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TRABAJO FIN DE GRADO

Modelado de un agente estratégico en el mercado eléctrico mediante optimización binivel

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RESUMEN DEL PROYECTO

Esta tesis desarrolla e implementa dos modelos de optimización para evaluar cómo las decisiones de contratación mediante Power Purchase Agreements (PPA) de un gran productor renovable afectan a los resultados del mercado eléctrico a corto plazo. En primer lugar, un modelo de casación del mercado eléctrico y, en segundo lugar, un modelo binivel estratégico del productor que maximiza beneficios eligiendo su nivel de exposición a PPAs, sujeto al equilibrio del mercado. El problema binivel se reformula mediante condiciones de Karush-Kuhn-Tucker y se transforma en un problema de programación lineal entera mixta (MILP). La implementación permite un análisis horario anual que cuantifica los compromisos entre beneficio privado, formación de precios y bienestar agregado bajo distintas configuraciones de capacidad solar y precios de PPA.

El rápido crecimiento de la generación renovable variable, especialmente la energía solar fotovoltaica, ha incrementado la volatilidad de los ingresos de los productores y ha introducido nuevos retos en el diseño de los mercados eléctricos. La naturaleza intermitente de estas tecnologías hace que los ingresos dependan fuertemente de los precios spot, que a su vez fluctúan con la demanda y la disponibilidad de recursos renovables. En este contexto, los Power Purchase Agreements (PPAs) se han consolidado como instrumentos contractuales clave para mitigar el riesgo de mercado.

Los PPAs son contratos bilaterales en los que un comprador acuerda con un generador la adquisición de energía a un precio fijo o indexado durante un horizonte temporal determinado. Estos contratos permiten estabilizar ingresos y facilitar la financiación de proyectos renovables. Sin embargo, cuando una parte significativa de la capacidad de generación queda comprometida bajo PPAs, la cantidad de energía ofrecida al mercado spot se reduce, alterando potencialmente la formación de precios y el despacho del sistema. Este trabajo analiza precisamente este mecanismo de retroalimentación entre decisiones contractuales y resultados de mercado.

El objetivo principal es desarrollar una metodología reproducible que vincule decisiones de contratación de PPAs con la casación endógena del mercado eléctrico, permitiendo evaluar sus efectos económicos antes de su implementación. Se asume que los compradores de PPAs no incrementan la demanda en el mercado spot si el contrato no se ejecuta, sino que sustituyen su proveedor.

Las principales contribuciones del trabajo son: (1) un modelo de casación del mercado eléctrico que permite analizar escenarios competitivos de forma eficiente; (2) un modelo binivel en el que el productor estratégico decide su exposición a PPAs mientras el operador del mercado resuelve la casación óptima; (3) una reformulación a un solo nivel basada en condiciones KKT que preserva la estructura de precios marginales; (4) una implementación modular en Python/Pyomo capaz de ejecutar simulaciones horarias a lo largo de un año completo; y (5) un conjunto de

herramientas de visualización que permiten analizar la interacción entre contratación, precios y bienestar social.

Los mercados eléctricos spot funcionan mediante la casación de ofertas de generación y demanda en intervalos temporales discretos, habitualmente de quince minutos. En este trabajo se adoptan intervalos horarios con fines de simplificación computacional, lo cual resulta suficiente para capturar la variabilidad intradiaria relevante de la generación solar. Los generadores presentan ofertas de cantidad y precio basadas en sus costes marginales o de oportunidad. El operador del mercado ordena dichas ofertas de menor a mayor coste hasta satisfacer la demanda total, determinando un único precio de casación aplicable a todos los agentes.

Este mecanismo puede formularse como un problema de optimización lineal cuyo objetivo es maximizar el bienestar social, entendido como la diferencia entre la utilidad agregada de los consumidores y los costes totales de generación. La solución del problema garantiza el equilibrio entre energía producida y consumida en cada intervalo temporal. Las variables duales asociadas a estas restricciones de equilibrio representan los precios marginales horarios del sistema.

El modelo binivel considera un nivel superior en el que el productor maximiza su beneficio total, decidiendo la proporción de su capacidad comprometida mediante PPAs, y un nivel inferior en el que el mercado realiza la casación óptima. Dado que el problema inferior es convexo, sus condiciones de optimalidad de Karush-Kuhn-Tucker (KKT) son necesarias y suficientes, lo que permite sustituirlo por un conjunto equivalente de restricciones.

