hours includes both the energy and capacity payments.
- To account for the contribution to the systems firmness from the consumption side, customer's exporting energy to the grid during such peak hours are also remunerated in the same way for lowering the system's net peak demand. This reflects the marginalist principle whereby any agent reducing consumption during peak hours effectively decreases both the required energy production and the firm capacity needs of the system[13].
- GENCOs are remunerated for their contribution to the system's firm capacity on an annual basis, at a marginal price equal to the marginal cost of providing one additional megawatt of firm capacity to the system at the peak hours of that year. The annual required firm capacity is equal to the peak demand increased by a small % as safety factor, given as an input to the model.

[13] This assumption is recognized as controversial. In many regulatory frameworks, the contribution of demand-side resources or DG to system adequacy is not explicitly remunerated, particularly when such resources do not participate directly in capacity markets. However, this modeling choice is adopted deliberately to reflect the view that decentralized resources can contribute to security of supply by reducing net peak demand and therefore should be assigned an economic value consistent with the marginalist pricing principle. Similar perspectives that attribute adequacy or firmness value to DER or demand-response mechanisms can be found in the literature, [89].

- The firm capacity and energy markets are assumed to be independent in the sense that they address different products. Therefore, it is assumed that GENCO's strategy in one market does not affect their strategy in the other one. Mathematically, this implies that the derivative of a GENCO's energy production with respect to the marginal price of firm capacity is effectively zero, and, likewise, the derivative of its firm capacity with respect to the energy marginal price is also zero. Although some interdependencies may exist (for instance, investment decisions in firm capacity could indirectly affect energy market behavior), this assumption is considered a reasonable simplification. It reduces the dimensionality of the problem and allows the equilibrium to be represented in a tractable way, without losing the main economic signals of each market.

2.2. Generation companies' objective functions

Each GENCO *g* maximizes its profits, that is, the income from both the energy and capacity markets minus their investment and operation costs. As in the previous chapter, discount rate R was omitted for simplicity in all the objective functions:

$$\text{Max}\left\{\sum_{y}\left[\sum_{t,h}\left(\left(\lambda^{E}_{h,y}-VC_{t,g,y}\right)\cdot q_{t,g,h,y}\right)+\sum_{t}\left(\left(\lambda^{C}_{y}\cdot DI_{t}-IC_{t,g,y}\right)\cdot p_{t,g,y}\right)\right]\right\},\forall g \qquad (39)$$

The first term represents the energy market incomes (hourly energy market prices $\lambda^{E}_{h,y}$times the hourly production $q_{t,g,h,y}$) minus the operation costs. The second term represents the capacity market incomes (annual firm capacity price λ^{C}_{y} times the firm capacity $DI_t \cdot p_{t,g,y}$, being this term the main change with respect to the GENCOs' objective function already in place in Chapter III), minus the investment costs ($IC_{t,g,y}$ times the installed capacity $p_{t,g,y}$). Note that it is the amount of firm capacity (i.e., installed capacity times firmness factor[14], $DI_t \cdot p_{t,g,y}$), and not the installed capacity (i.e., $p_{t,g,y}$), that is remunerated in the capacity market.

2.3. Customers' objective functions

Each DG customer segment *c* minimizes its net expenses, i.e., costs minus incomes:

[14] Firm capacity factors, or firmness factors, may also be known as "de-rating factors" in the UK or as "capacity credits" in the US.

$$\text{Min}\left\{\sum_{y}\left[TP_{c,y}\cdot cp_{c,y}+\sum_{t}IC_{t,c,y}\cdot p_{t,c,y}+\sum_{h}\left(\lambda^{E}_{h,y}+\lambda^{C}_{h,y}+TV_{c,y}\right)\cdot dq_{c,h,y}-\right.\right.$$
$$\left.\left.-\sum_{h}\left(\lambda^{E}_{h,y}+\lambda^{C}_{h,y}-TC_{c,y}\right)\cdot eq_{c,h,y}\right]\right\},\forall c \quad (40)$$

These costs encompass:

1) The cost of paying the power-based demand charge term $TP_{c,y}$ for their contracted power $cp_{c,y}$ (the first term inside the bracket [] in (40)).
2) The DG investment costs ($IC_{t,c,y}\cdot p_{t,c,y}$ summed per technology t).
3) The cost of purchasing energy from the grid ($eq_{c,h,y}$) at the energy market price $\lambda^{E}_{h,y}$ and the cost of purchasing the firm capacity at the capacity price $\lambda^{C}_{h,y}$ (second summatory inside the bracket [] in (40)). It includes the volumetric term $TV_{c,y}$ for purchases from the grid as an additional payment.
4) Customer's incomes come from the sales of surpluses in the energy market ($eq_{c,h,y}$) at the energy spot price $\lambda^{E}_{h,y}$ and the remuneration associated with its contribution to the firm capacity by reducing the net peak demand of the system, valued at the hourly capacity price $\lambda^{C}_{h,y}$ (third summatory inside the bracket [] in (40)). Surpluses are subject to the volumetric access tariffs term $TC_{c,y}$ which is discounted from the incomes This tariff scheme can also represent net metering by setting the surpluses term $TC_{c,y}$ equal to $-TV_{c,y}$, effectively achieving net metering in the customer's cost function.

Regarding the formulation previously presented in Chapter III, (40) adds the hourly generation capacity prices $\lambda^{C}_{h,y}$ that customers pay[15] for the energy required from the grid during peak hours H^{M}_{y}. Prices $\lambda^{C}_{h,y}$ must be set to guarantee that the total net cost paid by the customers equals the total income that GENCOs must receive from the capacity market, i.e., expression (41):

$$\sum_{c,h,y}\left(dq_{c,h,y}-eq_{c,h,y}\right)\cdot\lambda^{C}_{h,y}=\sum_{t,g,y}\lambda^{C}_{y}\cdot DI_{t}\cdot p_{t,g,y} \quad (41)$$

2.4. Installed capacity constraint

Maximum production for all generators, either CG or DG, is imposed by (3).

[15] Consider that, if during these hours $eq_{c,h,y}$ is positive (i.e., if a customer segment is selling energy), they will receive remuneration for this energy, as they are helping to reduce the system peak demand. However, as this would only be active during the peak demand hours, it is highly unlikely to happen.

2.5. Customers' constraints

Like in Chapter III, DG is modeled using constraints (4) & (5).

2.6. Game set-up constraints

2.6.1. Wholesale generation and demand balance constraint

Similarly to constraint (6) in Chapter III, the total customers net demand, $\sum_c dq_{c,h,y} - \sum_c eq_{c,h,y}$, must be met with the total CG production in the energy market:

$$\sum_{t,g} q_{t,g,h,y} + \sum_c eq_{c,h,y} = \sum_c dq_{c,h,y} : \lambda^E_{h,y} \quad (42)$$

Constraint (42) links CG and DG productions and therefore sets the energy market game. This constraint does not include non-supplied energy since one of the objectives of the capacity market is to eliminate the need for non-supplied energy in order to recover all investment costs (See the *missing money* problem in [9]). The energy market price is set to its dual variable $\lambda^E_{h,y}$.

2.6.2. The capacity market balance constraint

The firm capacity required in the system is set annually as a margin $(1 + CI)$ over the annual peak demand of the system. The latter corresponds to the maximum value, over a full year, of the hourly energy supplied from the grid to all customers together to match their net consumption, that is $\max_h\left(\sum_c dq_{c,h,y} - \sum_c eq_{c,h,y}\right)$. This firm's capacity must be met by the total firm capacity of the generation installed in the system. In addition, each generator contributes to the firm capacity in proportion to its installed capacity $p_{t,g,y}$ times its firm capacity factor DI_t, which is generation technology *t* dependent and related to its availability at peak hours [90]:

$$\sum_{t,g\in t} DI_t \cdot p_{t,g,y} = (1 + CI) \cdot \max_h\left(\sum_c dq_{c,h,y} - \sum_c eq_{c,h,y}\right) : \lambda^C_y \quad (43)$$

Indeed, the firm capacity factor DI_t represents the CG capacity expected to be available whenever needed (typically in peak hours) with a probability larger than a pre-set value (for instance 90%). Therefore, RES firm capacity factor DI_t is typically much lower than that of conventional generators [90], see for example Table 6 in section 5.1.6.

Note that:

- Constraint (63) links the CG power installed capacities and the DG productions, setting the game that represents the firm capacity market. The capacity market price is set to its dual variable λ^C_y.

- Price λ_y^C does not depend on *h* since the capacity market is run on an annual basis[16]. International energy exchanges are not considered in (43), which guarantees a certain level of national self-sufficiency.
- At each hour, the consumers' surplus of energy sold to the grid $eq_{c,h,y}$ can meet other clients' net demand $dq_{c,h,y}$. Consequently, these surpluses contribute to reducing the net peak demand of the electricity system, modeled through the maximum in (43), as in [90].
- Note that, in this model, 1 MW of installed capacity of DG reduces the mentioned net peak demand according to its corresponding generation at the net peak hour (which in the case of solar PV depends on the existing solar radiation), without applying the firmness factor. However, CG is required to cover the peak reduced by the firmness factor DI_t. Since this factor is based on worst-case scenarios (which is the usual assumption in reliability analyses), the same worst-case strategy to represent DG situations could also be used for the analysis of system security. However, the difficulties for the regulator to account for all after-the-meter DG may pose a challenge for this strategy.

An auxiliary variable d_y^M to model the grid net demand peak is used to avoid the non-differentiable maximum operator in the right-hand side of (43), so that (43) can be rewritten as:

$$\sum_{t,g} DI_t \cdot p_{t,g,y} \geq (1 + CI) \cdot d_y^M : \lambda_y^C \tag{44}$$

$$\sum_{c} dq_{c,h,y} - \sum_{c} eq_{c,h,y} \leq d_y^M : \lambda_{h,y}^C \tag{45}$$

Note that in (45), d_y^M automatically adjusts to the hourly grid demand at the moment when it reaches its maximum value (i.e., the largest value of the left-hand side across all hours of the simulation horizon). Increasing d_y^M at any other hour would not be optimal, since according to (44) this would require additional investments in power capacity that are never actually used. Therefore, if P_y^M denotes the non-empty set of peak hours in year y, the dual variables $\lambda_{h,y}^C$ of (45) are null for all hours except those in P_y^M, which are the only ones that bind (45).

2.7. Final joint energy & capacity equilibrium formulation

The final game is defined through the equilibrium optimization, in the sense of Nash, of (39) and (40), subject to (3) (for $s \in G$) and to (3), (4) & (5) (for $s \in C$), with (42) and

[16] The capacity market might be designed to cover several years ahead together. The extension of this in the modeling is straightforward, by including explicit mathematical summations. This can be useful when modeling real capacity auctions that typically consider bids for three- or four-year horizons.

(43) as the linking constraints of the game. Constraints (44) and (45) must replace (43) to avoid the non-differentiable maximum function in the right-hand side of (43).

3. RESOLUTION METHODOLOGY

This section, akin to section 3 of Chapter III, proves that the JECE can be solved with an equivalent minimization problem using a CV approach.

3.1. Lagrangian functions and KKT conditions

The equations in (46) are the Lagrange functions of (39) subject to (3) (for $s \in G$) and (40) subject to (3), (4) & (5) (for $s \in C$), with (42) and (43) as linking constrains.

$$\ell_g(q,p,\lambda^{PQ},\lambda^{E},\lambda^{C}) = \\ = \sum_{y}\left[-\sum_{t,h}\left(\left(\lambda^{E}_{h,y} - VC_{t,g,y}\right)\cdot q_{t,g,h,y}\right) - \sum_{t}\left(\left(\lambda^{C}_{y}\cdot DI_t - IC_{t,g,y}\right)\cdot p_{t,g,y}\right) + \right. \\ \left. + \sum_{t,h}\lambda^{PQ}_{t,g,h,y}\cdot\left(q_{t,g,h,y} - p_{t,g,y}\right)\right]$$

$$\ell_c(q,p,cp,dq,eq,\lambda^{E},\lambda^{C},\lambda^{PQ},\lambda^{CB},\lambda^{CP}) = \\ = \sum_{y}\left[TP_{c,y}\cdot cp_{c,y} + \sum_{t} IC_{t,c,y}\cdot p_{t,c,y} + \right. \\ + \sum_{h}\left[\left(\lambda^{E}_{h,y} + \lambda^{C}_{h,y} + TV_{c,y}\right)\cdot dq_{c,h,y} - \left(\lambda^{E}_{h,y} + \lambda^{C}_{h,y} - TC_{c,y}\right)\cdot eq_{c,h,y}\right] + \\ + \sum_{t,h}\lambda^{PQ}_{t,c,h,y}\cdot\left(q_{t,c,h,y} - p_{t,c,y}\right) + \\ + \sum_{h,y}\lambda^{CB}_{c,h,y}\cdot\left(\sum_{t} q_{t,c,h,y} + dq_{c,h,y} - D_{c,h,y} - eq_{c,h,y}\right) + \\ \left. + \sum_{h}\lambda^{CP}_{c,h,y}\cdot\left(dq_{c,h,y} + eq_{c,h,y} - cp_{c,y}\right)\right] \tag{46}$$

Their KKT conditions are:

$$
\begin{aligned}
&\frac{\partial \ell_g}{\partial q_{t,g,h,y}} = VC_{t,g,y} - \frac{\partial \lambda^E_{h,y}}{\partial q_{t,g,h,y}} \cdot \left(\sum_{t'} q_{t',g,h,y} \right) - \lambda^E_{h,y} + \lambda^{PQ}_{t,g,h,y} = 0 \\
&\frac{\partial \ell_c}{\partial q_{t,c,h,y}} = \lambda^{PQ}_{t,c,h,y} + \lambda^{CB}_{c,h,y} = 0 \\
&\frac{\partial \ell_c}{\partial cp_{c,y}} = TP_{c,y} - \sum_h \lambda^{CP}_{c,h,y} = 0 \\
&\frac{\partial \ell_c}{\partial dq_{c,h,y}} = \frac{\partial \left(\lambda^E_{h,y} + \lambda^C_{h,y} \right)}{\partial dq_{c,h,y}} \cdot \left(eq_{c,h,y} - dq_{c,h,y} \right) + \left(\lambda^E_{h,y} + \lambda^C_{h,y} + TV_{c,y} \right) \\
&\qquad + \lambda^{CB}_{c,h,y} + \lambda^{CP}_{c,h,y} = 0 \\
&\frac{\partial l_c}{\partial eq_{c,h,y}} = \frac{\partial \left(\lambda^E_{h,y} + \lambda^C_{h,y} \right)}{\partial eq_{c,h,y}} \cdot \left(eq_{c,h,y} - dq_{c,h,y} \right) - \left(\lambda^E_{h,y} + \lambda^C_{h,y} - TV_{c,y} \right) \\
&\qquad - \lambda^{CB}_{c,h,y} + \lambda^{CP}_{c,h,y} = 0 \\
&\frac{\partial \ell_g}{\partial p_{t,g,y}} = IC_{t,g,y} - \frac{\partial \lambda^C_y}{\partial p_{t,g,y}} \cdot \left(\sum_{t'} DI_{t'} \cdot p_{t',g,y} \right) - DI_t \cdot \lambda^C_{h,y} \\
&\qquad - \sum_h \lambda^{PQ}_{t,g,h,y} = 0 \\
&\frac{\partial \ell_c}{\partial p_{t,c,y}} = IC_{t,c,y} - \sum_h \lambda^{PQ}_{t,c,h,y} = 0
\end{aligned}
\tag{47}
$$

$$
\begin{aligned}
&\lambda^{CB}_{c,h,y} \quad \perp \sum_t q_{t,c,g,y} - eq_{c,h,y} + dq_{c,h,y} - D_{c,h,y} = 0 \\
0 \le \lambda^{PQ}_{t,s,h,y} &\perp q_{t,s,h,y} - p_{t,s,y} \qquad \le 0, s \in C \cup G \\
0 \le \lambda^{CP}_{c,h,y} &\perp dq_{c,h,y} + eq_{c,h,y} - cp_{c,y} \qquad \le 0 \\
&\lambda^E_{h,y} \quad \perp \sum_{t,g} q_{t,g,h,y} + \sum_c \left(eq_{c,h,y} - dq_{c,h,y} \right) \quad = 0 \\
&\lambda^C_y \quad \perp \sum_{t,g} DI_t \cdot p_{t,g,y} - (1 + CI) \cdot d^M_y \quad = 0 \\
0 \le \lambda^C_{h,y} &\perp \sum_c dq_{c,h,y} - \sum_c eq_{c,h,y} - d^M_y \qquad \le 0
\end{aligned}
$$

3.2. Joint energy & capacity conjectural variations definition

A CV approach [64] is applied to the game described above, where the same price-response conjectures as in Chapter III are used for the energy market (see Chapter III, section 3.3 for an explanation of the equality shown in (48)):

$$
\frac{\partial \lambda^E_{h,y}}{\partial \left(\sum_t q_{t,g,h,y} \right)} = -\theta^E_{g,h,y} \tag{48}
$$

$$\frac{\partial\left(\lambda_{h,y}^{E}+\lambda_{h,y}^{C}\right)}{\partial dq_{c,h,y}}=-\theta_{c,h,y}=-\frac{\partial\left(\lambda_{h,y}^{E}+\lambda_{h,y}^{C}\right)}{\partial eq_{c,h,y}} \tag{49}$$

Similarly, the CVs for the capacity market can be defined as the residual demand slope [65] of each GENCO in that market (see [91] for the equivalent conjecture in the energy market), i.e.:

$$\frac{\partial\lambda_{y}^{C}}{\partial\left(\sum_{t}p_{t,g,y}\right)}=-\theta_{g,y}^{C} \tag{50}$$

Crossed CVs between the energy and capacity markets (for example, the derivative of the electricity price $\lambda_{h,y}^{E}$ with respect to the capacities $p_{t,g,y}$) have been considered null (as in [92] for the energy and reserve markets). This is because the residual demand in each market only depends on the specific commodity traded in that market (energy in the energy market and capacity in the capacity market) since separated merit-order based dispatch is assumed (see [93] for the definition of other types of dispatches, like for example the so-called joint dispatches).

3.3. The equivalent cost minimization model

Assuming (48)-(50) and null crossed CVs , integrating the KKT conditions in (47) results in the optimization function (51) subject to (3), (4), (5) and (42)-(45):

$$\text{Min}\left\{\begin{array}{l}\displaystyle\sum_{g}\left(\begin{array}{l}\displaystyle\sum_{h,y}\left(\begin{array}{l}\displaystyle\sum_{t}VC_{t,g,y}\cdot q_{t,g,h,y}+\\ \theta_{g,h,y}^{E}\cdot 0.5\cdot\left(\displaystyle\sum_{t}q_{t,g,h,y}\right)^{2}\end{array}\right)\\ +\displaystyle\sum_{y}\left(\begin{array}{l}\displaystyle\sum_{t}IC_{t,g,y}\cdot pa_{t,g,y}+\\ \theta_{g,y}^{C}\cdot 0{,}5\cdot\left(\displaystyle\sum_{t}DI_{t}\cdot p_{t,g,y}\right)^{2}\end{array}\right)\end{array}\right)\\ +\displaystyle\sum_{c}\left(\begin{array}{l}\displaystyle\sum_{y}TP_{c,y}\cdot cp_{c,y}+\sum_{t,y}IC_{t,c,y}\cdot p_{t,c,y}\\ +\displaystyle\sum_{h,y}\left[\begin{array}{l}TV_{c,y}\cdot dq_{c,h,y}+TC_{c,y}\cdot eq_{c,h,y}\\ \theta_{c,h,y}\cdot 0.5\cdot\left(eq_{c,h,y}-dq_{c,h,y}\right)^{2}\end{array}\right]\end{array}\right)\end{array}\right\} \tag{51}$$

Note that different values for the CVs represent different degrees of oligopoly, with null CVs corresponding to perfect competition (since a system cost minimization problem is obtained), [43]. Note that (51) is also a generalization of the problem in Chapter III, which is recovered by setting null the CVs for the capacity market (i.e., setting $\theta_{g,y}^{L}:=0$) and deactivating constraint (44) (i.e., setting $CI:=-1$). The computation of these CVs is not addressed in this thesis, as it is a topic for a whole different work [83].

Moreover, deriving the Lagrangian function of (51) with respect to d_y^M results in the KKT of (47) and in (52):

$$\sum_h \lambda_{h,y}^C = (1 + CI) \cdot \lambda_y^C \tag{52}$$

which implies, according to (45) and since $\lambda_{h,y}^C = 0$ for $h \notin P_y^M$, the conclusion in expression (53):

$$\begin{gathered} \sum_{h,y} d_y^M \cdot \lambda_{h,y}^C = \sum_y d_y^M \cdot (1 + CI) \cdot \lambda_y^C \Leftrightarrow \\ \sum_{c,h,y} \left(dq_{c,h,y} - eq_{c,h,y}\right) \cdot \lambda_{h,y}^C = \sum_{t,g,y} DI_t \cdot p_{t,g,y} \cdot \lambda_y^C \end{gathered} \tag{53}$$

This proves that (41) holds true. Moreover, the electricity price is the dual variable $\lambda_{h,y}^E$ of the energy balance (42), and the capacity price the dual variable λ_y^C of capacity balance (43), both in the above optimization problem.