Las condiciones KKT incluyen factibilidad primal, factibilidad dual, estacionariedad y restricciones de complementariedad. Estas últimas son no lineales y se linealizan mediante una formulación big-M con variables binarias, transformando el problema en un MILP resoluble con solvers estándar. Los parámetros big-M se calibran de forma conservadora a partir de los datos de entrada para asegurar estabilidad numérica sin comprometer factibilidad.

Esta reformulación permite reinterpretar los ingresos del productor en términos de precios sombra asociados a la capacidad de generación, proporcionando una lectura económica clara del valor de la asignación entre mercado spot y contratos PPA.

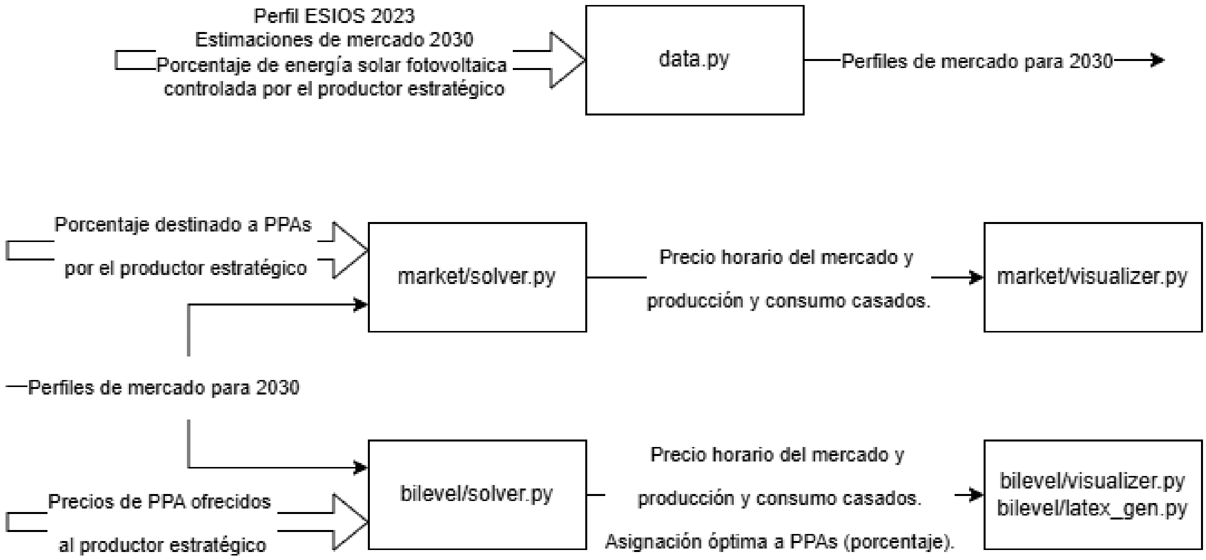

Figure 1: Arquitectura del sistema

El modelo utiliza perfiles horarios históricos basados en datos de ESIOS, escalados a proyecciones de capacidad y demanda para el año 2030. A partir de estos datos se construyen escenarios que varían tanto la proporción de capacidad solar controlada por el productor estratégico como las condiciones contractuales de los PPAs.

En el modelo de mercado se analizan distintos niveles de participación contractual para

observar su impacto en precios y despacho. En el modelo binivel se exploran distintos precios de PPA para determinar la asignación óptima de capacidad entre mercado spot y contratos. En ambos casos se registran variables clave como despacho horario, precios de casación, ingresos por contratos y mercado spot, pagos de consumidores y medidas de bienestar social.

La implementación computacional es modular y reproducible, estructurada en módulos de datos, resolución de mercado, resolución binivel y visualización. Todo el sistema está desarrollado en Python utilizando Pyomo y se resuelve mediante Gurobi, permitiendo ejecutar barridos de escenarios de forma automatizada.

La evaluación experimental compara un escenario competitivo de referencia (sin comportamiento estratégico) con soluciones obtenidas del modelo binivel. El análisis considera métricas de beneficio del productor, precios horarios, excedentes de consumidores y productores, bienestar social agregado, niveles de participación en PPAs y rendimiento computacional del solver.

Los resultados muestran que la participación en PPAs tiene un impacto significativo en la rentabilidad del productor renovable estratégico. En particular, el beneficio total aumenta aproximadamente 1.2, 1.3 y 1.8 veces para participaciones solares estratégicas del 5%, 10% y 20%, respectivamente, cuando se optimiza la asignación contractual.