4. DETAILED CONSTRAINTS FORMULATION

Sections 2 & 3 present a simplified version of the JECE model over which the mathematical demonstration of the equivalent optimization problem can be performed. Over that problem, any additional non-game-defining constraints can be added without compromising this demonstration [68]. In particular, constraints (13)-(36) and (38) can be added as new constraints of (51). Constraint (3) must be replaced by constraint (12) as explained in section 4.1 of Chapter III.

5. CASE STUDIES AND RESULTS

The case study shown herein was already published in [59], a JCR paper published in 2020 but produced in 2019. Therefore, input data for these cases is in accordance with data available in 2019. Where relevant, a comparison with more recent data is also presented.

This case study is selected to illustrate qualitatively the use of the model. It corresponds to a real-sized Spain-like system and is similar to the case-study described in Chapter III. The objective is to analyze the behavior of the different agents modeled and to compare the results yielded by the JECE presented in this chapter with the EOE presented in Chapter III. It is not intended to be a forecasting exercise comparable to the Spanish NECP. Input data and scenarios' descriptions

are explained in sections 5.1 & 5.2 respectively, while the results and their analysis are shown from section 5.3 onwards.

5.1. Assumptions and input data

5.1.1. Temporal horizon

The simulation period has been set from 2019 to 2039, using a single representative week of 168 hours per year to reduce the computational burden, according to the methodology described in [74]. In this approach, the representative week is constructed by selecting actual historical days through a genetic algorithm that minimizes the distance between the duration curves of several key variables (such as demand, net demand, renewable generation, and hourly ramps) computed for the full year and for the reduced synthetic period. As a result, the selected week reproduces the main chronological and operational characteristics of the system while keeping the problem computationally tractable, and it can capture both best- and worst-case scenarios in terms of RES availability from DG.

5.1.2. Demand

Demand growth has been set to 0.5% per year, resulting, in the last year of the simulation horizon, 2039, a total demand of 298 TWh, and an hourly peak demand of 47.4 GW. In contrast, the Spanish NECP forecasts for 2030 a total demand of 273.8 GWh.

5.1.3. Transmission & distribution network

Transmission and distribution network losses are considered in a simplified manner as explained in Chapter III section 4.8. Thus, the piecewise linear approximation for distribution losses was calibrated to achieve 6% distribution losses, and the transmission losses were set to a 3% of the total system demand.

5.1.4. Technologies

The technologies to invest in are combined-cycle gas turbines (CCGT), open-cycle gas turbines (OCGT), wind, solar photovoltaic (PV), and storage facilities (batteries) for CG, and PV and battery facilities for DG. As described in section 4.1 of Chapter III, already operating thermal generation plants are modeled individually, including their start-up, shut-down, and ramping constraints. The expected lifespan is assumed to be 30 years for both OCGT and CCGT units, 45 years for coal-fired units, and 60 years for the currently existing nuclear power plants, so that their closure is considered by the model. No closure of currently existing hydro plants or RES generators is considered.

5.1.5. Investment costs

Investment costs for all CG and DG technologies have been estimated from [94], and are considered equal across all scenarios. The time evolution of these costs (Figure 5, in real costs) is set with the same methodology as in Chapter III, and it is considered to be the same across all scenarios.

5.1.6. Firmness factors

In the absence of more specific available information, the firmness factor (see Table 6) for each technology (DI_t in constraint (44) of the JECE model) has been set equal to the availability factors published by the Spanish regulator at the time of the study ([95]), with two considerations: a) OCGT firmness factor, missing from [95], has been set to the same value (93%) as for CCGT, and b) the firmness factor of battery storage facilities, as it was absent from [95], was set to 0%, assuming them to be short-term storage. Although the focus of this work are not the calculation of these factors, but including them to properly model the firm capacity market, it is worth to comment that these factors have been recently reviewed. For instance, in the UK, short-term storage facilities have a 5% firmness factor (also called de-rating factor in the UK), while longer-term storage facilities (≥8 hours) can have up to around 95% factor.

Table 6: Firmness factors for all technologies

Technology	**Firmness factor DI_t [%]**
Nuclear	87
Anthracite coal	90
Lignite coal	89
Other (foreign) coals	94
CCGT	93
Hydro	59
Wind	22
PV	11
OCGT[17]	93
Other	30
2-hour battery storage	0

[17] Although absent in [95], it was set to the same value as CCGT.

The values in Table 6 were, at the time these studies were performed, the only ones publicly available from official Spanish sources related to the technologies' firmness, although they were estimated for computing ancillary services payments. It can be argued that the firmness of RES generation in this table should be lower, which could be true in a system without large-scale battery storage. However, the combined operation of RES generation and battery storage in the long-term can provide firm partially dispatchable capacity, contributing significantly to meet the constantly varying demand for electricity, [96].

In general, the above firmness values should be estimated based on probabilistic studies that account for the expected firmness of each technology when energy generation is scarce, which usually occurs during demand peak hours (see for example [90] for a study on the ERCOT system).[18]

5.1.7. Conjectural variations

For both cases, GENCOs' and customers' energy the conjectures ($\theta^{S}_{g,h,y}$ and $\theta_{c,h,y}$) have been set to the same values as in Chapter III (Table 4, estimated from historical data, [83]), and for the capacity market case, GENCOs' capacity conjectures ($\theta^{L}_{g,y}$) have been set proportional to their energy conjectures ($\theta^{S}_{g,h,y}$)[19]. These values can be found in Table 7. Note that, in the proposed model, customer segments do not have a capacity conjecture parameter because they do not engage directly in the capacity market.

[18] Measuring how much each technology contributes to guaranteeing the power supply is a more complex topic than considering unique firmness factors, as it depends not only on the characteristics of the technology but also on the characteristics of the whole system (the mix of generation technologies, the shape of the demand curve, etc.). Reference [9] explains this issue in more detail.

[19] Being the proportionality factor the relation between the investment and variable costs of the expected marginal technology in the capacity market (OCGT). The hypothesis behind this is that any GENCO would have the same market power in both markets of the power system.

Table 7: Energy and capacity CV for all agents.

Agent	Energy CV [€/MWh²]	Capacity CV [k€/MW²]
Large GENCOs	5	38.8
Mid-sized GENCOs	3	25.2
Small-sized GENCOs	0	0
Metallurgy and food industries	3	-
Chemistry, mining and paper industries	3	-
Food and services commerce	1	-
Other customer segments	0	-

5.2. Scenarios description

To analyze the impact that access tariffs and the market design (either EOE or JECE auctions) have on the evolution of CG and DG investment decisions, a set of 24 scenarios have been built and simulated. These scenarios result from 12 different combinations of the grid access tariffs and the 2 market designs, as detailed below:

- Regarding the grid-access tariffs, both the volumetric ($TV_{c,y}$ and $TC_{c,y}$) and demand charge ($TP_{c,y}$) tariff terms are varied from a 100% volumetric tariff term weight to a 100% demand charge tariff term weight, in 10% steps (11 different scenarios). In all cases, both terms have been estimated so that the overall tariff incomes allow to recover, in 2019[20], the total amount of system regulated costs as published in [84], assuming that no DG was installed in the system at that year. The current tariffs in Spain (33% of incomes coming from the volumetric term and 67% from the demand charge term, as stated in [84]) have also been considered, so, in the end, there is a total of 12 tariff scenarios. Besides, in all cases, both volumetric terms are considered equal, i.e., $TV_{c,y} = TC_{c,y}$. Values for the 0%, 67% and 100% scenarios were already shown in Table 5, where, for simplicity, other scenarios were omitted. Annual tariff increments have not been considered.

[20] As in 2019 there are no DG investments allowed, demand is constant, and tariff incomes depend only on the different terms of the tariff. Therefore, these terms can be adjusted so a certain percentage of the incomes comes from the volumetric term, and the rest comes from the demand charge term.

- Regarding the market design, 2 possibilities are considered: either there is no capacity market, and the model represents an EOE market, as in Chapter III, with constraint (44) disabled ($CI \coloneqq -1$ in (44)), or there is a firm capacity market in the sense of the proposed JECE by including constraint (44) with a capacity index of 10% ($CI \coloneqq 0.1$ in (44)).

Regarding the representation of uncertainty, the methodology described in [74] has been applied. This methodology builds a shorter representative period that approximates historical duration curves of the most relevant variables such as the RES and their ramps, the demand, etc. Therefore, as mentioned in section 5.1.1, this methodology can synthesize several years of historical data into a single week that represents, to some extent, possible scenarios in the past on both the demand and the interruptible generation, and yielding similar results to those obtained by modeling all the hours of each year (see [74] for more details). Moreover, the synthesized week approach of [74] requires less computational resources in comparison with other alternatives like for example the application of stochastic programming.

5.3. Simulation results

The results are the DG and CG investment decisions, the energy and capacity market prices, the power contracted by the consumers, and the hourly distribution of the demand for the 24 scenarios considered. The results shown and analyzed hereafter focus mainly on the last simulation year (2039) since it is the most representative year (it embraces all investments decided by the model).

5.3.1. Decentralized generation investments results

Figure 13 shows the cumulative DG capacity investments as a function of the tariff scenario. Marker types in this figure refer to EOE or JECE market designs, while green and blue lines correspond, respectively, to PV and battery storage facilities:

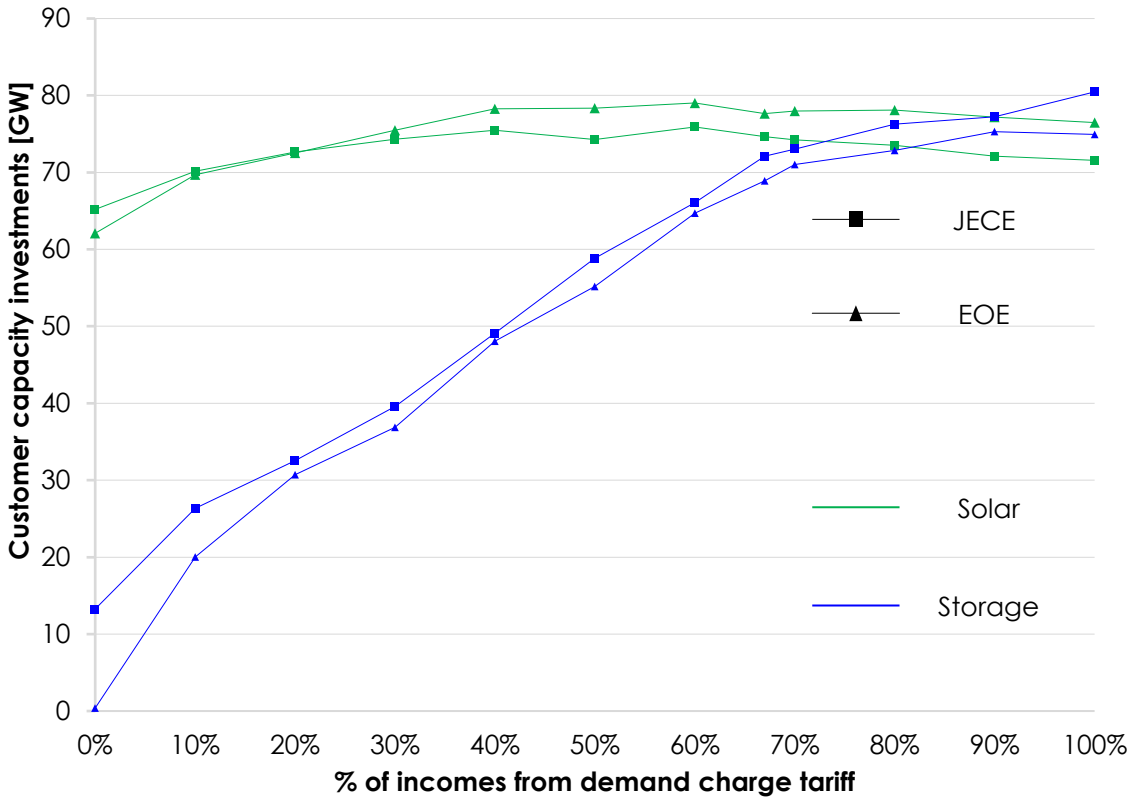

Figure 13: Cumulative DG investments in 2039.

Analyzing Figure 13 leads to the following outcomes:

- There is a positive correlation between DG storage investments and the weight of demand charge tariff incomes, for both market designs. This could be expected, since increasing the weight of the demand charge tariff term incentivizes consumers to decrease their peak demand retrieved from the grid by installing DG storage (storage has load-shifting capabilities and is an adequate technology for peak shaving). However, this correlation decreases for a weight of incomes of the demand charge tariff term above 70%, due to a diminishing returns effect, see [97] and [98].
- DG storage investments are higher in the JECE model than in the EOE one. Indeed, in the EOE model, storage is used to reduce the demand charge tariff term payments corresponding, for each customer segment, to a reduction of its individual peak demand. However, in the JECE model, consumers are also interested in lowering the system peak to decrease their payments in the capacity market. This is more evident when the demand charge tariff is null, since for the EOE model (with 0% of incomes of the demand charge tariff term) DG storage investments are null, while for the JECE model they are not.

DG PV investments are affected by two effects:

- On one hand, synergies with DG storage (see [99]) cause DG PV to increase, as can be seen for 0% to 40% of incomes of the demand charge tariff term.

However, unlike DG storage, DG PV cannot be used for peak shaving, as the peak demand takes place during nighttime, about 21:00 (according to data from the Spanish TSO, [100]), which makes DG PV investments less profitable for higher demand charge tariff terms.

- On the other hand, the volumetric term of the tariff behaves as an incentive to reduce consumption from the grid by installing DG PV. Logically this effect is more remarkable for larger volumetric tariff terms (for 0% to 40% of incomes of the demand charge tariff term), as can be seen in Figure 13.
- The combination of both effects results in the inverted bathtub curves shown in Figure 13. However, the second effect is stronger in the EOE model due to higher average energy prices, causing both lines to cross for a weight close to 20%.

The following subsections show how DG storage investments are related to the reduction in the contracted power of consumers and how DG PV investments are linked with the reduction in the consumers' total demand.

5.3.2. Contracted power and demand

Figure 14 shows the total net energy demanded by customers from the grid (scale on the right-hand side of the figure) and the total contracted power (CP) by customers (scale on the left-hand side of the figure) per weight of the demand charge term of the access tariff for both market designs.

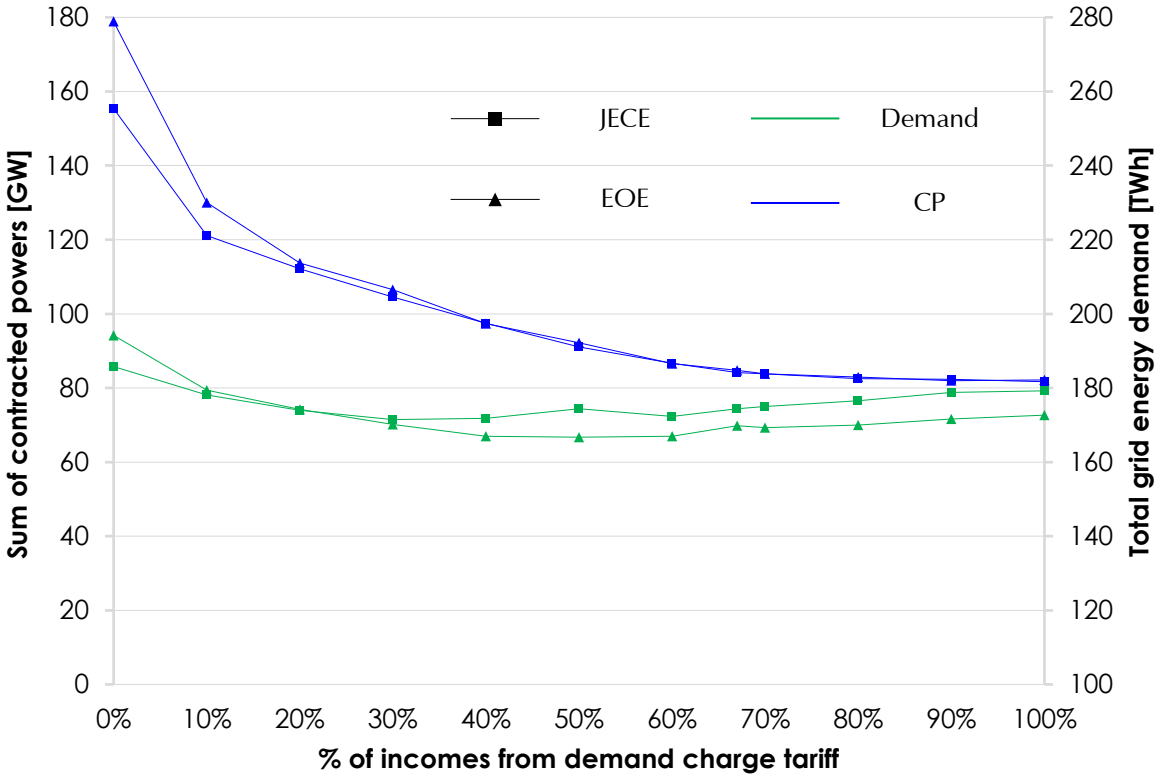

Figure 14: Total contracted power and customer demand in 2039.

Figure 14 shows that:

- As expected, both CP curves follow an inverse path to the one followed by the DG storage investment curves shown in Figure 13. This reinforces the conclusion that one of the main drivers for installing DG storage is the reduction of the weight of the demand charge term in the access tariff.
- There is almost no difference in the total resulting contracted power for the two different market designs whenever the weight of the demand charge tariff term is above 20%. This suggests that the increment in DG storage investments associated with the JECE (versus the EOE) market design, identified previously in Figure 3, is not directly related to the weight of the demand charge tariff term but rather to the reduction of the capacity payments that installing DG storage entails in the JECE (see Figure 16) which is in turn not considered in the EOE.
- Total grid demand curves show an inverse shape of that of the DG PV investment ones in Figure 13 (even, the lines associated to both market models cross for a weight close to 20% in both cases), indicating that load-defection (i.e., the reduction in grid consumption using self-generation to lower the volumetric tariff costs) is the main driver behind DG PV investments in both market models.

The following subsections analyze how these results impact the wholesale energy market by looking at the resulting CG investments and market prices.

5.3.3. Centralized generation investments results

Figure 15 shows the total CG new capacity investments (over the current existing capacity in the Spanish system) for the different weights of the demand charge term of the tariff and the two market model designs.

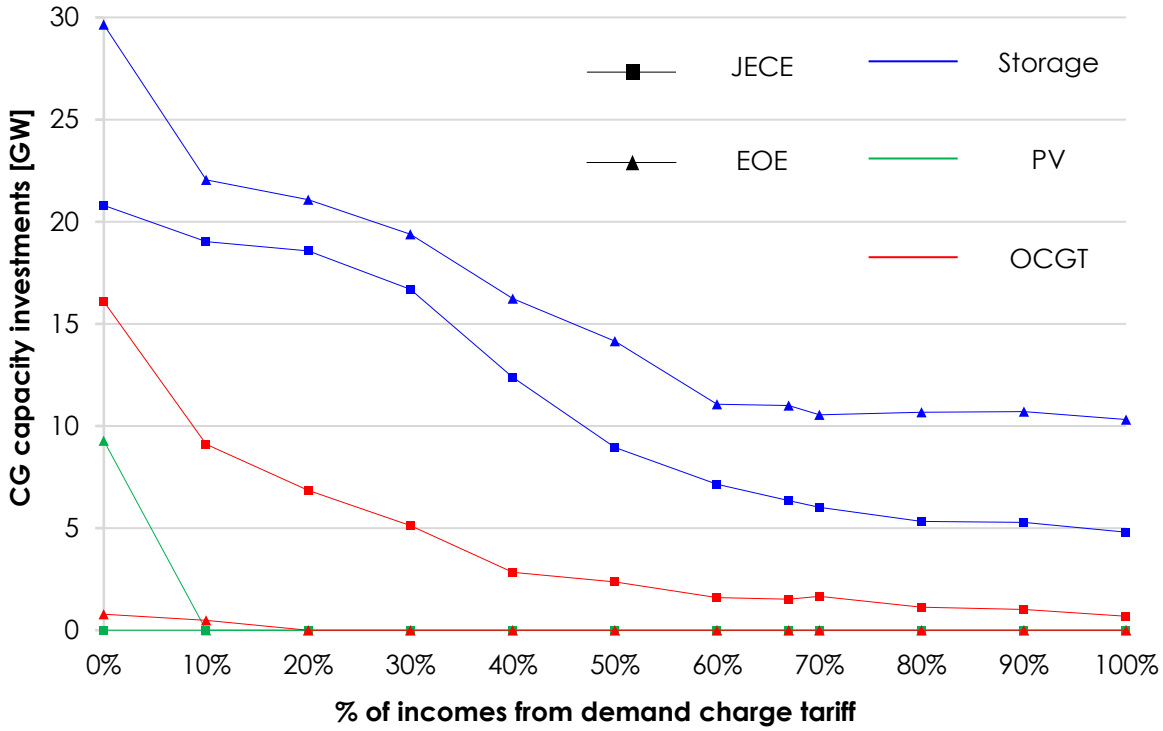

Figure 15: Cumulative CG investments in 2039.