El comportamiento óptimo de asignación de PPAs depende de la escala de la capacidad estratégica. Para participaciones solares pequeñas, la decisión de contratación presenta un comportamiento tipo umbral, con baja participación por debajo de cierto precio de PPA y alta participación por encima de este. A medida que aumenta la participación solar, la transición se vuelve más suave y aparecen asignaciones intermedias más frecuentes, reflejando una mayor interacción entre decisiones contractuales y condiciones de mercado.

Los PPAs afectan principalmente la redistribución del excedente entre agentes y la estructura de precios del mercado spot. Sin embargo, el bienestar social agregado se mantiene relativamente estable en la mayoría de los escenarios analizados, lo que indica que el principal efecto de los PPAs en este marco es redistributivo más que de eficiencia global.

Desde el punto de vista computacional, se observa que los tiempos de resolución aumentan con la participación solar estratégica. Esto se debe al mayor acoplamiento entre las decisiones contractuales del nivel superior y el problema de casación del nivel inferior, lo que incrementa la complejidad del MILP resultante y la variabilidad del rendimiento del solver.

En conjunto, los resultados indican que los PPAs son un instrumento relevante para mejorar la rentabilidad de productores renovables con alta capacidad, aunque sus efectos sobre el bienestar agregado son limitados. El marco propuesto permite analizar de forma sistemática cómo decisiones contractuales de largo plazo interactúan con la formación de precios en mercados eléctricos competitivos.

Todos los resultados son reproducibles mediante los scripts y configuraciones proporcionadas. La estructura modular del código permite replicar los experimentos o adaptar el modelo a otros sistemas eléctricos. Las utilidades de exportación a LaTeX generan automáticamente figuras y tablas asociadas al análisis, facilitando la verificación de resultados.

Palabras clave: Acuerdos de Compra de Energía; optimización binivel; mercado eléctrico; energía solar; bienestar social

Modeling a Strategic Agent in the Electricity Market through Bilevel Optimization

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ABSTRACT

This thesis develops and implements two optimisation models to evaluate how a large renewable producer's Power Purchase Agreement (PPA) contracting decisions feed back into short term market outcomes. First, an electric market clearing model and, second, a strategic producer's bilvel model that maximizes profits choosing the exposure level to PPAs, while respecting the market clearing optimality. The bilevel problem is reformulated using Karush-Kuhn-Tucker optimality conditions and linearised a mixed integer linear program (MILP). The resulting implementation enables an hourly, year long scenario analysis that quantifies trade offs between private profit, price formation and aggregate welfare across a wide range of solar ownership and PPA price configurations.

The rapid deployment of variable renewable energy, particularly solar generation, has introduced new sources of revenue risk for producers and new design challenges for markets and regulators. Power Purchase Agreements (PPAs) are bilateral contracts through which a buyer and a generator agree on a price (fixed or indexed) and delivered energy quantities over a specified period. PPAs are being increasingly used to stabilise revenue streams and finance renewable projects. While PPAs reduce exposure to volatile spot prices for the contracting party, large portfolios of contracted energy can materially change the residual supply faced by short-term markets and thereby influence price formation. This work asks: when a single producer controls a sizeable share of renewable capacity, how do its contractual choices feed back into spot prices, dispatch patterns, and aggregate welfare? Answering this question is essential for generators assessing contract design and for policymakers who must balance investment incentives against market efficiency.

The main objective is to provide a tractable, reproducible methodology that links PPA portfolio choice with endogenous market clearing so that the economic consequences of contracting strategies can be assessed beforehand. In this project it is assumed PPA buyers do not enter the spot market and will seek another renewable supplier, so demand does not increase if the producer refuses a PPA. To achieve this objective these are the key components: (1) a market clearing model to sweep through market configurations faster when the strategic producer is not maximising profits; (2) a formal bilevel model where the leader (producer) selects PPA exposure and the follower (market operator) clears supply and demand; (3) a single level reformulation of the bilevel model based on KKT conditions that preserves meaningful marginal price information while enabling use of standard solvers; (4) a modular Python/Pyomo implementation configured for hourly simulation over extended horizons for both models; and (5) visualisation modules to create an analysis demonstrating how increasing strategic control of solar capacity affects profit, price distributions, and social welfare.

For readers unfamiliar with electricity markets: short-term (spot) electricity markets match supply and demand for each scheduling interval (typically by the quarter of an hour). Generators offer quantities at prices reflecting their marginal costs or opportunity value; the market operator accepts offers from lowest to highest cost until demand is met and sets the clearing price equal to the marginal accepted offer. Spot prices therefore reflect system scarcity and can change rapidly with demand or variable renewable output. In this project the market clearing model uses the uniform price system, meaning all producers and consumers are paid or pay the same price.

To tranform this market clearing mechanism into a optimization problem it is formulated into a linear programming model (LP). The objective of the model is to maximize social welfare, which is the difference between the total effective utility for consuemrs and the total effective cost for producers. Effective in this case means that cleared, sold or bought, in the market. The model will choose which of the producers and consumers bid will be cleared in order to maximize the social welfare. It is fundamental to note that the market must be in a equilibrium, meaning the amount of energy sold and bought must be the same for each time period where bids are given, which in our case is hourly. This equilibrium is ensured by the equilibrium constraints, which its dual variables give the marginal price, market price, for each hour.

For the bilevel model, the lower-level is the market clearing model, which yields the hourly marginal prices used for payments by its dual variables from the equilibrium constraints. Because the lower level is convex, its KKT conditions (primal feasibility, dual feasibility, stationarity and complementarity) are necessary and sufficient for optimality and can be embedded into the upper level to produce a single stage optimisation. Complementarity relations are non-linear and are linearised using a big-M technique together with binary variables, which transforms the problem into a MILP, tractable for commercial solvers. The big-M parameters are computed dynamically from input data with conservative multipliers to balance feasibility and numerical stability. The reformulation exposes economically meaningful variables that capture the implicit value of leaving capacity available to the spot market. In particular shadow prices, accessed by dual variables, associated with generation capacity. Exploiting stationarity and complementarity allows the original nonlinear spot-revenue term from the objective function to be rewritten in linear terms involving these shadow prices.

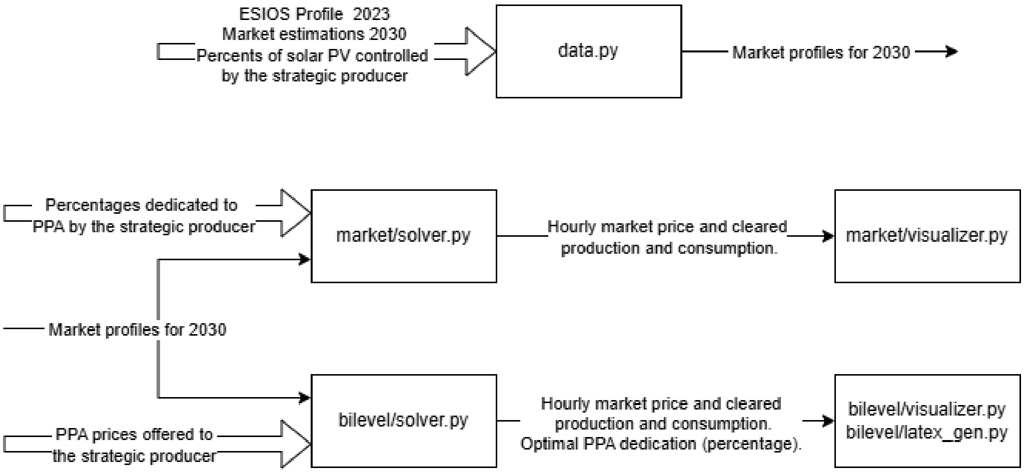

Figure 2: Architecture of the system

The setup, seen in 2, uses hourly historical profiles (processed from ESIOS) scaled to 2030 capacity and demand estimates to build realistic temporal variability. Scenario sweeps vary the fraction of solar capacity controlled by the strategic producer. At the same time, for the market model there is a list of PPA percentages dedicated by th strategic producer to see the effect on the market; and for the bilevel model a list of PPA prices to find the optimal dedication to PPA contracts. For both cases the model reports the hourly dispatch, clearing prices, contract

and spot revenues, consumer payments a social welfare measure. The codebase is modular and reproducible: data ingestion (‘data.py‘), market solver (‘market/solver.py‘), bilevel solver (‘bilevel/solver.py‘), visualisation and LaTeX export modules, and a configuration and main modules that orchestrates scenario batches. The models are implemented in Pyomo and solved with Gurobi.