Although investment options consider CCGT, OCGT, wind power, PV, and storage technologies, results show that, for the set of investment costs assumed in this work (Figure 5), only new investments in OCGT, PV, and storage technologies take place. Figure 15 also shows that:

- OCGT investments take place almost only in the JECE market model option. Indeed, as this technology has both a low investment cost (lower than CCGT, wind, and PV) and a high firmness factor (DI_{OCGT}=93%), it is the perfect technology to provide the firm capacity required by constraint (44). Instead, for the EOE market the system prefers to resort to storage investments, which are no longer fully valid for the JECE market model option, since their contribution to the firmness requirements is considered null in this study.
- In addition, OCGT investments in the JECE model option decrease when the weight of the demand charge tariff term increases. This can be explained by the fact that, as previously commented, higher weights of the demand charge tariff term incentivize consumers peak reductions (see Figure 18), thus reducing the right-hand side of constraint (44), and therefore the need for investments in CG peak (i.e., low investment cost although high production cost) technologies.
- CG storage investments in both market model options decrease for higher weights of the demand charge tariff term. This is reasonable since higher weights of the demand charge tariff term incentivize flattering the demand

by increasing DG storage investments (Figure 13), and therefore reducing the need for CG storage (Figure 18).

- As there is no firm capacity constraint in the EOE model other than the generation-demand balance, constraint (62), there is no hard requirement for OCGT investments. This leads to larger DG storage investments in the EOE model instead of the OCGT investments of the JECE one. CG storage investments are always significantly higher in the EOE model than in the JECE one. Moreover, it was verified that the few hours with OCGT production in the JECE model correspond to hours with CG storage discharge in the EOE model. This is also a consequence of a possible underestimation of the firmness factor of the CG storage technology (Table 6).
- New CG PV investments only take place in the EOE market model option whenever the access tariff is fully volumetric. This, in combination with the high DG PV investments in all scenarios, shows that the economies of scale in centralized PV investment costs do not offset the effect of the access-tariff costs (at least for the cost scenario used in this work). This also suggests the very significant impact that self-generation may have in the coming years in the evolution of the power sector, as many reports already highlight [78].

The next subsection analyzes how energy market prices are related to both CG and DG investments.

5.3.4. Energy market prices

Figure 16 presents, as a function of the weight of the demand charge tariff term, the annual average values of the hourly energy price $\lambda^{E}_{h,y}$ (JECE energy price) and the hourly capacity price $\lambda^{C}_{h,y}$ (JECE capacity price) for the JECE market. It also shows the annual average value of the hourly energy market price for the EOE market (dual variable of the generation-demand constraint, noted as Market price EOE), as well as the annual average of the total hourly supplied energy market price for the JECE market, computed as the sum of the hourly energy price $\lambda^{S}_{h,y}$ and the hourly capacity price $\lambda^{L}_{h,y}$.

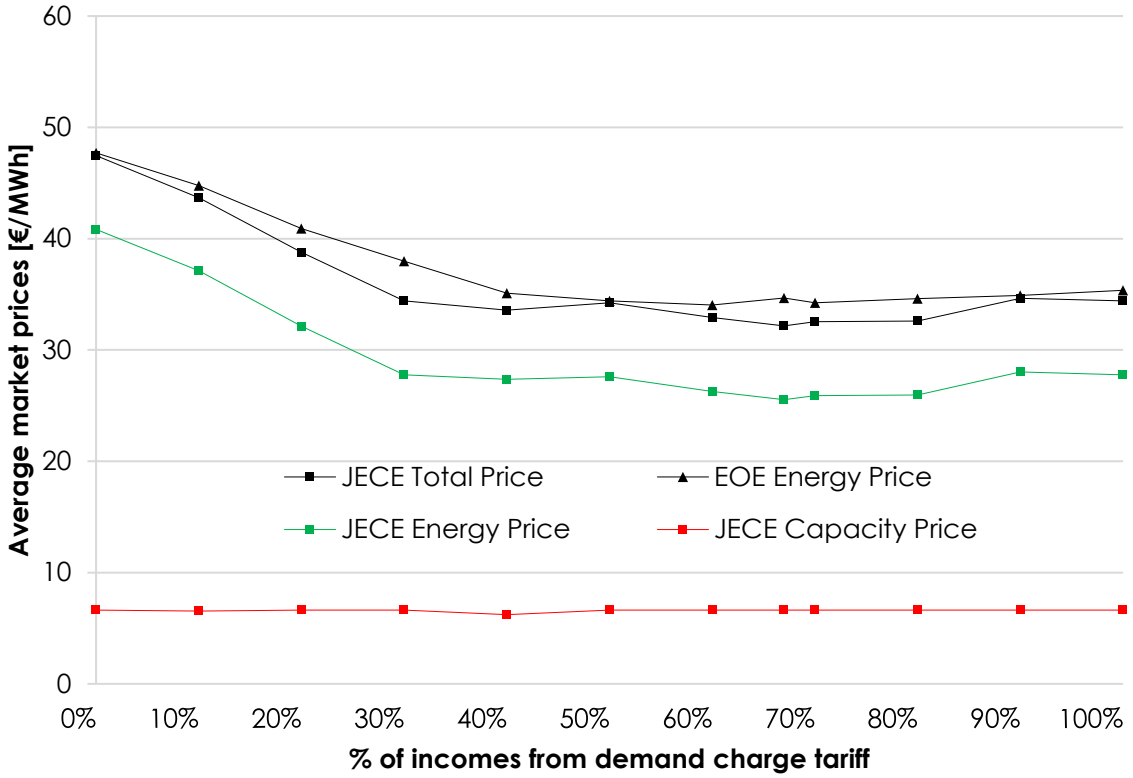

Figure 16: Average market prices in 2039.

Also, Figure 17 shows the distribution of these total hourly energy market prices for both market models (sum of $\lambda^E_{h,y}$ and $\lambda^C_{h,y}$ in the case of JECE and only $\lambda^E_{h,y}$ in the case of EOE) using classical boxplots.

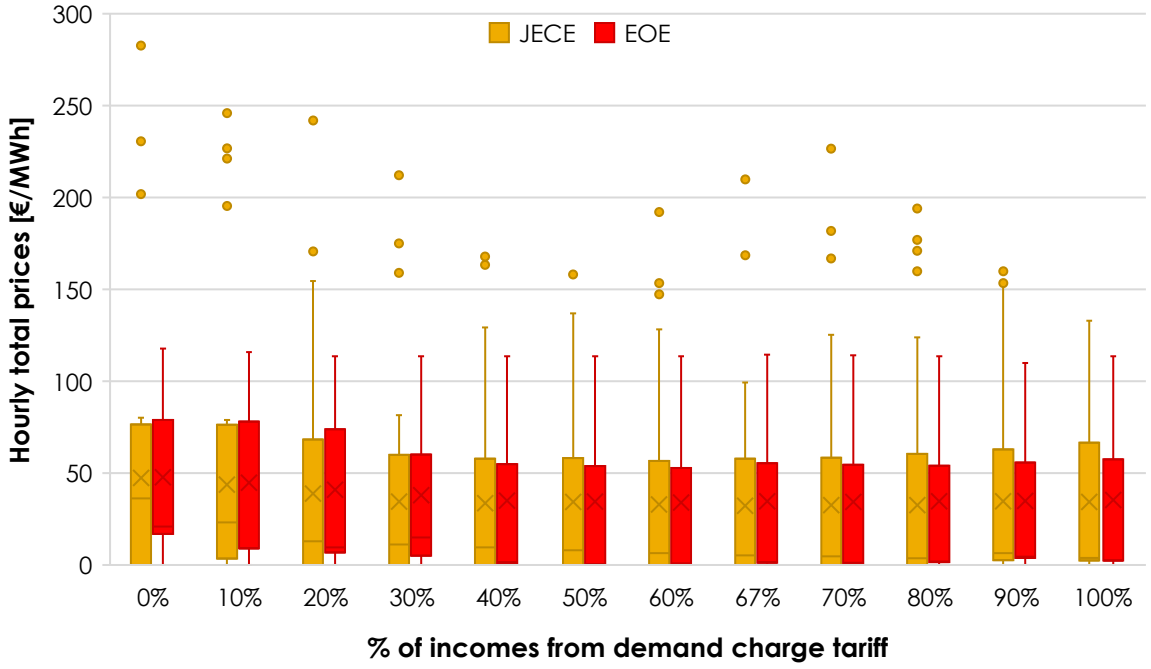

Figure 17: Hourly market price distribution in 2039.

Figures 16 & 17 show that:

- The annual average capacity market prices $\lambda^{C}_{h,y}$, for the JECE market, remain almost constant among all tariff scenarios. This is straightforward since OCGT is the marginal technology in all scenarios in the capacity market (limited to those hours where the capacity constraint (4) becomes active).
- Total annual average energy prices are higher in the EOE model than in the JECE model. The reason behind this is that higher CG storage investments in the EOE model (see Figure 15) internalize their investment costs in the energy market price. However, EOE also leads to a cleaner mix (i.e., with lower CO_2 emissions due to a lower thermal generation), once again possibly due to the underestimation of the firmness capacity of DG storage.
- However, the price distribution is wider in the JECE model than in the EOE model. This is because $\lambda^{C}_{h,y}$ of the JECE model is positive only during the few peak hours, causing critical-peak pricing ([101]), being null during all the other hours of the year, providing a better economic signal of the system's capacity scarcity.
- Below 40%, the lower the weight of the demand charge tariff term is, that is, the higher the weight of the energy base tariff term is, the higher the average market price is, and the larger the variability of the hourly market prices is. This is due to the also higher average value and larger variability of the grid demand in those conditions (see Figure 18 in the next subsection), as a result of lower DG investments (see Figure 13).

To explain these variabilities in prices, the next subsection shows the distribution of the hourly demand.

5.3.5. Hourly demand distribution

Figure 18 shows the distribution of the hourly demand for each scenario.

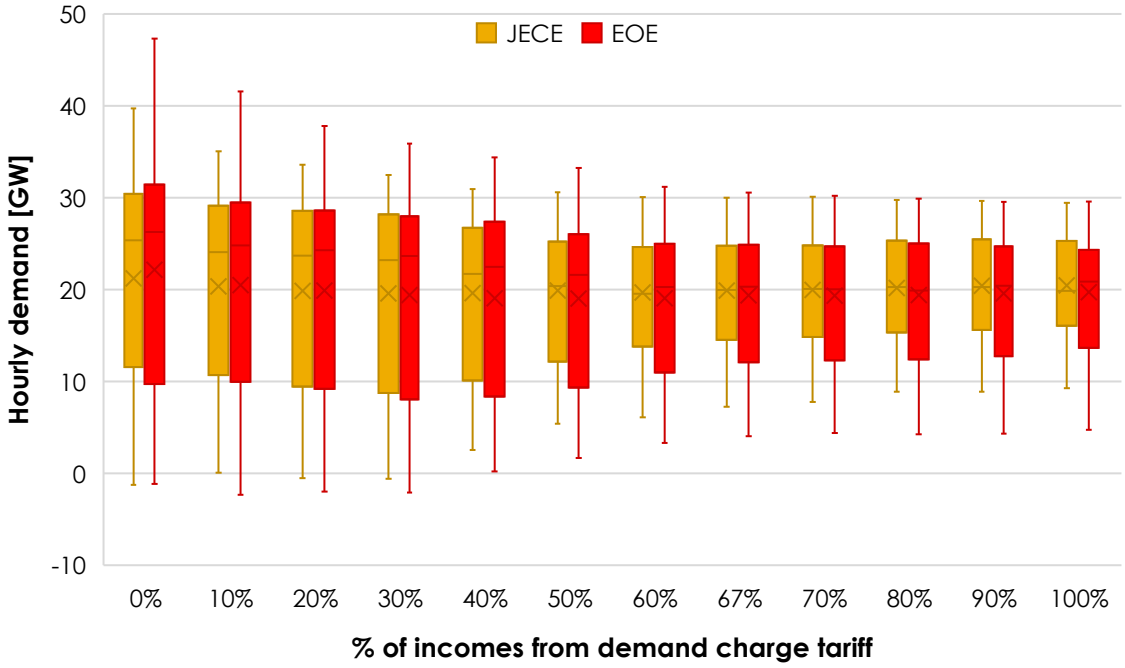

Figure 18: Hourly demand distribution in 2039.

Figure 18 shows that:

- The lower the weight of the demand charge tariff term is, the larger the variability of the hourly grid demand profiles is, since incentives for load shifting are lower. It results in lower DG storage investments and higher CG storage investments.
- Peak demand is higher in the EOE market model option than in the JECE one except for weights of the demand charge tariff term above 70%, for which the peak grid demands for both market model options are almost the same. It shows again that the demand charge tariff term represents an incentive to reduce peak consumption, coherently with Figure 14, in which of could be observed that the contracted power (peak grid demand per customer) was almost equal in both market model options for high weights of the demand charge tariff term.
- For a low weight of the demand charge tariff term (below 30%) results even show negative total grid demand for a few hours. This means that, for those hours, GENCOs consume and store the energy that customers are producing. These extreme scenarios occur due to the high DG PV investments combined with the low DG storage investments (see Figure 13), and the high CG storage investments (see Figure 15).

5.4. Computational results

The model has been programmed with GAMS v28.2 and solved using CPLEX [86], on an Intel i7-4790 CPU at 3,6 GHz with 32 GB of RAM. Each case study consists of approximately 5.0 million constraints and 4.0 million variables, of which 1.9 million

are discrete (such as those for start-ups and shutdowns modeling) and 2.1 million are continuous. However, in order to carry out the differentiations performed in section 3, all integer variables were relaxed. The problem resolution lasts around 30 minutes.

6. CONCLUSIONS

Case studies based on a real-sized Spanish-like power system are used to compare the outcomes of the proposed JEC market against an EO market approach. These studies analyze how the model's economic signals, market structure, and parameter choices affect investments and system performance.

The main conclusions drawn from the case studies are:

- The economic signal sent by the capacity market to the consumers incentivizes collaborating in reducing the total system (grid) peak demand. However, this economic signal is only efficient for weights of the demand charge term of the access tariff below 70% of the full amount collected by the access tariff. For higher values, the impact of the capacity market on the grid peak load dilutes and the system's peak demand is like that of an EO market.
- A market design based on both energy and capacity markets leads to a power system with less variability in the total grid demand and with lower average market prices, due to higher incentives to invest in DG storage facilities to be used for peak shaving. EO markets, instead, lead to more frequent and spiky episodes of scarcity hours with very high prices. Peaker generation technologies, such as open-cycle gas turbines, need these high prices to recover their investment costs.
- In comparison with an EO market, the JEC market design leads to higher investments in peak technologies and lower utility-scale storage investments. However, these results are heavily conditioned by the firmness factors, particularly the assumption of null firmness factors for utility-scale storage technologies. This assumption, based on the publicly available data of the Spanish TSO, the so-called availability factors, corresponds to storage technologies based on batteries not able to generate at full capacity for more than 2 hours, providing indeed very poor support to the security of supply of the system.

The following chapter extends the model presented within this chapter by specifying, developing and testing the upper level to finalize the bilevel model.

7. METHODOLOGICAL CONTRIBUTIONS

Building on the foundation established in Chapter III, this chapter expands and generalizes the model of Chapter III to jointly address CG and behind-the-meter DG

expansion planning and operation, now with explicit representation of both energy and capacity markets within a Nash equilibrium framework. The model's structure enables the equilibrium to be reformulated as a cost-minimization problem, greatly improving computational tractability and flexibility in incorporating additional system constraints. Exogenous access tariffs are included to ensure the recovery of regulated and policy-driven costs, with a security-of-supply margin enforced through firm capacity requirements.

The main features and contributions of the model are:

- Represents both CG and DG investments using a single-level equilibrium formulation for both investment and operation decisions, unlike [102] which uses a bi-level mathematical formulation.
- Can be solved with a novel equivalent quadratic optimization model derived from the KKT conditions of the JECE, as in [103].
- The model includes, like in Chapter III's model, operational constraints such as power ramps, start-ups and shut-downs, etc. in an hourly and detailed way.
- The model endogenously computes the marginal capacity price. This price provides an economic signal for GENCOs to invest, for example, in firm peak generation capacity (highly dispatchable plants). It also allows GENCOs to recover their capacity investment costs without relying on the very high prices of power scarcity hours, as it would happen in an EOE market ([104]).
- This work also proposes an hourly mechanism for integrating the capacity payment into the hourly electricity price for the final customers.
- The indirect role of DG, which does not actively participate in the capacity market, is considered in the model. Indeed, DG can reduce the peak of the finally consumed net grid demand and, consequently, the system capacity requirements.
- Analyzes a real-sized, Spanish-like power system for the years 2019-2039.

Chapter V. UPPER LEVEL: CENTRALIZED TARIFF OPTIMIZATION MODEL

1. INTRODUCTION

This chapter develops and tests a new bilevel model to provide insights into electricity tariff design, accounting for the expansion of both centralized (CG) and distributed generation (DG) driven by those tariffs.

The model explicitly considers the relationship between the electricity tariffs, the generation assets operation, and the endogenous electricity market prices with CG and DG investments by using a long-term GEP mathematical model with unit commitment (UC) constraints [105]. Previous chapters set the foundation for this bilevel model, by developing and testing its lower level. This chapter formulates the upper proposed level and its resolution approach, based on an iterative algorithm to compute the values of the tariff terms to achieve a pre-set income regulatory target. An overview of the structure of the proposed bilevel problem can be found in Figure 19.

The authors presented in [44] a conceptual bilevel multi-follower framework, with policy and regulatory decisions at the upper level and CG/DG operation and investment decisions at the lower level. This structure allows to analyze phenomena such as load-defection, grid-defection, and the death spiral, since lower-level agents react to upper-level regulatory decisions. In this framework, the regulator's objective is to design a cost-effective tariff system that ensures cost recovery while meeting security-of-supply and sustainability constraints, whereas each follower seeks to maximize its own profit. The model addresses a key limitation of most DG investment studies (see Table 1), which consider electricity prices as an exogenous input, neglecting the impact of CG and DG investments. However, [44] only proposed the conceptual framework, without the full mathematical formulation. A very simplified mathematical formulation was later developed in [32] but still with exogenous prices. The model presented in this chapter continues this research line by implementing the full bilevel framework with endogenous electricity prices.

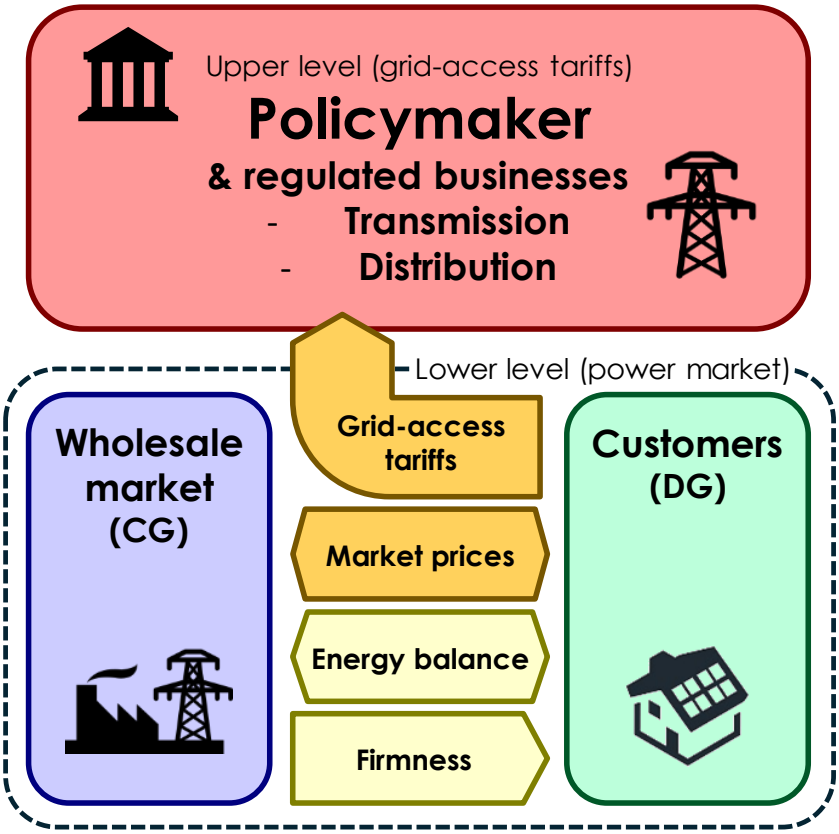

Figure 19: Proposed bilevel model structure.

As it is well known, the design of grid access tariffs is of major importance and depends on what the regulator is trying to achieve [106]. For example, some energy policies consider that tariffs should be designed to promote economically efficient or environmentally friendly installations to support, and not discourage, the energy transition. Others may put the focus on purely economic factors such as proper cost allocation along all users of the grid, [9]. This work focuses, not on proposing a normative design for tariffs, but rather on the development of a computational model capable of adjusting them numerically considering the impact they have on the system agents and how they react to them. The model accounts for the optimal and likely responses of both GENCOs and end-users, capturing the dynamic interactions between investment decisions and tariff structures. The aim is to identify tariff trajectories that are consistent with predefined cost recovery goals while remaining compatible with rational actor behavior across the system and reasonable regulatory principles imposed as constraints.

This chapter is structured as follows: section 2 presents an overview of the bilevel model structure, section 3 defines a computational iterative algorithm to solve it, and sections 4 & 5 present a set of case studies to show how the model responds both in terms of simulation results & computational results, respectively. Finally, section 6 presents the main contributions of this chapter and section 6 presents the main conclusions.

2. COST RECOVERY BILEVEL MODEL

This section presents the formulation of the bilevel model proposed in this thesis for the regulated costs recovery problem.

2.1. Hypotheses

In addition to the hypotheses presented in Chapter III section 2.1 and section 2.1, this model assumes that:

- The energy-related (volumetric) term is assumed to be the same for energy imported from or exported to the grid. Using a single tariff term for both directions simplifies the formulation by reducing the number of decision variables and, consequently, the complexity of the optimization problem.
- Tariff terms are now decision variables, and customers at the lower level can react to their values.
- It is assumed that every customer pays their fair share in terms of the cost they produce to the grid, ensuring equity.
- The hourly volumetric tariff profile of the customers is the same for all the years of the simulation horizon. This assumption reduces significantly the complexity of the model, since there are effectively less decision variables, and therefore, degrees of freedom to optimize. However, this entails the limitation of being unable to optimize this profile shape.

Several constraints can be applied to the annual evolution tariffs to provide sensible signals for the customers. For example, in this model those considered are: 1) tariffs are monotonically increased year by year and 2) a maximum annual increase for each tariff is imposed. While other constraints may be specified and incorporated into the model, within this thesis only those two are considered.

2.2. Upper level: the centralized tariff optimization model

In this chapter, the first level of the proposed bilevel model focuses on the design of the grid access tariffs to cover the regulated grid costs over a period of years. To this aim, the access tariffs are specified by groups of customers according to different criteria (for example, based on similar consumption patterns, similar location-related circumstances, similar voltages levels, etc., [107]).

As in Chapter III & , in this chapter the customers are again categorized according, first, to their type (residential, industrial or commercial customers) and, second, to their economic activity (metallurgy, chemistry, mining, wood/paper, food, hotels and restaurants, services, etc.) or household type (block, single-family, etc.). It is assumed that customers belonging to the same category (or segment) behave similarly. Moreover, it is also assumed that grid-tied is the most attractive option (both financially and in terms of security of supply, when compared to off-grid

alternatives), i.e., that grid defection is the worst-case scenario for the regulator and the grid[21].

The following generic tariff structure has been considered (see [9] and [107]):

- A power related demand charge term, $tp_{c,y}$ [€/MW], that customers pay for their contracted power $cp_{c,y}$, i.e., for their peak power throughout the year. This term already appeared in Chapter III & □ as $TP_{c,y}$.
- A volumetric term, $te_{c,h,y}$ [€/MWh], proportional to the customer segment's energy consumed from ($dq_{c,h,y}$) or sold to ($eq_{c,h,y}$) the grid. This term is equivalent to both volumetric terms in Chapter III & □ ($TV_{c,y}$ & $TC_{c,y}$) if they are equal in value.

This structure is aligned with current EU tariff structures ([108]) that consider that the network costs constitute most of the total costs of the system, which are determined by two fundamental variables: a customer's installed contracted power and the energy consumed.

Under these assumptions and considering the above tariff structure, the upper-level problem can be formulated as follows:

$$\min_{tp_{c,y},te_{c,h,y}} \sum_{y} \left| INCSP_y - inc_y \right| \tag{54}$$

s.t.

$$inc_y = \sum_{c} tp_{c,y} \cdot cp_{c,y} + \sum_{c,h \in y} te_{c,h,y} \cdot \left(dq_{c,h,y} + eq_{c,h,y} \right) \tag{55}$$

The objective function is the difference between $INCSP_y$, the cost incurred by the customers' use of the grid (the cost for the use by GENCOs is deflated) minus the income inc_y from the tariffs, and $cp_{c,y}$, $dq_{c,h,y}$ and $eq_{c,h,y}$ are the contracted power and the energy bought or sold from or to the grid by each customer, and are optimal from the point of view of the second level given the values of the tariffs $tp_{c,y}$ and $te_{c,h,y}$ fixed by the policymaker in the first level. Parameter $INCSP_y$ is the cost incurred by the customers' use of the grid (the cost for the use by GENCOs is deflated) being the objective function the difference between such a cost and the incomes from the tariffs.

[21] As most grid costs are sunken costs to be recovered along the lifetime of grid assets, grid-defection can compromise recovering these costs.

In terms of distributing the tariffs among the customers, there are two different main approaches in the literature that can be used, see [106]: the application of long-term marginal costs and the causality principle. Although the former aims to achieve a better economic signal, it entails difficulties in its implementation since it requires the detailed representation of the grid and its associated costs. For this reason, the most usual solution applied in practice is the causality principle that ensures that every customer pays their fair share in terms of the cost they produce to the grid, ensuring equity. Regarding this topic, this model assumes that the hourly volumetric tariff profile of each year is the same and equal to the profile shape of the initial year y_0, and the model can only homothetically increase or decrease the whole profile. Therefore, it must hold:

$$\frac{te_{c,h',y_0}}{te_{c,h,y_0}} = \frac{te_{c,h',y}}{te_{c,h,y}} \tag{56}$$

which is mathematically equivalent to the following expression, where only one variable exists per customer and year for energy, reducing the actual set of decision variables:

$$te_{c,h,y} = \frac{TE_{c,h,y_0}}{TE_{c,y_0}} \cdot te_{c,y} \tag{57}$$

Finally, the following additional constraints can be considered in the model:

- Tariffs are monotonically increased year by year:

$$tp_{c,y+1} \geq tp_{c,y} \qquad (tp \rightarrow te) \tag{58}$$

- A maximum annual increase for each tariff is imposed:

$$tp_{c,y+1} \leq (1 + INC^{MAX}) \cdot tp_{c,y} \qquad (tp \rightarrow te) \tag{59}$$

Thus, the optional evolution of the tariffs throughout the temporal horizon leads to a tariff staircase function, which is reasonably realistic and simplifies the understanding of the tariff structure.

2.3. Lower level: the centralized & decentralized joint energy & capacity model

The second level is the model described in detail in □. This section presents a summary of the mathematical formulation presented in that chapter.

2.3.1. The generation companies' and customers' objective functions

Omitting, for simplicity, the discount rate R and considering that the buying and selling terms of the tariffs are identical, the objective function of each GENCO and

each customer to be optimized simultaneously (in the sense of a Nash equilibrium) are (60) and (61) respectively:

$$\underset{q_{t,g,h,y},p_{t,g,y}}{\text{Max}} \left\{ \sum_{y} \left[\sum_{t,h} \left(\left(\lambda^{E}_{h,y} - VC_{t,g,y} \right) \cdot q_{t,g,h,y} \right) + \sum_{t} \left(\left(\lambda^{C}_{y} \cdot DI_{t} - IC_{t,g,y} \right) \cdot p_{t,g,y} \right) \right] \right\}, \forall g \quad (60)$$

$$\underset{cp_{c,y},dq_{c,h,y},eq_{c,h,y}}{\text{Min}} \left\{ \sum_{y} \left[TP_{c,y} \cdot cp_{c,y} + \sum_{t} IC_{t,c,y} \cdot p_{t,c,y} + \right. \right.$$
$$\left. \left. + \sum_{h} \left(\left(\lambda^{E}_{h,y} + \lambda^{C}_{h,y} + TE_{c,h,y} \right) \cdot dq_{c,h,y} - \left(\lambda^{E}_{h,y} + \lambda^{C}_{h,y} - TE_{c,h,y} \right) \cdot eq_{c,h,y} \right) \right] \right\}, \forall c \quad (61)$$

On one hand, the first term of each GENCO objective function in (60) is the energy market profit, while the second one is the capacity market profit, computed both as the market incomes, minus the costs. On the other hand, the first term of each customer objective function in (61) is the cost of the demand charge access tariff, the second represents the DG investment costs, and the third adds up the purchasing and selling energy costs and incomes from or to the grid.

2.3.2. Game set-up constraints

The linking constraints that set the game are:

$$\sum_{t,g} q_{t,g,h,y} = \sum_{c} dq_{c,h,y} - \sum_{c} eq_{c,h,y} : \lambda^{E}_{h,y} \quad (62)$$

$$\sum_{t,g} DI_{t} \cdot p_{t,g,y} = (1 + CI) \cdot \max_{h} \left(\sum_{c} dq_{c,h,y} - \sum_{c} eq_{c,h,y} \right) : \lambda^{C}_{y} \quad (63)$$

The first constraint allows all market agents to meet the demand in the energy market while the second meets the peak demand in the capacity market. Their dual variables, $\lambda^{E}_{h,y}$ in the case of (62) and λ^{C}_{y} in the case of (63), represent the energy and capacity prices, respectively, as they appear in (60) & (61).

2.3.3. The CG-DG remaining constraints

Maximum production for all generators, either CG or DG, is imposed by (3). Likewise to Chapter III, DG is modeled using constraints (4) & (5). Finally, the hourly CG and DG operation and investments constraints are those described in Chapter III section 4.

3. RESOLUTION METHODOLOGY

To address the previously described bi-level problem, a heuristic iterative algorithm has been developed in this thesis. In each iteration *k*, the upper level determines

tariffs such that the resulting regulated incomes (inc_y^k, computed as in (55)) align as closely as possible with the regulated costs ($INCSP_y$) set as inputs to the model. The algorithm parts from the hypothesis that the revenue from a specific tariff term depends linearly and solely on the price of that tariff term. Although this hypothesis does not hold stricto sensu due to both inter-temporal constraints and the equilibrium nature of the lower-level problem (in which a change in any agent's subproblem may affect the whole problem), it allows for the iterative improvement of the solution until the relative difference between the resulting regulated incomes inc_y^k and the regulated incomes setpoint $INCSP_y$ decreases below a sufficiently small error margin (set as ϵ in the algorithm). Figure 20 shows, in a simplified manner, how the algorithm optimizes tariffs until modelled incomes approach sufficiently the income setpoint. Note that in Figure 20, $tx_{c,y}^k$ acts as placeholder for both $tp_{c,y}^k$ and $te_{c,y}^k$.

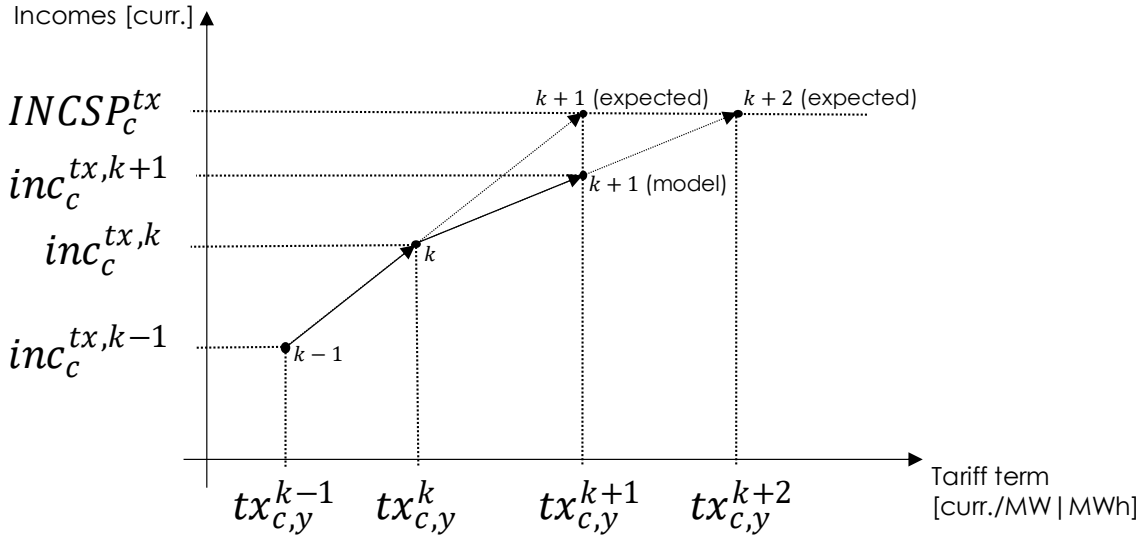

Figure 20: Simplified algorithm graph.

With these hypotheses, the algorithm is as follows:

0) **Initialize**: Set $k = 0$. Select an error margin $\epsilon > 0$. Consider an initial set of tariffs $tp_{c,y}^{k=0}, te_{c,y}^{k=0}$.
1) **Solve the JECE lower-level model**: The following quadratic optimization problem must be solved to obtain the JECE for tariffs $tp_{c,y}^k, te_{c,y}^k$ (see section 3.3 for more details):

$$\text{Min}\left\{\begin{array}{l}\sum_{g}\left(\sum_{h,y}\left(\begin{array}{l}\sum_{t} VC_{t,g,y}\cdot q_{t,g,h,y}+\\ \theta^{E}_{g,h,y}\cdot 0.5\cdot\left(\sum_{t} q_{t,g,h,y}\right)^{2}\end{array}\right)+\sum_{y}\left(\begin{array}{l}\sum_{t} IC_{t,g,y}\cdot p_{t,g,y}+\\ \theta^{C}_{g,y}\cdot 0{,}5\cdot\left(\sum_{t} DI_{t}\cdot p_{t,g,y}\right)^{2}\end{array}\right)\right)+\\ +\sum_{c}\left(\sum_{y} TP_{c,y}\cdot cp_{c,y}+\sum_{t,y} IC_{t,c,y}\cdot p_{t,c,y}+\sum_{h,y}\left[\begin{array}{l}TE_{c,y}\cdot\left(dq_{c,h,y}+eq_{c,h,y}\right)\\ \theta_{c,h,y}\cdot 0.5\cdot\left(eq_{c,h,y}-dq_{c,h,y}\right)^{2}\end{array}\right]\right)\end{array}\right\} \quad (64)$$

subject to the constraints described in section 4 of □.

where $TP_{c,y}=tp^{k}_{c,y}$, $TE_{c,y}=te^{k}_{c,y}$ and: (65)

$$\theta^{E}_{g,h,y}=-\frac{\partial\lambda^{E}_{h,y}}{\partial\left(\sum_{t} q_{t,g,h,y}\right)}$$

$$\theta_{c,h,y}=-\frac{\partial\left(\lambda^{E}_{h,y}+\lambda^{C}_{h,y}\right)}{\partial dq_{c,h,y}}=\frac{\partial\left(\lambda^{E}_{h,y}+\lambda^{C}_{h,y}\right)}{\partial eq_{c,h,y}} \quad (66)$$

$$\theta^{C}_{g,y}=-\frac{\partial\lambda^{C}_{y}}{\partial\left(\sum_{t} p_{t,g,y}\right)} \quad (67)$$

2) **Calculate incomes**: Compute incomes inc^{k}_{y} from the results of the JECE lower-level model solution as follows:

$$inc^{tp,k}_{c,y}=tp^{k}_{c,y}\cdot cp_{c,y} \quad (68)$$

$$inc^{te,k}_{c,y}=\sum_{h} te^{k}_{c,h,y}\cdot\left(dq_{c,h,y}+eq_{c,h,y}\right) \quad (69)$$

$$inc^{k}_{y}=\sum_{c}\left(inc^{te,k}_{c,y}+inc^{tp,k}_{c,y}\right) \quad (70)$$

3) **Check convergence**: If the relative difference between incomes inc^{k}_{y} and the incomes setpoint $INCSP_{y}$ is lower than the predefined error margin ϵ, i.e., if expression (71) holds, convergence has been achieved and the current tariff set $tp^{k}_{c,y}, te^{k}_{c,y}$ are selected as the solution, exiting the algorithm. Else, continue to step 4).

$$\frac{\left|INCSP_{y}-inc^{k}_{y}\right|}{INCSP_{y}}\leq\epsilon \quad (71)$$

4) **Compute the next set of tariffs**: If convergence wasn't achieved as per step 3) tariffs are computed as follows. If $k=0$, compute $tp^{k+1=1}_{c,y}, te^{k+1=1}_{c,y}$ applying a pre-set percentage increase $\delta>0$ uniformly throughout the temporal horizon to $tp^{k=0}_{c,y}, te^{k=0}_{c,y}$, i.e.:

$$tp_{c,y}^{k+1=1} = tp_{c,y}^{k=0} \cdot (1 + \delta) \qquad (tp \rightarrow te) \tag{72}$$

Otherwise (i.e., $k \geq 1$):

$$tp_{c,y}^{k+1} = tp_{c,y}^{k} + \left(incsp_{c,y}^{tp,k} - inc_{c,y}^{tp,k}\right) \cdot \frac{tp_{c,y}^{k} - tp_{c,y}^{k-1}}{inc_{c,y}^{tp,k} - inc_{c,y}^{tp,k-1}} \cdot x \qquad (tp \rightarrow te\ ) \tag{73}$$

being $incsp_{c,y}^{tp,k}$ the expected incomes allocated among tariff terms in direct proportion to the current total incomes, i.e.:

$$incsp_{c,y}^{tp,k} = INCSP_y \cdot \frac{inc_{c,y}^{tp,k}}{inc_y^k} \qquad (tp \rightarrow te) \tag{74}$$

Expression (73) estimates the next iteration's tariff values by extrapolating the observed sensitivity of tariff revenues to tariff levels. Specifically, it calculates the ratio between the change in revenues and the change in tariff prices observed over the previous iteration, effectively deriving an empirical slope. This slope is then applied to the gap between the current revenues and the target revenues in (74) allocated to this tariff term. Finally, a random factor x based on a random symmetrical distribution $X(\mu, \sigma)$, with $\mu = 1$, multiplies the slope to introduce random variability without introducing bias, to avoid local optima, empirically improving convergence robustness. This factor aligns with the principles of metaheuristic search algorithms, where unbiased, symmetric noises are introduced to facilitate gradient approximation and improve convergence properties in complex problems [109].

5) **Force upper-level constraints**: In this step, constraints (58), i.e., tariffs must not decrease year-over-year, and (59), i.e., tariffs cannot grow year-over-year more than a pre-set percentage INC^{MAX}, are forced by re-setting tariffs for the next iteration $tp_{c,y}^{k+1}$ and $te_{c,h,y}^{k+1}$, as follows:

$$tp_{c,y+1}^{k+1} \coloneqq \max\left(tp_{c,y+1}^{k+1}, tp_{c,y}^{k+1}\right) \qquad (tp \rightarrow te\ ) \tag{75}$$

$$tp_{c,y+1}^{k+1} \coloneqq \min\left(tp_{c,y+1}^{k+1}, tp_{c,y}^{k+1} \cdot (1 + INC^{MAX})\right) \qquad (tp \rightarrow te\ ) \tag{76}$$

6) **Next iteration**: Set $k \coloneqq k + 1$ and go to step 1) for the next iteration.

Note that all calculations in each step are performed for all years y and customer segments c. Through this iterative approach, the case studies prove that the algorithm achieves a solution that aligns the tariff structure with the predefined cost inputs, while accounting for the dynamic responses of system participants.

It should be noted that the proposed algorithm does not guarantee convergence. Therefore, an iteration limit must be imposed to prevent infinite execution in cases where no feasible solution exists or convergence cannot be achieved. In the latter

case, convergence may sometimes be attained by initializing the algorithm with alternative starting points, since different initial conditions may lead to different convergence behavior.

In addition, solution uniqueness is also not guaranteed, and different initial conditions may provide different equivalent solutions, since there is no mechanism implemented to favor some customer segments over others. As a result, some solutions may impose a disproportionate burden on specific segments. Although criteria could be defined to compare, rank, and assess the fairness of alternative solutions, this is left for future work.

4. CASE STUDIES AND RESULTS

The case studies selected to illustrate the use of the model corresponds to a real-sized Spain-like system and are based on the case studies described and used in previous chapters.

4.1. Assumptions and input data

In order to create an academic case-study for validating the proposed model, the same dataset as for was used. Customers were segmented into 5 industrial segments, 3 commercial segments and 4 residential segments. Investments are allowed for CG in CCGT, OCGT, wind power, solar photovoltaic and batteries. For DG, only solar and battery investments are allowed, plus wind power only for industrial customers. Due to economies of scale factors, industrial customers have lower investment costs than commercial customers, and commercial customers have lower investment costs than residential customers. The details can be found in Chapter III & .

4.1.1. Algorithmic parameters

The tariff income setpoint that the upper level must fulfill ($INCSP_y$) was set to a 1% annual increase starting from 2024. The starting tariffs (i.e. those set to the first iteration, k=0) have been set as equal for all years, equal to 2024 values, situation that can be referred to as a Business as Usual (BAU) scenario (i.e., what would occur if no additional actions were to be taken by the policymaker). The initial tariff increment δ was set to 1%, the random distribution $X(\mu, \sigma)$ to generate x for (73) was set to a Normal distribution with σ = 5%, and the maximum allowed error margin ϵ was set to 0.5%.

4.1.2. Computational assumptions

Start-ups and shut-downs and ramping constraints have been omitted at the lower level to improve computational time.

4.2. Scenarios description

Four scenarios have been defined to test the bilevel model:

- **Unconstrained case** (scenario U): a base-case scenario disabling the monotonical constraint (58) and the capped constraint (59).
- **Monotonically growing tariffs case** (scenario M): This scenario includes constraint (58), i.e., tariffs must increase or remain equal year by year.
- **Capped increase case** (scenario C): This scenario includes constraint (59), i.e., tariffs must increase annually less than INC^{MAX}, which in this scenario has been set to 5%.
- **Both constraints case** (scenario MC): This scenario includes both constraints (58) and (59).

4.3. Simulation results

In all presented cases convergence was achieved, i.e., tariff income in each year resulted equal to the expected setpoint, considering the tight error margin $\epsilon = 0.5\%$.

4.3.1. Unconstrained case (scenario U)

This scenario represents the base case scenario without any constraints (58) and (59). Results from this scenario are not expected to be realistic, as those constraints are very likely to be assumed by any policymaker, but rather a way to calibrate the model and see how it reacts to the input dataset.