Experiments compare a competitive baseline (no strategic behaviour) against bilevel solutions across a grid of scenarios. The evaluation focuses on strategic profit, hourly market prices, producer and consumer surplus decomposition, social welfare, PPA participation shares, and solver performance, including runtime statistics and optimality gaps.

The results show that PPA participation can substantially increase the profitability of the strategic renewable producer. Across all strategic solar share scenarios, higher PPA prices lead to increased PPA allocation and higher total profits. The impact of ignoring PPAs is significant, with optimal PPA participation increasing total profit relative to a no-PPA case by approximately 1.2 times, 1.3 times, and 1.8 times for 5%, 10%, and 20% strategic solar shares, respectively.

The optimal PPA allocation exhibits different behavioural patterns depending on the strategic solar share. For small shares, the decision behaves like a threshold response, with low participation below a given PPA price and almost full participation above it. As the strategic solar share increases, the transition becomes more gradual and intermediate PPA allocations become more frequent. This indicates increasing complexity in the interaction between contractual decisions and market participation.

PPA participation also affects market outcomes beyond the producer's own revenue. Changes in contracting levels alter the amount of energy offered to the spot market, which in turn affects market prices and the distribution of surplus among participants. However, aggregate social welfare remains relatively stable across all scenarios, indicating that the main effect of PPAs in this framework is redistribution rather than large changes in overall efficiency.

From a computational perspective, solution times increase significantly with the strategic solar share. Higher shares lead to stronger coupling between the contracting decision and the market-clearing problem, resulting in longer runtimes and higher variability in solver performance. This shows that the same mechanisms that drive economic behaviour also increase computational complexity.

Overall, the results indicate that PPA participation plays an important role in shaping producer profitability and market outcomes. While welfare effects are modest, profitability gains can be substantial, especially for producers with larger shares of solar generation. The framework provides a structured way to analyse how long-term contracting decisions interact with electricity market outcomes as strategic solar ownership increases.

The framework can be used to explore how different contractual settings affect market outcomes under varying levels of strategic ownership. For generators, it helps identify PPA price ranges where contracting increases total profit compared to full market exposure. For regulators and market designers, it can be used as a scenario analysis tool to study how increasing contractual participation may affect prices and surplus distribution under different levels of market concentration.

All experiments are reproducible from the provided scripts and configuration files. Data preprocessing (ESIOS profiles), model instances and plotting scripts are modularised so users can reproduce scenario sweeps or adapt the pipeline to alternative markets. The LaTeX export utilities generate the figures and tables referenced in the results chapter (profit vs PPA price, PPA share vs price, monotone price curves, Pareto frontiers, runtime tables), facilitating inspection and replication of the reported figures.

Keywords: Power Purchase Agreements; bilevel optimization; electricity market; social welfare

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Chapter 1

Introduction

Electricity systems are undergoing a profound transformation driven by decarbonization objectives and the increasing electrification of economic activities. The growing deployment of renewable generation, together with emerging electricity intensive applications such as green hydrogen production, is increasing the importance of contractual mechanisms that reduce uncertainty and support investment. Among these mechanisms, Power Purchase Agreements (PPAs) have gained relevance as long term contracts between electricity producers and offtakers that define energy volumes and pricing arrangements over a given period. While PPAs are primarily designed to provide revenue stability and reduce exposure to market volatility, an increasing share of contracted renewable generation may also influence spot market outcomes and producer incentives. This project examines how PPAs affect the market clearing process and whether a large share of contracted renewable generation can alter spot prices, dispatch decisions, social welfare, and the revenue of a strategic producer through its participation decisions between PPAs and the spot market.

1.1 Context and motivation

The transition toward low carbon electricity systems brings both opportunities and challenges. Renewable energy sources contribute to emissions reduction and energy independence, but their variability can also increase uncertainty in generation availability and electricity prices. In this context, PPAs have become an important instrument for supporting renewable deployment, as they reduce revenue uncertainty for producers and provide greater price certainty for offtakers, facilitating investment in new projects.

Although PPAs reduce market risk for contracting parties, their growing adoption may also affect how electricity markets operate. When part of a producer's generation is committed through long term contracts, a smaller share remains exposed to spot market incentives and variations in market prices. As a result, increasing PPA participation may influence market clearing outcomes, dispatch decisions, and price formation, particularly when contracted renewable generation represents a significant share of total supply.