4.3.1.1. *Access tariffs and resulting incomes*

Figure 21 shows the access tariffs in scenario U after convergence, both for its volumetric (ET, undotted lines) and demand charge (PT, dotted lines) components:

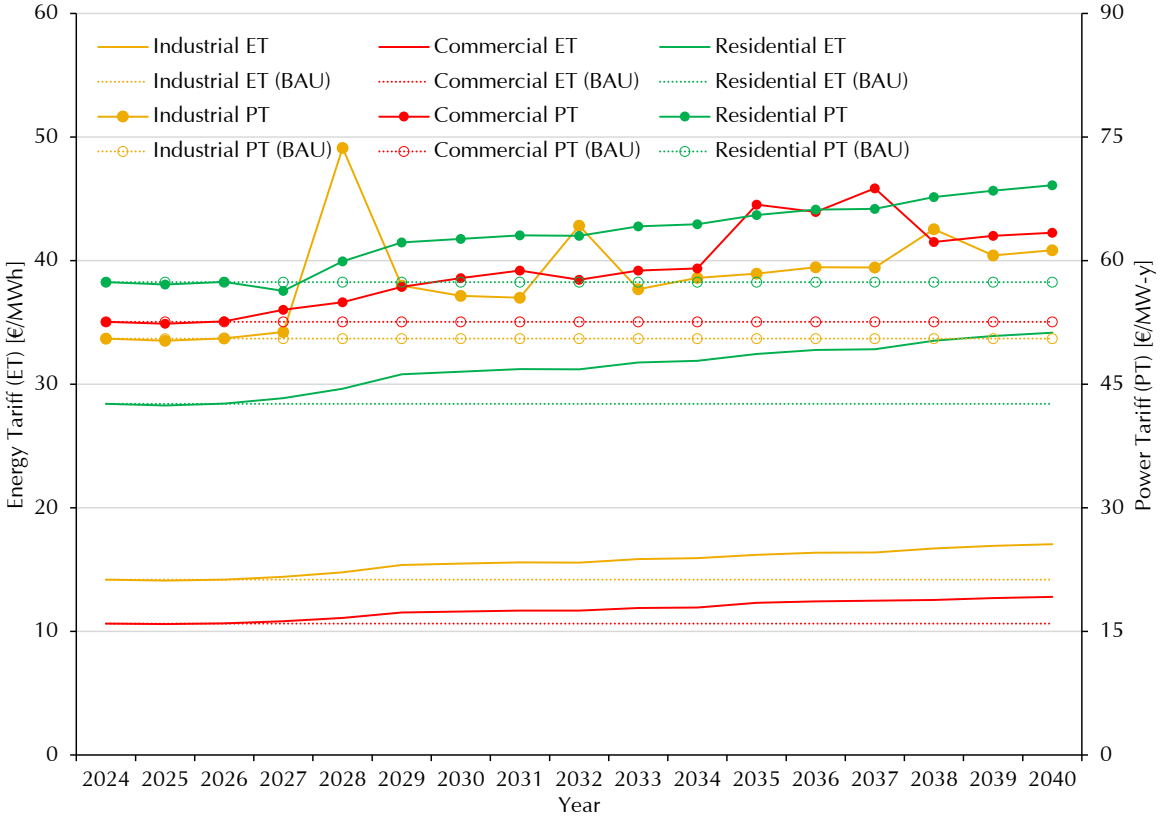

Figure 21: Access tariffs, scenario U.

As Figure 21 shows:

- Residential tariffs (green curves) register almost monotonical growth throughout the simulated period, having both high terms growth years from 2028 through 2030, coinciding with the planned closure of 3.3 GW of older thermal power plants in that same period 2028-2030. To replace this missing generation, new investments are required, part of them in customer-side DG. This causes a reduction in total tariff incomes, prompting an overall increase in tariffs. Since residential customers have lower reaction capabilities (due to higher DG investment costs), the algorithm will allocate a higher share of this increase to them.
- Volumetric terms of commercial and industrial customers also see a continuous increase in their tariffs throughout the simulation period, but lower than those of residential customers, due to their lower investment costs in DG.
- The algorithm uses the demand charge tariff terms for commercial and industrial customers to fine-tune total system income to the predefined setpoint $INCSP_y$. This fine-tuning arises partly from setting the error margin ϵ to a very small value (0.5%), which forces the algorithm to search for precise

adjustments. However, this produces unrealistic dynamics. In scenario U, tariffs are unconstrained, so the algorithm may generate abrupt year-to-year swings (e.g., increases of around 10% followed by similar decreases) to match the income target. Because the lower level has perfect foresight, customers anticipate that such increases will be short-lived and therefore delay DG investments. Investors would not typically expect tariff spikes to be immediately reversed, and a sudden tariff increase would more likely trigger immediate DG investment. Thus, the limitation lies in the unconstrained volatility of tariff trajectories in scenario U, not in the assumption of perfect foresight itself.

Figure 22 shows the resulting tariff income after convergence:

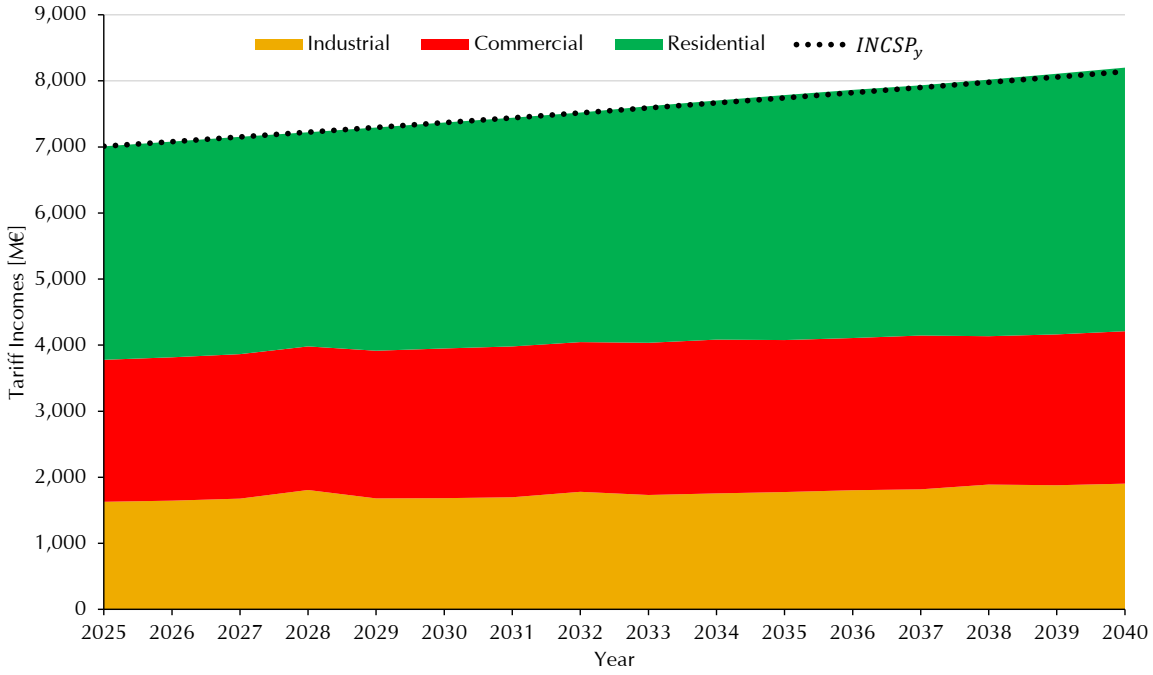

Figure 22: Resulting tariff incomes, scenario U.

As seen in Figure 22:

- Most of the tariff income increases are supported by residential customers. Indeed, these are the customers with the highest investment cost when installing DG capacity, which makes them less capable of responding to tariff increases.
- Although, as seen in Figure 21, industrial and commercial customers see their tariffs increase, this does not translate into an increase in their tariff expenses, due to their capacity to invest in DG as a response with lower investments costs and thus lower economic impact.
- The punctual increments in power tariff terms for industrial customers in 2028 and 2032 are reflected in those years as an increase in the tariff income from these customers. Indeed, this is more of a fine-tune of the model to achieve

the setpoint subject to the low error margin ϵ (0.5%) rather than an actual expected behavior.

4.3.1.2. *Centralized & decentralized generation investments results*

Figure 23 shows the resulting generation investments, both for DG and CG and scenario U. Although the model provides wind power investments both for CG and DG (industrial customers only), results only show wind power investments in DG[22]:

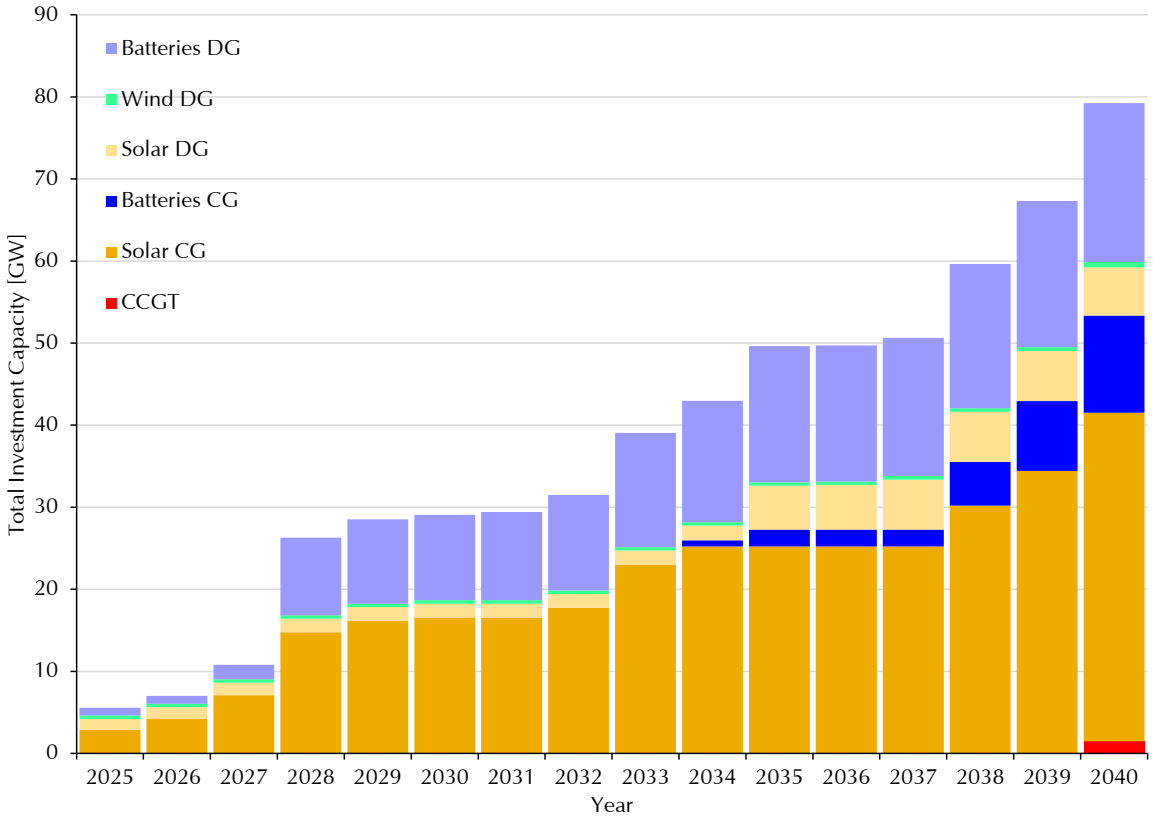

Figure 23: Generation investments, scenario U.

As seen in Figure 23:

- DG investments start growing significantly in 2028, coinciding with the first peak of demand charge tariff terms used to fine-tune total incomes. These initial investments are mainly in batteries, which can only perform peak shaving (reducing contracted power and therefore contracted power-based tariff payments) but do not lower total grid consumption, since the energy charged into the battery must be previously drawn from the grid or from PV production.

[22] The absence of CG wind investments is a methodological artifact of using a single representative week with the methodology explained in [74]. This temporal reduction tends to overvalue short-term storage combined with solar PV, making it appear more competitive than wind on an annual basis. However, the approach does not capture seasonal dynamics (particularly long winter periods with low solar availability) where wind would provide a critical complement.

- Significant investments in DG generation (mainly solar and, to a lesser extent, wind) appear from 2035 onwards. This timing coincides with an increase in the demand charge tariff term for industrial customers, which the algorithm raises and maintains for three years to fine-tune total system incomes to the predefined setpoint. As the peak-shaving capacity of DG batteries (which grow steadily from 2032 to 2035) reaches its limit, additional solar capacity becomes necessary to further reduce contracted power.
- Overall, almost all CG investments are made in solar. Indeed, when accompanied by enough battery capacity, solar can provide energy with a very low overall cost, at the expense of only supplying it during sun hours. However, batteries can overcome this limitation.
- Most batteries are installed in DG, after the meter. This way, both the contracted power and the peak demand of the system are reduced, reducing both demand charge tariff payments and the firm capacity required by the system, as described in □.

4.3.2. Monotonically growing tariffs case (scenario M)

This scenario adds a constraint to avoid decreasing tariffs. Therefore, the single-year peaks in tariffs seen in scenario U should not appear on this scenario.

4.3.2.3. *Access tariffs and resulting incomes*

Akin to Figure 21, Figure 24 shows the access tariffs in scenario M after convergence both for its volumetric (ET, undotted lines) and demand charge (PT, dotted lines) components.

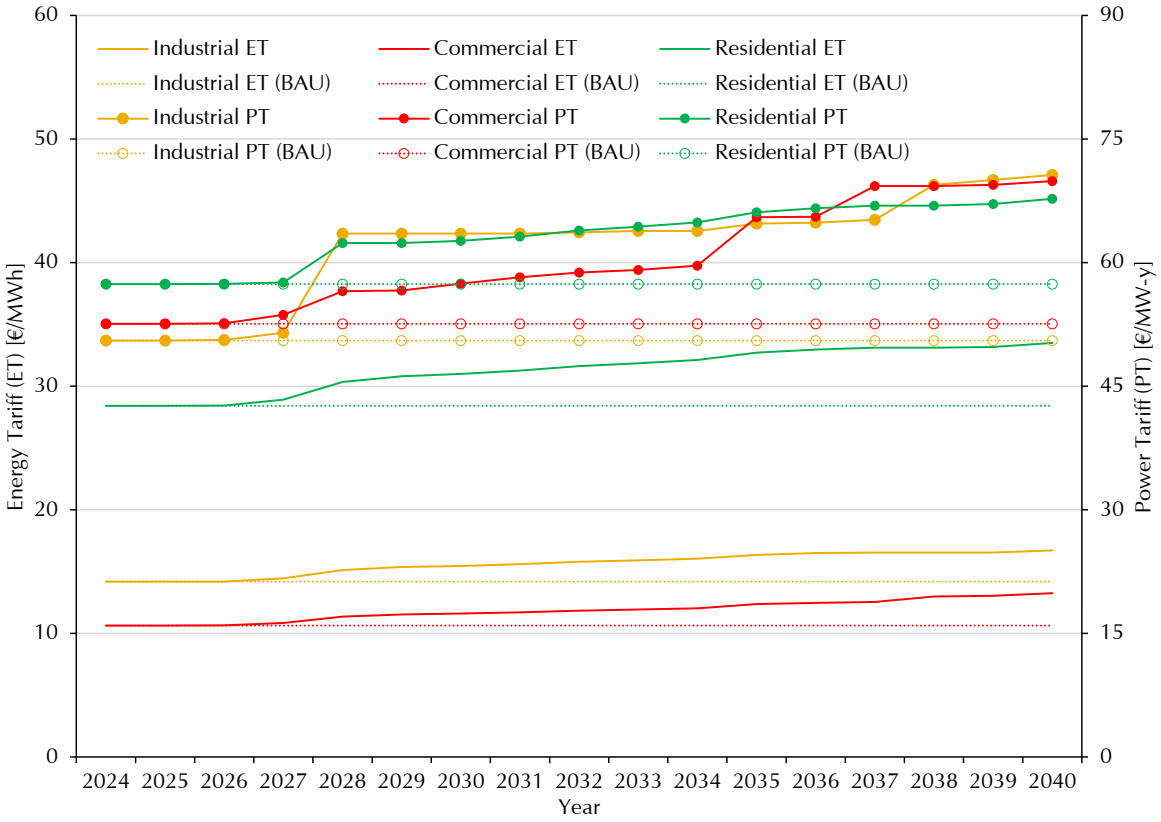

Figure 24: Access tariffs, scenario M.

As seen in Figure 24:

- Compared to scenario U (see Figure 21), the volumetric tariff components in these two scenarios exhibit very similar outcomes. This similarity arises because, in scenario U, DG investments (see Figure 23) are predominantly directed toward battery storage up to the year 2035, which does not contribute to a reduction in energy consumption. As a result, total energy consumption remains essentially the same in both scenarios U and M, leading to equivalent revenues from volumetric tariff components and creating an identical economic signal for investment in DG generation.
- 2028, as in scenario U, also coincides with a large increase in the power tariff of industrial customers. However, in this scenario the increase is maintained for the following years. Hence, this increase is lower in the case of industrial customers, but larger for the demand charge tariffs of the rest of the customers, to achieve the income in this year without surpassing the income setpoint in the following years.

- demand charge tariffs for residential and commercial customers see an almost constant annual increase from 2030 to 2034, which translates into steady annual increments in incomes throughout these years.
- 2035 and 2037 show another large increase in demand charge terms for commercial customers. This coincides with the increments observed in scenario U during the same time period, which arise from the algorithm fine-tuning total system incomes to the target $INCSP_y$ within a very tight error margin.
- Whereas in scenario U residential customers sustained most of the tariff growth, in this scenario commercial and industrial customers see the largest growth in their demand charge tariff terms. This results in, as we will see in Figure 25, a much more balanced income distribution among segments.

Figure 25 shows the resulting total tariff income in scenario M per customer segment and year.

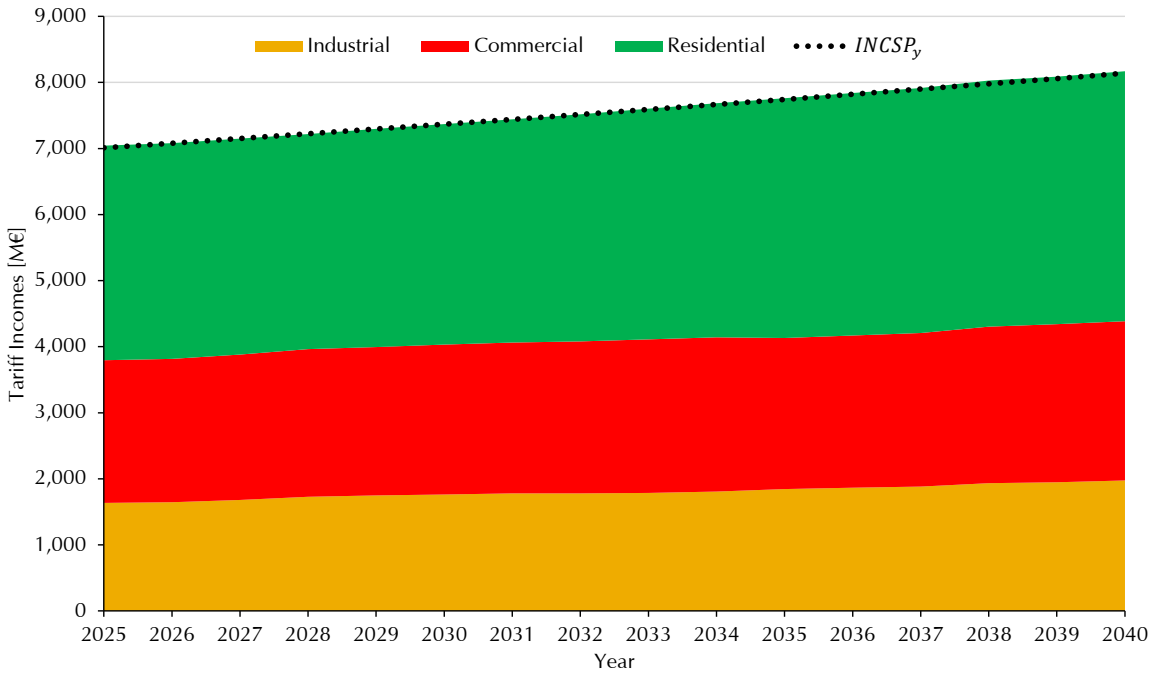

Figure 25: Tariff incomes, scenario M.

As seen in Figure 25:

- Each segment keeps their share of income nearly constant throughout all the simulation horizon. Interestingly, only adding the monotonically increasing constraint to tariff terms evolution seems to make the model less reliant on using the low response capacity of residential customers to achieve the required income growth, and it results in a more equitable tariff distribution.
- However, income growth is not constant for each segment. Some years (e.g., 2028) have a subtly larger growth rate for commercial and industrial, while other years (e.g., 2030-2034) residential customers sustain a larger part of the

growth. This is more a consequence of how the algorithm works rather than an actual conclusion of the model.

4.3.2.4. *Centralized & decentralized generation investments*

Figure 26 shows the resulting generation investments in scenario M per year.