These market effects emerge through the contracting decisions of market participants. For a producer, allocating generation between PPAs and the spot market involves a strategic trade off between revenue certainty and exposure to potentially more profitable but uncertain market prices. A higher participation in PPAs may stabilize revenues, while greater spot market participation may increase opportunities to benefit from favorable price conditions. Understanding this allocation decision is therefore essential to study how PPA participation affects market outcomes.

From a system perspective, these contracting choices matter beyond the producer's individual revenues. For market operators and system planners, changes in the amount of generation committed through PPAs may influence the volume of electricity available for spot market clearing, market prices, fulfillment of participant orders, and overall welfare outcomes. Understanding these effects is increasingly relevant as renewable penetration and long term contracting continue to expand.

To address these questions, this project develops a modeling framework to determine the optimal PPA participation of a strategic producer and quantify the resulting effects on both producer performance and electricity market outcomes. In addition to identifying the optimal allocation between PPAs and spot market participation, the model evaluates how different contracting decisions affect producer revenue, spot prices, participant order fulfillment, dispatch outcomes, and welfare effects. Furthermore, the analysis explores different combinations of generator capacity and PPA prices to assess how contractual and system conditions shape both producer incentives and market performance.

1.2 Objectives

The main goal is to build a bilevel optimization model that integrates PPA choices with market clearing to study their interactions. Specific objectives:

1. Formulate a lower-level market clearing model that determines spot prices and fulfillment orders for the participants.
2. Formulate an upper-level model for the strategic producer's PPA portfolio and market participation choices to maximize the total revenue.
3. Evaluate impacts on producer revenue, spot prices, and social welfare across scenarios of PPA penetration.

1.3 Alignment with Sustainable Development Goals

All United Nations members approved in 2015 the 2030 agenda for sustainable development. It provides a common line of action based on 17 sustainability development goals [13].

Making the market more stable and efficient for producers and consumers will facilitate growth in both the electric market and industry. It will strengthen the incentives for heavy industries to move to electrification, while favoring renewable energy consumption. The proposed model helps regulators and policy makers study efficient use of PPAs while avoiding market manipulation.

The primary SDGs aligned with this project are:

- Goal 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.
- Goal 11: Make cities and human settlements inclusive, safe, resilient and sustainable.
- Goal 12: Ensure sustainable consumption and production patterns.

Chapter 2

State of the Art

This chapter reviews the literature and practical solutions on market based revenue optimization for renewable producers and the modeling of Power Purchase Agreements (PPAs). It explains the core concepts, summarizes common modelling techniques, surveys key related works, and highlights limitations in current approaches. The aim is to identify gaps that motivate the proposed study.

2.1 Fundamental Concepts

2.1.1 Electricity Spot Markets, Market Clearing and Pricing

Electricity spot markets are short term trading platforms where electricity is bought and sold for delivery during a specific time period. In many European electricity markets, trading takes place in 15 minute intervals. However, this project uses hourly periods to simplify the analysis and the formulation of the optimization model.

Producers submit offers indicating the quantity of electricity they are willing to generate and the price at which they are willing to sell it. At the same time, consumers or retailers submit bids representing their expected demand. The market operator aggregates these offers and bids and determines which generators are dispatched to satisfy demand.