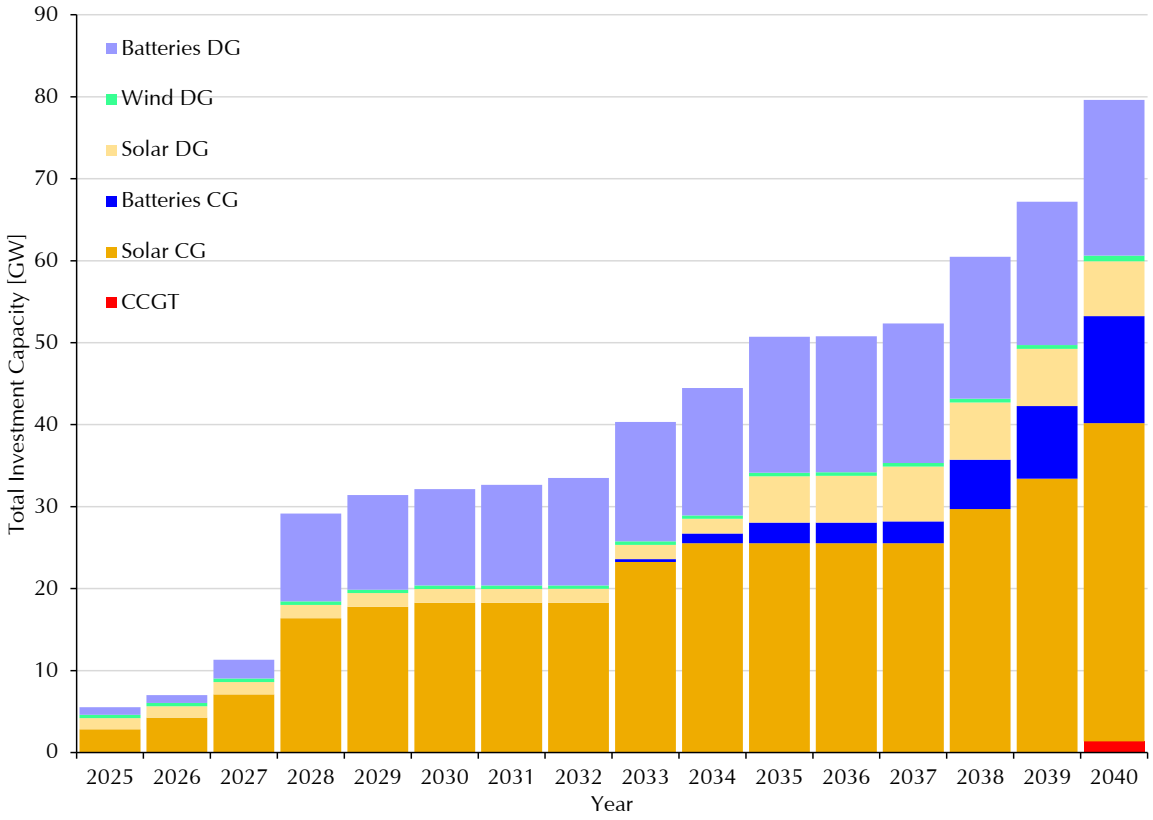

Figure 26: Generation investments, scenario M.

As seen in Figure 26:

- The first years of the simulation result almost identical to scenario U, up to 2028.
- From 2028 onwards, there are higher investments in after-the-meter DG batteries. This difference is caused by the larger demand charge tariff terms, as batteries can peak-shave and reduce the contracted power, a larger demand charge tariff is an economic signal to invest in this technology.
- In the same period, there are larger investments in utility-scale solar (CG). This is explained by the synergy with batteries: as battery capacity expands, it becomes possible to store a greater share of solar generation peaks and shift that energy to other hours. Even when the batteries are installed behind the customers' meters, their effect on the system reduces curtailment and increases the effective value of additional solar capacity, making further CG solar investments more attractive.

4.3.3. Capped increased case (scenario C)

This scenario, with respect to scenario U, adds a 5% cap to the year-over-year increase of all tariff terms. Such a restriction can, in principle, render the model infeasible if the required revenues cannot be recovered under the imposed cap. In practice, this was the scenario that took the longest to converge, requiring roughly 30 times more iterations than the others.

4.3.3.5. *Access tariffs and resulting incomes*

Figure 27 shows the access tariffs in scenario C after convergence both for its energy (undotted lines) and demand charge (dotted lines) components.

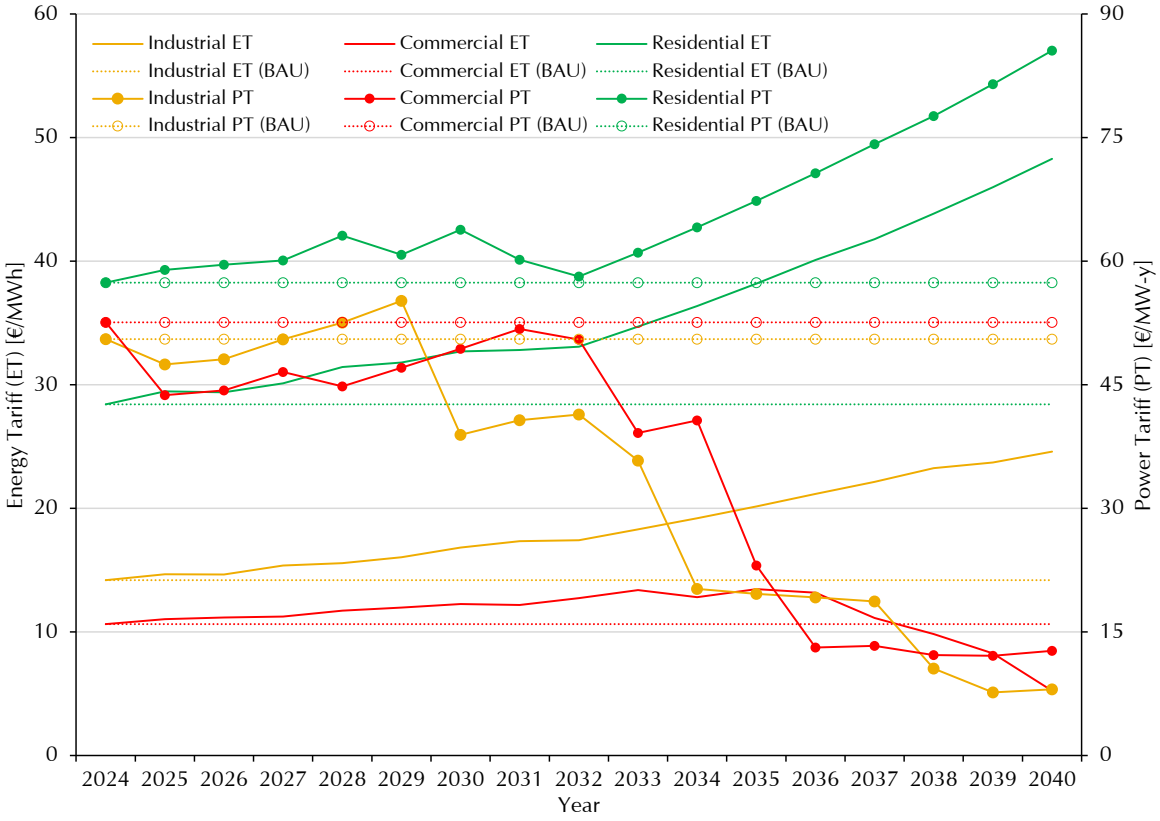

Figure 27: Access tariffs, scenario C.

As seen in Figure 27:

- Contrary to what is seen in scenario M, scenario C clearly places most of the economic burden on residential customers. As these customers have very high investment costs in any DG technology, their ability to respond to larger tariffs is lower than that of the other customer segments.
- As this scenario allows for decreasing tariffs, the algorithm seems to find that industrial customers would respond better with higher volumetric tariffs and lower demand charge tariffs. Indeed, we can see that throughout all scenarios most of DG investments are performed in batteries, which respond to the demand charge term of the tariff. The economic signal for after-the-

meter generation is still not there, even with this shift in the demand charge-to-volumetric tariff term ratio.

Figure 28 shows the resulting tariff incomes in scenario C per customer segment and year.

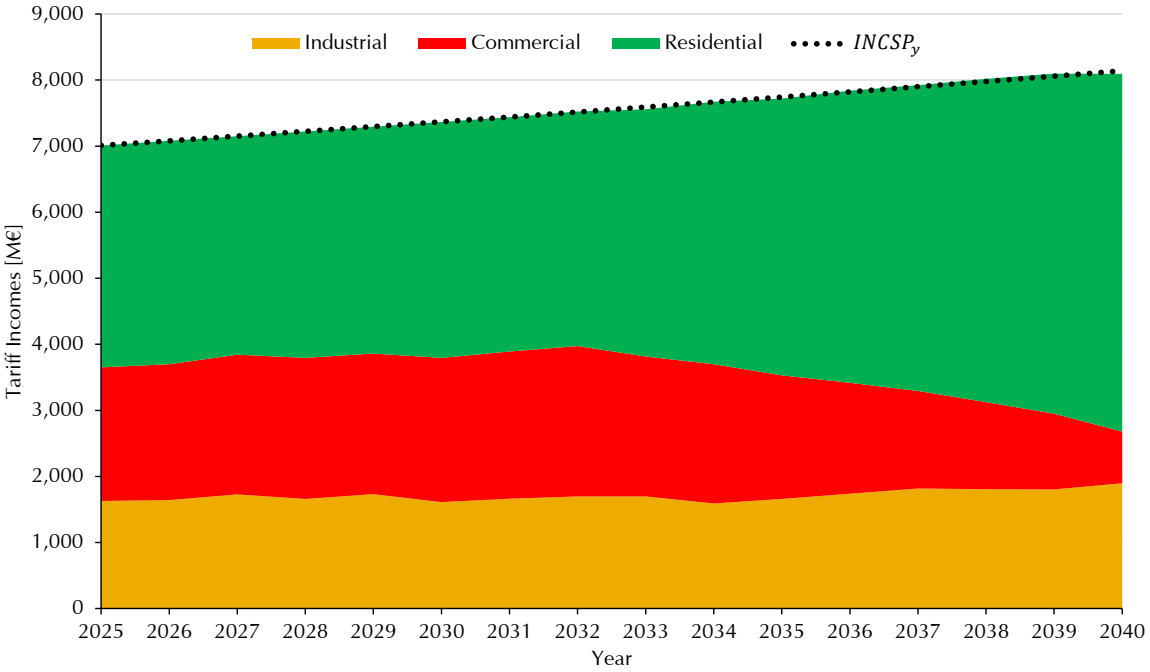

Figure 28: Tariff incomes, scenario C.

As shown in Figure 28:

- Residential customers support not only most of the regulated income growth, but also (from 2032 onwards) most of the economic burden previously placed on commercial customers.
- Industrial customers keep their tariff expenses almost constant throughout the simulated period, despite the shift between the demand charge and volumetric terms as seen in Figure 27.
- Commercial customers reduce their tariff expenses unrealistically, as the algorithm lowers both their tariff terms. By contrast, industrial customers do not experience a similar reduction, even though they have greater market power thanks to lower DG investment costs. This outcome reflects a limitation of the policymaker's optimization in the model: the algorithm fine-tunes tariff terms in a way that produces inequitable results across customer segments, which should be interpreted as a modeling artifact rather than a rational regulatory decision.

4.3.3.6. *Centralized & decentralized generation investments*

Figure 29 shows the resulting generation investments from scenario C.

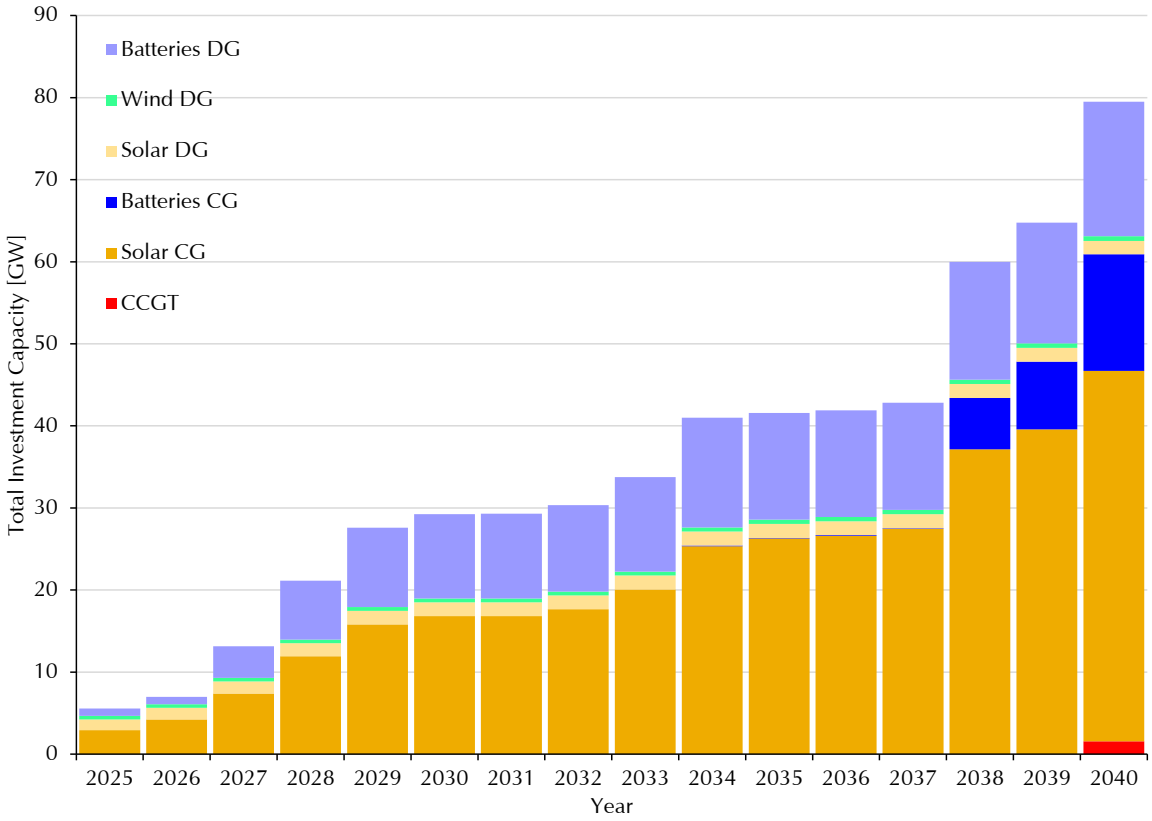

Figure 29: Generation investments, scenario C.

As shown in Figure 29:

- This scenario is marked by overall less investment in DG. Indeed, since the customers that have a lower investment cost see a large decrease in their tariffs, the economic incentive for those investments almost disappears.
- Instead, in the last year of the simulation we see larger investments in utility-scale solar (solar CG), and larger utility-scale battery investments. However, these investments are committed at a later year in the simulation, partly due to the lower amount of DG batteries supporting lower solar production absorption.
- Even when the tariff burden for industrial customers shifts from demand charge to volumetric, incentives to invest in after-the-meter generation remain weak, as batteries continue to dominate most behind-the-meter investments.

4.3.4. Both constraints case (scenario MC)

This scenario includes both constraints of the last two scenarios: tariff terms can only increase year-over-year, and their annual growth must be lower than 5%.

4.3.4.7. *Access tariffs and resulting incomes*

Figure 30 shows the access tariffs in scenario MC after convergence both for its volumetric (undotted lines) and demand charge (dotted lines) components.

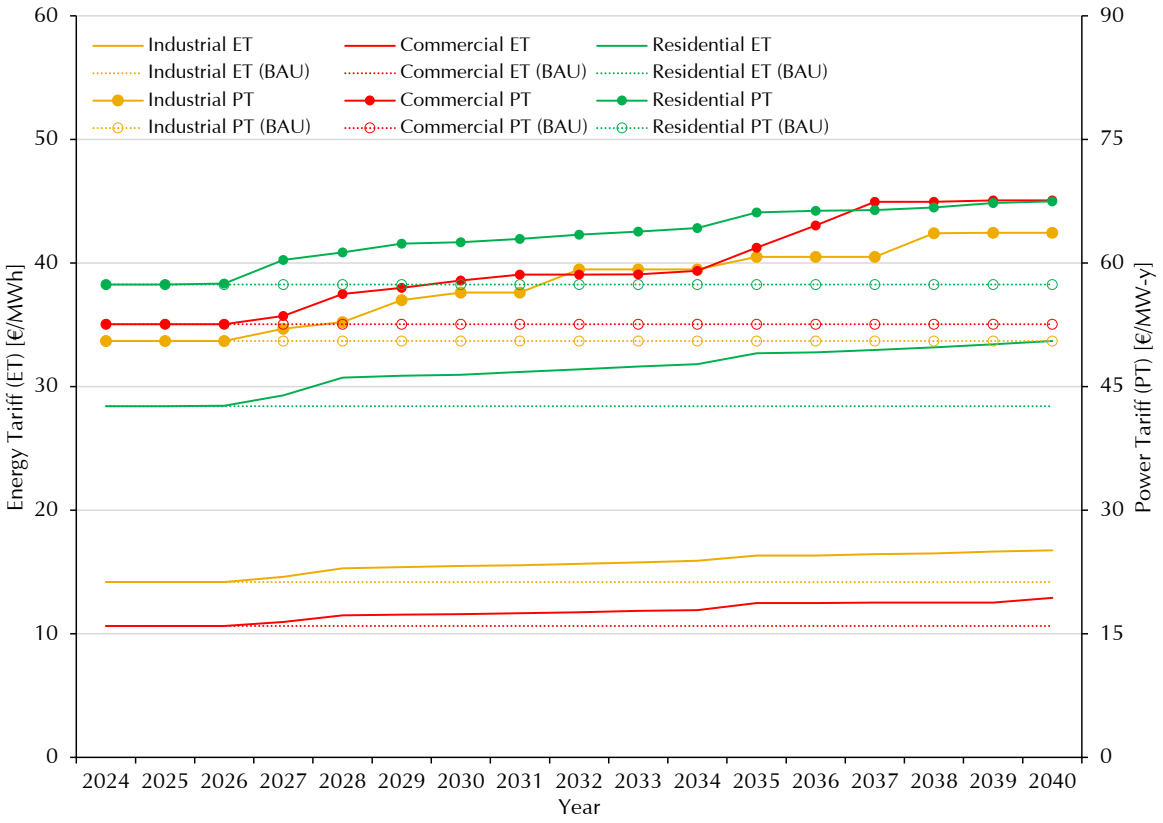

Figure 30: Access tariff terms, scenario MC.

As can be seen in Figure 30:

- Residential tariffs increase moderately compared to the other segments, with smoother trajectories in both demand charge and volumetric terms.
- Commercial and industrial tariffs experience stronger increases, especially in their demand charge components. This reflects the algorithm's strategy of allocating a greater share of income growth to those customer groups that, in principle, have more capacity to respond through DG investments.
- The steepest annual increases are concentrated in the commercial demand charge tariff during 2028 and 2035–2037, consistent with the income fine-tuning dynamics already observed in other scenarios.
- Volumetric tariffs rise steadily for all customer groups, with residential ETs remaining the highest throughout the horizon, while industrial ETs stay lowest. This preserves the relative structure of tariff levels among the three groups.
- Overall, the scenario produces a more progressive adjustment path than U or M: large spikes are smoothed out, but the cumulative burden is shifted more clearly toward commercial and industrial customers. Their greater ability to invest in batteries (also incentivized by the increases in their demand charge tariff terms) allows them to absorb part of the solar generation peaks, making the overall system more efficient.

Figure 31 shows the resulting tariff income in scenario MC per customer segment and year:

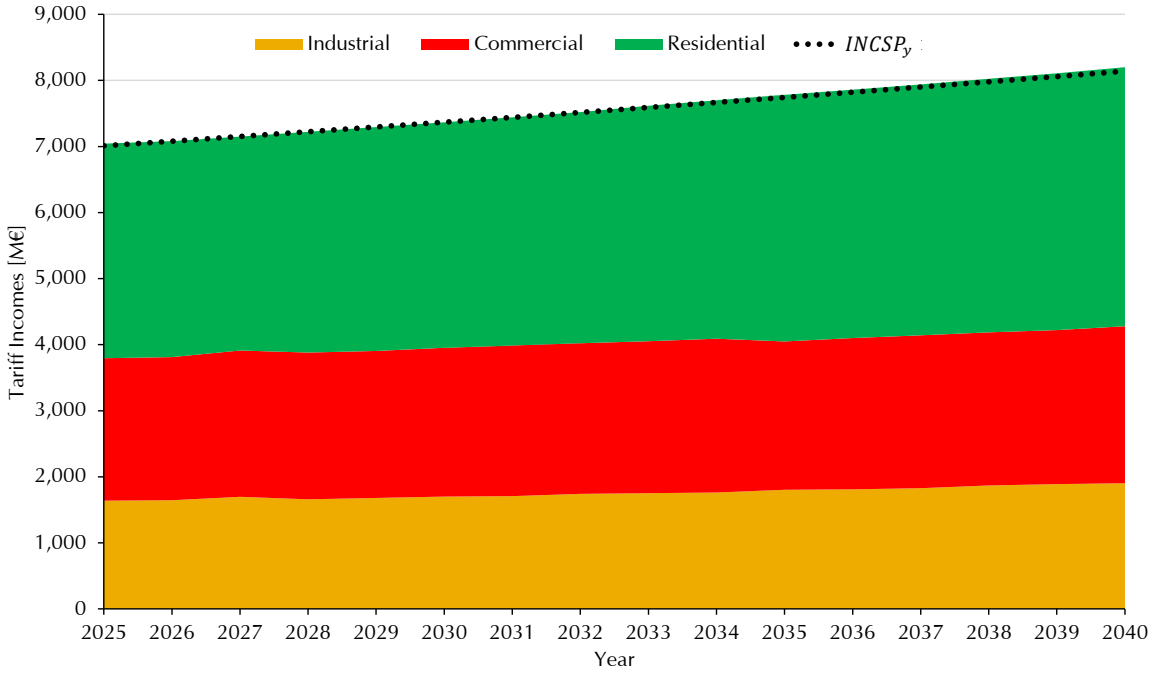

Figure 31: Tariff incomes, scenario MC.

As shown in Figure 31:

- In this scenario, there is not a clear segment that sustains most of the growth. Indeed, this is the most equitable scenario in this sense.
- As in all other scenarios, small fluctuations appear over some years, but overall, there is a similarly constant increase throughout the three segments.

4.3.4.8. *Centralized & decentralized generation investments*

Figure 32 shows the resulting generation investments from scenario MC:

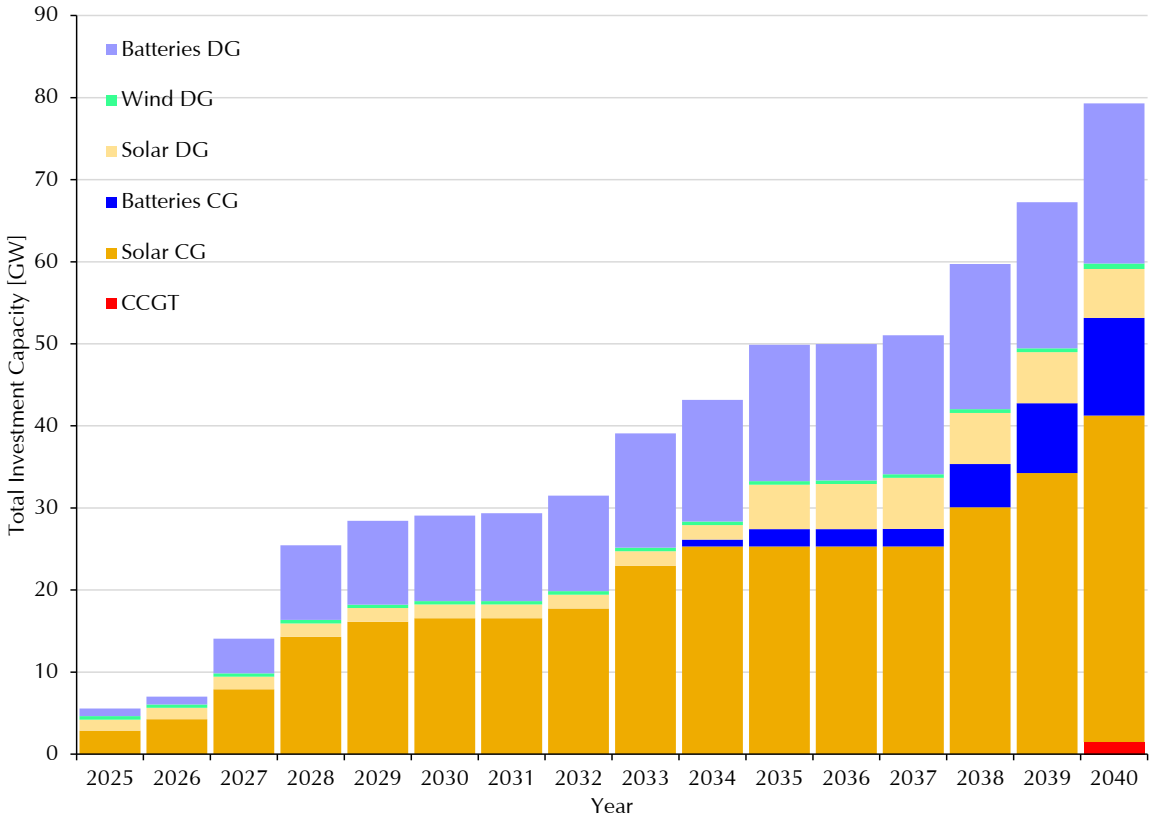

Figure 32: Generation investments, scenario MC.

As can be seen in Figure 32:

- Generation investments in this scenario result similar to those in scenario M.
- The main differences are lower investments both in DG batteries and CG solar in years 2028-2035, the former due to the lower overall demand charge tariffs (see Figure 30), and the latter due to the lower total battery capacity in those years.
- DG solar investments also result lower than in scenario M. As volumetric tariffs are similar in these two scenarios, this can only be due to the lower exploitation capability of solar generation due to the lower total battery capacity.

5. COMPUTATIONAL RESULTS

5.1. Model resolution

From the model presented in □, unit commitment, ramping, and secondary reserve constraints and variables were removed. Removing these was decided to reduce the lower-level computation time to 5 minutes instead of the 30 minutes needed for the cases analyzed in □[23]. Indeed, the model in □ contains 5.0 million constraints

[23] It may be argued that long-term planning problems do not require short execution times, since their results are not as time sensitive as those of short-term operational problems. However, extensive calibration and testing are required to yield reliable results. Moreover, shorter execution times make it possible to refine the model more

and 4.0 million variables, while the lower-level model of this chapter contains 2.3 million constraints and 1.5 million variables. However, the methodology allows us to increase the complexity of the lower level if needed and if enough computation time is available.

The problem was programmed in C# using the OPTANO Modeling Framework [110] for the lower-level, and compiled using .Net 8.0. The model was used to simulate 17 years (2024-2040) of a Spain-like system, simulating one week (168 hours) per year. Each lower-level iteration took 5 minutes and 6 GB of RAM to solve using Gurobi [58] on an Intel Core i7-4790 CPU @ 3.60GHz.

5.2. Convergence analysis

Scenario U converged, i.e., the relative difference between tariff incomes as outputs from the lower-level model inc_y and the tariff setpoint $INCSP_y$ resulted lower than $\epsilon = 0.5\%$ for all years, in 4 iterations. Figure 33 shows the total tariff income per year on each iteration, which can be useful to analyze the convergence.:

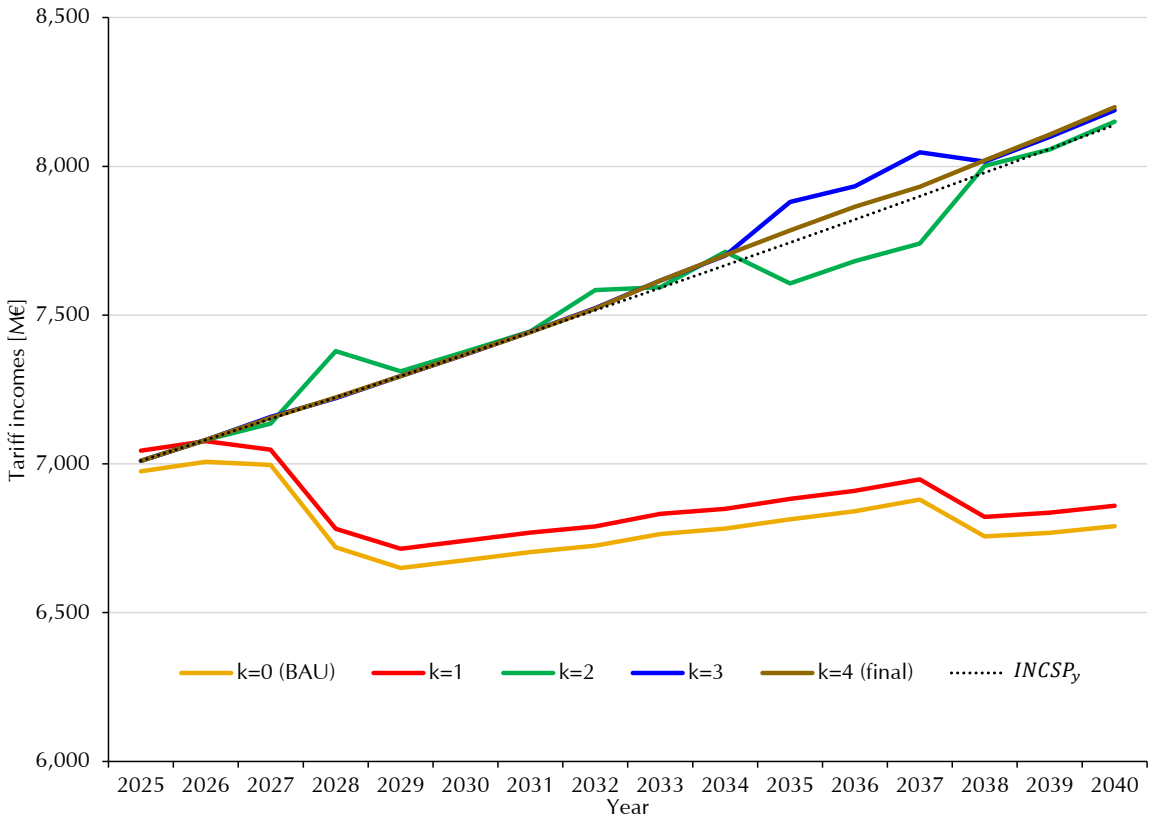

Figure 33: Convergence analysis, scenario U.

As can be seen, the algorithm starts with a $\delta = 1\%$ increment across all tariffs in iteration 1, and it is reflected with an almost 1% increase in incomes in all years from

effectively, as each cycle of execution, evaluation, and adjustment can be completed more quickly. This iterative process leads to more accurate and robust final outcomes.

BAU (iteration 0). Then, iteration 2 almost achieves convergence, except for a few years in 2028, 2032 and 2035-2037. These coincide with the years of finely tuned demand charge terms shown in Figure 21. Most of these years are solved already by iteration 3, except the last 3, which requires a final fourth iteration to converge.

Scenario M also converged in 4 iterations, with its convergence shown in Figure 34:

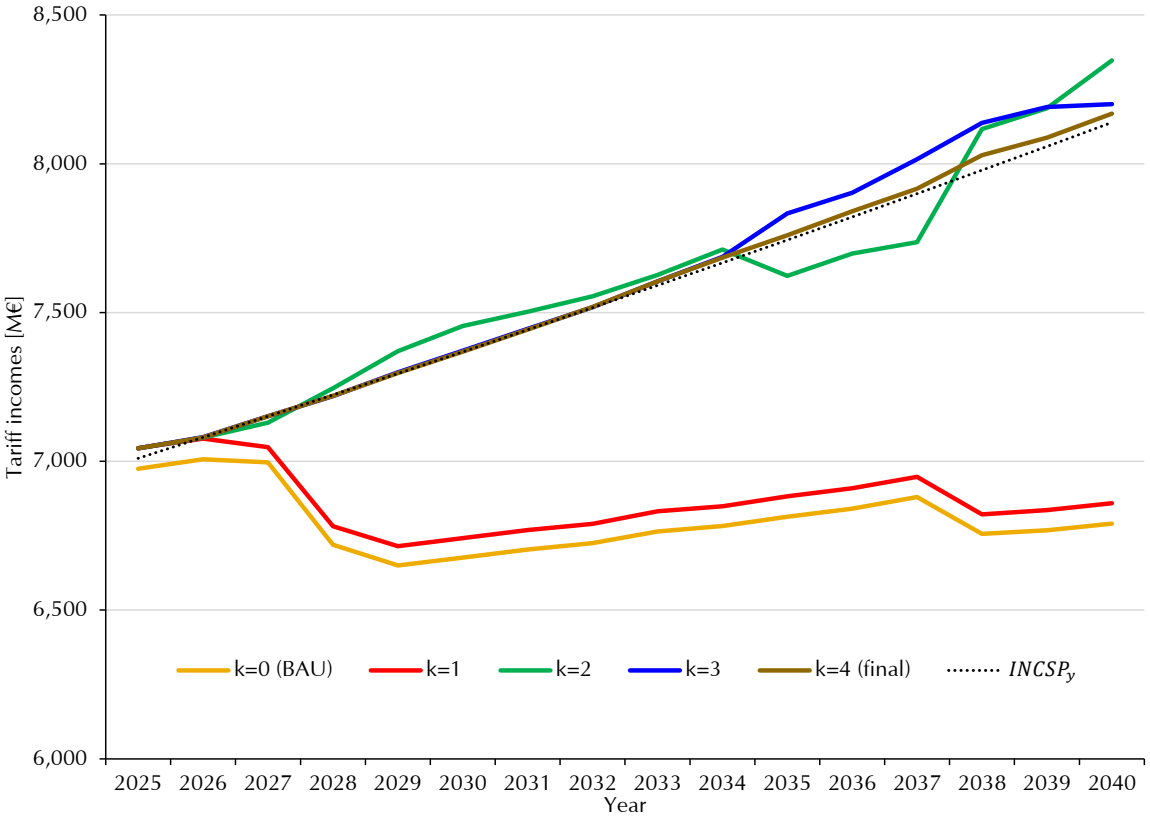

Figure 34: Convergence analysis, scenario M.

As seen in Figure 34, convergence in this scenario is similar to that of scenario U. However, 2028 seems to converge in all iterations from 2 onwards, indicating that the issue in that year can be softened by keeping the tariffs for the following years at the level decided for 2028. Keeping them at that level causes some overshooting in the following years, up to 2035. This overshoot is solved by the third iteration, which only has mismatched from 2035 to 2040. Finally, the fourth iteration also achieves convergence.

Scenario C took 163 iterations to converge. To analyze its convergence only the first 8 and final 5 iterations are presented, in two different graphs, Figure 35 and Figure 36 respectively:

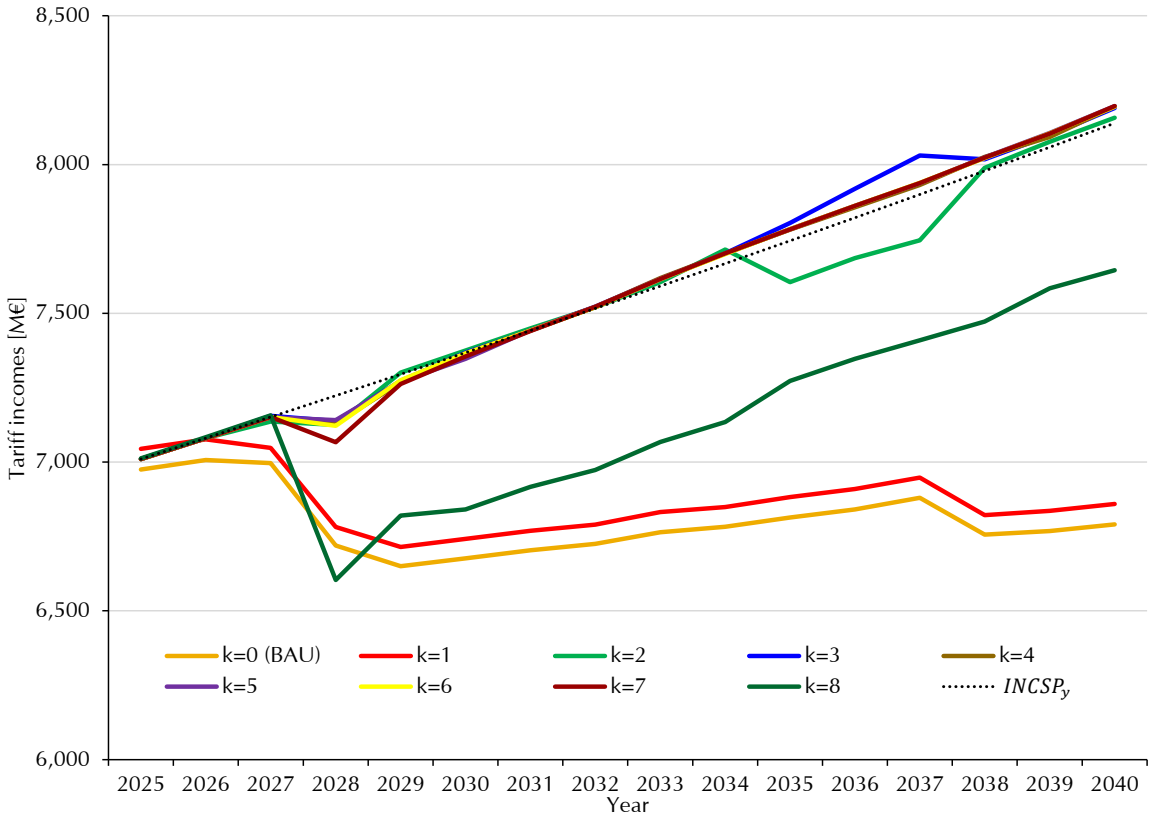

Figure 35: Convergence analysis (initial), scenario C.

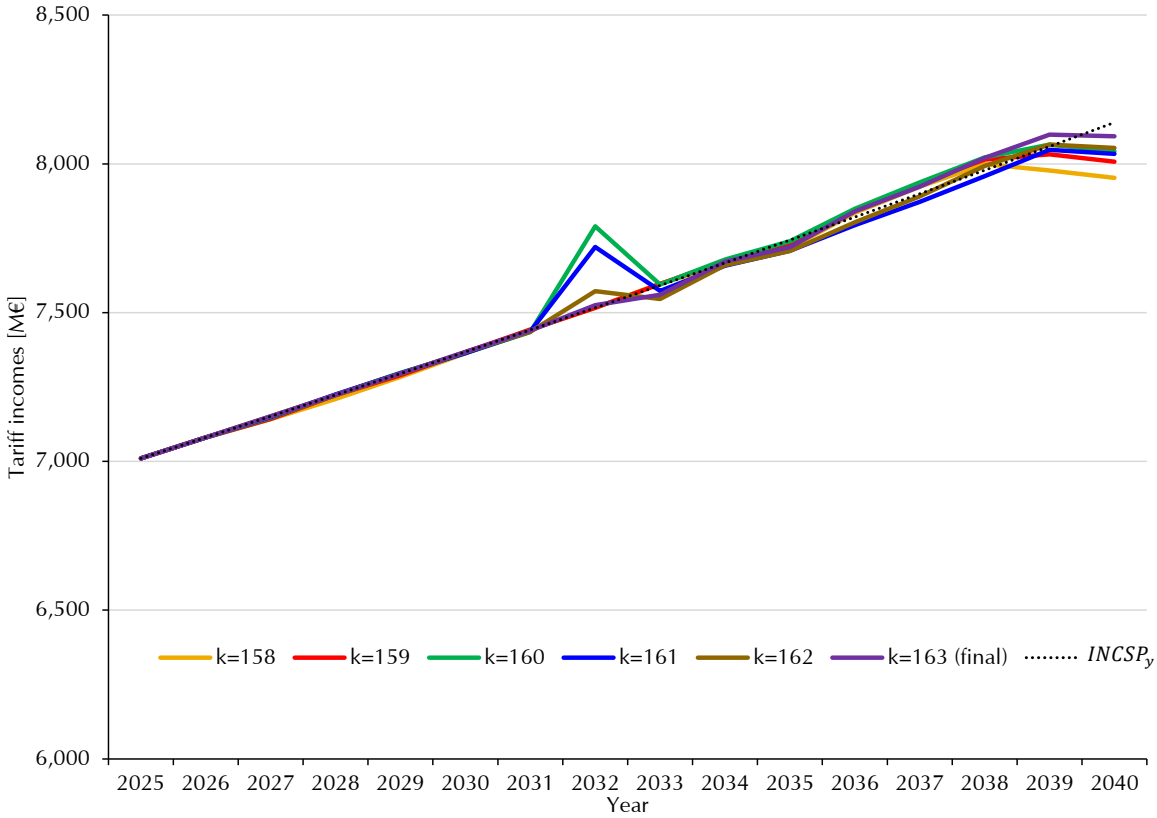

Figure 36: Convergence analysis (final), scenario C.

As seen in Figure 35, 2028 is the main problematic year in the first iterations. Convergence is almost achieved by iteration 5, with an error of only 1.1%, but the

two subsequent iterations fail to reduce it under the 0.5% error margin. Iteration 8 worsens the problem, and iterations diverge from then onwards. By iteration 158, as seen in Figure 36, convergence is almost achieved except for years 2032 and 2040 (the first being one of the problematic years in scenario U), but in this case subsequent iterations reduce the error until by iteration 163 it is reduced under the 0.5% error margin, thus achieving convergence.

Finally, the convergence of scenario MC, which only took 5 iterations, is presented in Figure 37:

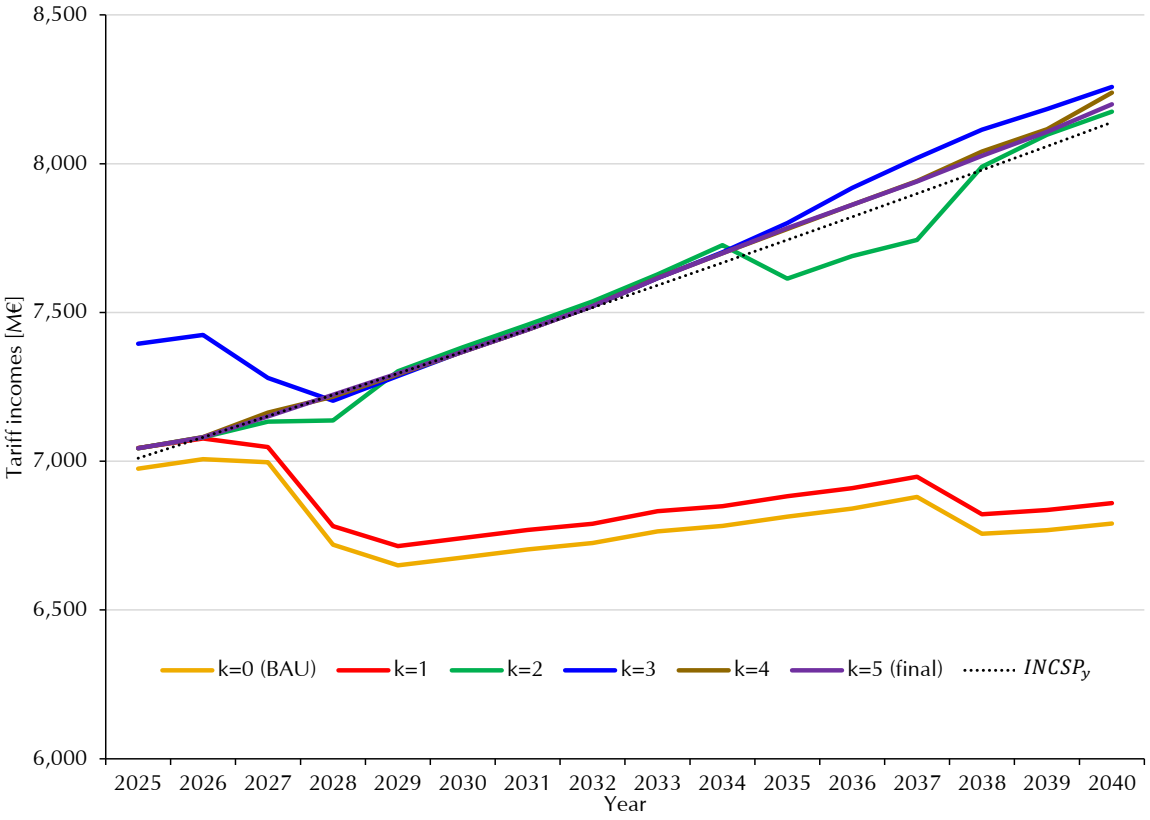

Figure 37: Convergence analysis, scenario MC.

As seen in Figure 37, iteration 2 is similar to scenario U, having problems converging between years 2028 and 2035-2037. However, the error in those years is lower than in the second iteration of scenario U, showing that constraints seem to guide the optimization by reducing the search space. Iteration 3 shows problems only in the initial and final years of the simulation, but iteration 4 solves the first and iteration 5 solves the second, finally achieving convergence.

Scenario MC had less problems to converge than scenario C, which may seem strange since any feasible solution for scenario MC is also feasible in scenario C. Indeed, in heuristic problem solving, limiting the search space very often improves optimization performance, as it seems to be the case scenario MC. In scenario C, the algorithm tries to focus on swapping the demand charge and volumetric tariff terms for industrial customers, which worsens convergence and introduces other

kinds of problems into the solution. That strategy is not feasible in scenario MC (as it breaks monotonically growing tariffs constraint), therefore the algorithm does not explore that possibility in this scenario.

6. CONCLUSIONS

The case studies resulting from the presented bilevel problem show that regulatory constraints on tariff evolution, such as enforcing monotonic growth or capping annual increases, may significantly affect both tariff distribution and investment patterns. Specifically, the unconstrained scenario disproportionately burdens residential customers due to their limited ability to respond through DG investments, while the imposition of monotonic growth yields a more equitable distribution of costs across segments. Notably, industrial and commercial customers, with lower investment costs in DG, are more responsive to economic signals embedded in demand charge tariffs, particularly through investments in behind-the-meter batteries.

Furthermore, the convergence analysis highlights the trade-offs inherent in regulatory constraints. While additional constraints reduce the feasible space and, paradoxically, improve convergence performance, they may also prevent the algorithm from exploring cost-optimal tariff reallocations. The observed convergence behavior across scenarios underscores the importance of carefully balancing regulatory robustness with computational tractability in bilevel tariff design models.

In summary, the model provides a powerful framework for regulators aiming to design equitable and economically efficient access tariffs that support the energy transition and take into account the reactions of the market agents. By internalizing customer behavior in tariff optimization, the proposed bilevel approach offers a more realistic and responsive regulatory planning tool, capable of adapting to evolving investment trends and policy priorities.

7. METHODOLOGICAL CONTRIBUTIONS

This chapter expands the equilibrium models presented in previous chapters by formulating and fully developing the upper level on top of it for the regulated cost recovery problem, resulting in a bilevel problem that integrates tariff decisions at the upper level and the joint operation and investment decisions of CG and DG at the lower level.

In addition, this chapter:

- Formulates the upper level as a centralized tariff optimization model that numerically adjusts grid access tariffs, considering the expected optimal

responses of both GENCOs and DG customers, thus capturing the interactions between tariff structures and investment & operation decisions, and allowing the regulator to define tariffs design strategies at the upper level, in terms of costs recovery and tariffs evolution.

- Develops and implements an iterative heuristic algorithm for the upper-level problem, employing a feedback mechanism based on observed sensitivities of tariff revenues to tariff levels.
- Analyzed a real-life-sized case study, particularly a Spain-like system, simulated for 17 years, with hourly detail for one week per year.
- Defined and analyzed four scenarios: Unconstrained, Monotonically Growing Tariffs, Capped Increase, and Both Constraints; to evaluate the effects of regulatory constraints on tariff evolution, cost allocation, and investment signals for CG and DG technologies.
- Provided a detailed analysis of the algorithm convergence for all the scenarios, showing how constraints can both improve convergence speed and guide the optimization process towards feasible and realistic solutions.

Chapter VI. CONTRIBUTIONS, CONCLUSIONS, AND FUTURE WORKS

1. CONCLUSIONS

This section presents the main conclusions of this thesis, which contributes a novel tool for the quantitative analysis of grid tariff design, combining a detailed representation of the strategic behavior of market agents with regulatory constraints on tariff evolution. As will be seen, the results of the case studies underline the importance of aligning regulatory objectives with the economic signals embedded in tariff structures to facilitate an efficient and equitable energy transition.

1.1. Investment dynamics and market interactions

The results of applying the developed investment equilibrium model to a Spain-like power system reveal fundamental insights into the dynamics between CG, DG, and tariff design. DG investment decisions are found to be primarily driven by high volumetric or demand charge access-tariffs and by the market power of DG customers; more balanced access tariff structures generally lead to lower DG investments. The relationship between CG and DG investments is complementary: an increase in DG investments tends to correspond with a decrease in CG investments, and vice versa, depending on the prevailing tariff scenario (i.e., higher tariffs generally cause investments to shift to DG from CG). Furthermore, wholesale market prices are shown to be sensitive to the demand profile, with higher peaks, averages, or deviations in demand resulting in increased prices. Importantly, scenarios characterized by high volumetric versus high demand charge tariffs illustrate a misalignment of incentives: the reduction in total contracted power can be much greater than the reduction in CG demand peak, demonstrating the potential for inefficiencies in the analyzed access-tariff structures.

1.2. Impact of market design: energy-only versus joint energy & capacity markets

The extension of the equilibrium model to incorporate both energy and capacity markets yields new insights into market behavior and investment outcomes. Case studies indicate that the introduction of a capacity market sends an effective economic signal that incentivizes DG customers to contribute to peak demand reduction. However, the effectiveness of this signal is contingent on the proportion of the demand charge term in the access tariff: when this term exceeds 70% of total tariff income, the impact of the capacity market on peak load diminishes, and system outcomes converge to those of an energy-only market.

The JECE model produces a power system with reduced variability in grid demand and lower average market prices, as incentives to invest in DG storage for peak shaving are strengthened. Conversely, EO markets are characterized by more frequent scarcity events and high prices, which are necessary for peak

technologies to recover their investments. The comparison further shows that joint market designs tend to encourage greater investments in peak technologies while reducing investments in utility-scale storage, though these results are highly dependent on the firmness assumptions for storage technologies.

1.3. Tariff regulation and system incomes

The application of the bilevel modeling framework highlights the significant influence of regulatory constraints on tariff evolution and cost allocation. The analysis demonstrates that unconstrained scenarios can lead to inequitable cost distributions, particularly placing a disproportionate burden on residential customers with limited capacity to invest in DG. In contrast, the imposition of monotonic growth constraints produces a more balanced allocation of costs across customer segments and enhances the responsiveness of industrial and commercial customers to demand charge tariff signals, especially regarding investments in behind-the-meter batteries. The convergence analysis across scenarios illustrates the dual effects of regulatory constraints: while they limit the feasible solution space and often improve algorithmic convergence, they may also restrict the ability to explore cost-optimal reallocations. Ultimately, the bilevel model provides a robust and flexible framework for regulatory planning, enabling the internalization of customer behavior in tariff optimization and supporting the design of access tariffs that are both equitable and economically efficient in the context of the energy transition. Nevertheless, it should be noted that the model optimizes tariff trajectories solely on economic efficiency grounds; it does not explicitly incorporate other fairness criteria, such as cost-causality principles or the equitable allocation of network usage costs, which may also be central to regulatory decision-making.

2. METHODOLOGICAL CONTRIBUTIONS

This section presents the methodological contributions of this thesis. The work presented makes significant advances in the mathematical modeling of power systems, market equilibrium, and tariff design in modern power systems. The sequence of models, from the single-level energy-only equilibrium (EOE) and joint energy & capacity equilibrium (JECE) to the integrated bilevel framework, offers a powerful set of tools for analyzing the impacts of behind-the-meter decentralized generation (DG), regulatory design, and customer behavior on system cost recovery and long-term system evolution. By combining mathematical innovation, computational efficiency, and policy-relevant scenario analysis, the thesis contributes with a robust methodological foundation for addressing the challenges of the ongoing energy transition.

2.1. Energy only equilibrium among generation companies & customers

The methodological contributions of this thesis begin in Chapter III by formulating an investment model with generation companies (GENCOs) operating as

centralized generation (CG) agents, and DG customers competing in a market equilibrium. This model explicitly distinguishes between the decision-making processes of these two agent types and incorporates essential system features such as distribution network losses, tariff structures, contracted power, unit commitment (UC) constraints, and a diverse array of generation technologies, including storage and solar photovoltaic (PV). The model can simulate the long-term evolution of a large-scale power system with endogenous market prices and exogenous tariffs, and it accommodates scenarios involving both load-defection and grid-defection with a simplified representation of network losses. A significant mathematical contribution is the derivation of a novel equivalent quadratic optimization problem, based on the Karush-Kuhn-Tucker (KKT) conditions of the EOE model, which greatly facilitates its computational tractability. Furthermore, the electricity price in this equilibrium model is an output determined by the interplay of CG and behind-the-meter DG investments. The capabilities of this model are demonstrated through an in-depth case study of a Spain-like power system over the period 2019–2037, including analyses of alternative tariffs and market power scenarios.

2.2. Joint energy and capacity equilibrium among generation companies and customers

Building upon the foundational work of the previous chapter, generalizes the equilibrium model to encompass both energy and capacity markets. Employing a Nash equilibrium formulation, this unified framework simultaneously captures the expansion planning and operational decisions of both CG and behind-the-meter DG, enabling the joint representation of investment choices across all market agents. A major advancement is the demonstration that the equilibrium can be reformulated and efficiently solved as a quadratic optimization problem derived from the KKT conditions of the JECE, thus significantly reducing computational burden and simplifying the addition of further system constraints. The model maintains a high degree of operational realism by including hourly constraints such as power ramps, start-ups, and shut-downs. One of the key innovations is the endogenous calculation of the marginal capacity price. This feature provides a robust economic signal to assess the expected prices of a potential capacity market. It also allows GENCOs to invest in firm, dispatchable capacity, while ensuring cost recovery even in the absence of energy scarcity. A key aspect is that the indirect impact of DG on system capacity requirements is explicitly incorporated, despite DG's lack of direct participation in the capacity market, by accounting for its role in reducing the net grid peak demand. These advances are validated with a real-sized case study of a Spanish-like power system over the years 2019–2039.

2.3. Bilevel model for regulated cost recovery

The final methodological contribution of this thesis is the development of a bilevel problem that integrates the previously established equilibrium model at the lower level with a newly formulated upper level dedicated to regulated cost recovery through tariff design. The upper-level model is constructed as a centralized tariff optimization problem that numerically adjusts grid access tariffs by accounting for the expected optimal responses of both GENCOs and DG customers, thereby capturing the dynamic interactions between tariff structures and investment and operation decisions. To solve this complex problem, the thesis develops and implements an iterative heuristic algorithm for the upper level, employing a feedback mechanism based on observed sensitivities of tariff revenues to tariff levels. This approach ensures that the resulting tariffs closely track predefined regulated cost recovery targets. As in the previous section, the bilevel model has been validated with a real-sized case study of a Spanish-like power system over the years 2024–2040.

3. RESEARCH WORKS DEVELOPED ALONG THIS PHD THESIS

From the beginning of the development of this thesis, the doctoral student has carried out his research activity in the field of operations research and power sector modeling. In particular, the research work directly related to this thesis has led to 3 research papers, 2 of them on high-impact research journals:

- The first paper was published in the European Energy Markets 2017 (EEM17) conference, entitled "Towards a simplified approach for modeling policymakers' decisions in the power sector" [44]. This paper proposed the overall framework of the model which is developed in this thesis.
- The second one is "An Equilibrium Approach for Modeling Centralized and Behind-the-meter Distributed Generation Expansion" and was published in Electric Power Systems Research (EPSR) [59]. This paper presents the EOE model that is discussed in Chapter III.
- The third one is entitled "Joint Energy and Capacity Equilibrium Model for Centralized and Behind-the-Meter Distributed Generation" and was published in the International Journal of Electrical Power and Energy Systems (IJEPES) [88]. This paper presents the JECE model that is discussed in □.

During this PhD thesis, the student has published additional complementary publications indirectly related to his thesis. These include:

- "Synthetizing representative periods for chronological hourly electricity generation expansion models" [74], published in the European Energy Markets 2018 (EEM18) conference, about using a genetic algorithm to design synthetic representative periods used in long-term generation expansion models. The

methodology presented in this publication was used to generate the hourly profiles for all case studies within this thesis.

- "Joint Centralized and Distributed Electricity Generation Expansion in a Decarbonized Scenario: The Spanish Case" [99], also published in the European Energy Markets 2018 (EEM18) conference, which describes several decarbonization scenarios for the Spanish sector using the lower level model presented in of this thesis.
- "Generation Expansion Planning Based on Positive Net Present Value" [72], published in the European Energy Markets 2019 (EEM19) conference. This paper analyzes the impact of adding a constraint that forces positive profitability in long-term generation expansion models.
- "Residential DER Cooperative Investments", published in the European Energy Markets 2019 (EEM19) [111]: presents a model that analyzes cooperative investments in generation capacity by a group of residential prosumers.
- "Profitability analysis of Spanish CCGTs under future scenarios of high RES and EV penetration", published in the European Energy Markets 2019 (EEM19) [112]: analyzes the profitability of several power plants using a long-term generation expansion planning model.
- "Costs impact of a transition to hydrogen-fueled vehicles on the Spanish power sector", published in the 4th Annual APEEN Conference [113] and a revised version in Utilities Policy [114]: describes the integration of hydrogen-powered vehicles in a long-term generation expansion model.
- "Joint analysis of the Portuguese and Spanish NECP for 2021-2030" [115], published in the European Energy Markets 2020 (EEM20): analyzes the Spanish and Portuguese national energy and climate plans (NECP) using a long-term generation expansion planning model.
- "Electricity cost of green hydrogen generation in the Iberian electricity market" [116], published in the 14th IEEE PowerTech Conference - PowerTech 2021: about modeling hydrogen generation in the long-term and assessing its costs.
- "Analysis of the Portuguese and Spanish NECPs Using the CEVESA MIBEL Market Model" [117], published in the 20st International Conference on the European Energy Market 2024 (EEM24): a continuation of the analysis in [115] with the 2024 updated versions of the Spanish and Portuguese NECPs.
- "Model-Based Analysis of Sustainable Energy Transition: A Case Study of Portugal's Regional Wind and Solar Power Generation" [118], published in the 20st International Conference on the European Energy Market 2024 (EEM24): about how investing in RES in different regions of Portugal may affect their captured prices and, hence, their profitability.
- "Analysis of NECP-based scenarios for the implementation of wind and solar energy facilities in Portugal" [119], published in Energy, expands [118] as a full journal paper.

- "Business Model for Energy Community Developers and Assets Investors" [120], published in the 21st International Conference on the European Energy Market 2025 (EEM25): on the topic of developer-driven energy communities.
- "Analysis of the New Portuguese and Spanish NECPs Using Cevesa Market Model" [121], published in the 21st International Conference on the European Energy Market 2025 (EEM25): concludes the research of [115] and [117] analyzing the latest updates on the Spanish and Portuguese NECPs.
- "Strategies for Fair Distribution of Collective Benefits in Renewable Energy Communities" [122], published in the 21st International Conference on the European Energy Market 2025 (EEM25): compares several common strategies from cooperative game theory to allocate the profits of an energy community with the application of marginal pricing.

The doctoral student has also co-supervised the following final degree or master thesis:

- "Modeling strategies and computational analysis of bilevel mathematical programing problems for the characterization of regulator-agent decisions in the electricity sector", developed by graduate student Miguel Martinez Velazquez.
- "An electricity generation expansion model with ICEV and PEV investments", developed by graduate student Rosendo Castañón Naseiro.
- "Modelling rational behavior of decision making by economic agents in distributed generation investment", developed by graduate student Gonzalo Suardíaz Álvarez del Manzano.
- "Study of the supply of hydrogen as fuel for transport and its influence in the power sector", developed by graduate student Borja Olavarría García-Perrote.
- "Modelling cooperative behavior among consumers in the investment decision-making in distributed generation: a theoretical approach", developed by graduate student Javier García Blanco.
- "Comparison of the single-level and bi-level approaches in a simplified tariff design for regulated cost recovery", developed by graduate student Alejandra Aranguren Alonso.
- "Impact of the hydrogen economy on the electricity sector", developed by graduate student Alejandra Barceló Álvarez.
- "Logistical reformulation of the Madrid food bank: benefits of a decentralized model", developed by graduate student Guillermo Cerezo de Osma.
- "Profitability analysis of electricity generation technologies based on the CEVESA market model", developed by graduate student Juncal Guerrero Rodríguez.

And a journal paper is currently being worked on by the student, in which he will publish the bilevel model described in of this thesis. It will be submitted for publication in the following months after defending this thesis.

4. CONTRIBUTION LIMITATIONS & FUTURE WORK

Future lines of research may stem from this thesis by, for example, extending the developed model by incorporating other possible demand-response mechanisms such as demand flexibility or other means of demand management such as load-shifting, or explicitly modeling cross-sector resources such as electric vehicles or green hydrogen production.

In addition, further refining of the upper-level search algorithm or improving the efficiency of the lower level may allow us to include again the remaining parts of the model (i.e., hydro reservoir modeling instead of the statistical hydro model used in this thesis, the thermal unit commitment & ramping constraints omitted in the case studies, etc.) into the bilevel problem.

Future research could also improve the CG side of the model, for example to include secondary reserve constraints. Indeed, as secondary reserve dispatch is another game-setting linking constraint, it will necessarily alter the formulation of the JECE presented herein. Therefore, further mathematical demonstrations will be needed to prove that the resulting JERCE (Joint Energy, Reserve and Capacity Equilibrium) can be solved using an equivalent optimization problem. In addition, for the long-term simulation of secondary reserve, further research must be performed as to how RES, batteries or hydrogen electrolyzers may provide this ancillary service to the grid. Furthermore, international interconnections have started to provide cross-border ancillary services such as secondary reserve, a possibility that needs to be incorporated into the model.

Future research is also needed on the customers' side of the model, with, for example, the addition of electrolyzers as flexible consumers (with market power in accordance with their size), possibly with on-premises RES generation. Also, the model could consider the aggregation of different customers into energy communities (also known as collective self-consumption) may affect the JECE presented in the lower-level model, as they might gain market power; and how this may affect the resulting tariffs from the bilevel model presented herein. Another limitation of the presented model is that DG is not considered for firm capacity requirements of the system, while it is expected that DG may provide some firmness to the system. This topic requires further research both in terms of mathematical modeling and power systems regulation.

Finally, future research can also focus on improving the bilevel model. Considering the heuristic nature of the upper-level search algorithm, parallelization techniques

may be applied, transforming it into a population-based heuristic algorithm that explores multiple branches of the search space in parallel. This approach would be particularly well suited for distributed cloud computing environments, where computational resources can be dynamically allocated to efficiently manage large-scale, complex simulations. Other advanced metaheuristic algorithms, such as genetic algorithms or particle swarm optimization, may enhance the algorithm's exploration and exploitation capabilities. Additionally, incorporating adaptive mechanisms to automatically tune heuristic parameters during the optimization process could further improve convergence speed and solution quality. The combination of these advances would contribute to the development of a more robust and scalable tool for tariff optimization and long-term planning in evolving power systems.

Although not directly related with the model presented in this thesis, the methodology used to synthesize representative periods to reduce temporal granularity in order to simplify the computation complexity of the problem has a major limitation regarding accurately representing battery operation. Indeed, further research is required along this research line.

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