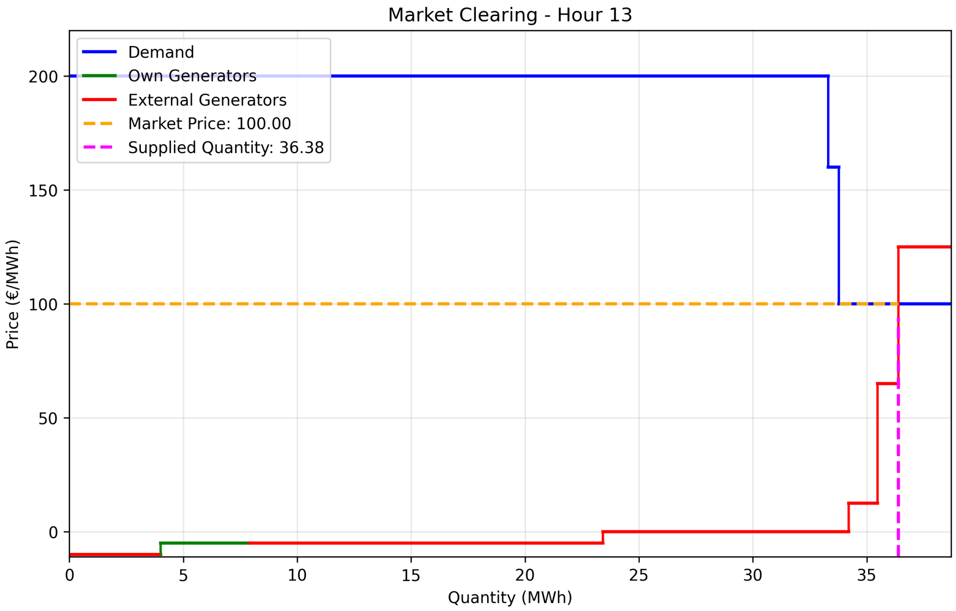


Figure 2.1: Example of market clearing for a single trading hour.

Figure 2.1 shows an example of the market clearing process for one trading hour obtained from the market clearing model used in this project. The supply curve, shown in red, is constructed by ordering generation offers from the lowest to the highest price. The demand curve, shown in blue, represents the electricity requested by consumers. A portion of the supply curve is highlighted in green, representing the generating units owned by the producer under study. In this example, these units participate in the market without exercising any strategic behaviour and submit offers according to their normal market conditions. The intersection of the supply and demand curves determines the quantity of energy traded and the market price. Generators with offer prices below or equal to the market price are dispatched, while generators with higher offer prices are not selected.

Many electricity markets use a uniform pricing mechanism. Under this design, all dispatched generators receive the same market price regardless of their individual offer prices. Similarly, all consumers pay the same price for the electricity purchased during that period. This approach provides a transparent market signal and encourages generators to offer electricity at their marginal cost.

From a modelling perspective, market clearing is commonly represented as an optimization problem. The decision variables determine the amount of electricity generated and consumed, while the associated dual variables provide the resulting market prices. This project assumes a uniform pricing system, meaning all producers and consumers transact at the same price per MWh.

2.1.2 Power Purchase Agreements (PPAs)

PPAs are long term contracts between electricity producers and offtakers that fix a quantity and a price (or a pricing rule) over a period. They can take the form of fixed price contracts, contracts for differences, or indexed/variable arrangements. For producers, PPAs reduce price risk and secure revenue, but they also remove volume from the spot market and can affect price formation when contracted volumes are large.

Volume	**PPA**	**Price**	**Summary**
Fixed	Baseload	Fixed / Floor	Hourly delivery obligations
Fixed	Fixed volume (defined period)	Fixed / Floor	Delivery obligations for the period (annual / quarterly / monthly)
Variable	As produced	Fixed / Variable	Agreed percentage of production
Variable	Route to market	Variable	Off taker trades on market for a commission

Table 2.1: Types of PPAs according to volume and price structure.

Table 2.1 summarises representative PPA structures according to volume commitments and pricing arrangements. Different contract types may be attractive depending on the risk preferences, operational flexibility, and commercial objectives of market participants. Baseload PPAs, characterised by fixed hourly delivery obligations and fixed or floor prices, are generally suited to offtakers seeking supply certainty and price stability, while producers with predictable generation profiles may benefit from stable revenues. Fixed volume contracts defined over annual, quarterly, or monthly periods offer greater temporal flexibility and may appeal to participants able to manage delivery deviations within a settlement horizon. By contrast, as produced PPAs are particularly relevant for renewable generators with variable output, since contracted quantities follow realised production and reduce imbalance exposure. Finally, route to market agreements are often attractive for smaller or independent renewable producers lacking market trading capabilities, as the offtaker or intermediary manages spot market participation in exchange for a commission. In this project the focus falls on as produced PPAs.

In the proposed model, a fixed price PPA structure is adopted. This choice is motivated by analytical considerations and by the role of PPAs in reducing revenue and price uncertainty between market participants. From a modelling perspective, a fixed price contract allows the analysis to focus on the interaction between contracted volumes, bidding behaviour, and spot market price formation without introducing additional complexity associated with alternative pricing arrangements. This simplification facilitates the interpretation of the effects of long term contracting decisions on short term market outcomes.

2.1.3 Strategic behavior and market power

When a producer controls a non trivial share of supply, its contracting decisions (including PPAs) may influence spot prices. Strategic behaviour can take several forms: withholding quantity from the spot market (either physically or by contracting it away), bidding at prices that differ from marginal cost, or choosing contract structures that change the residual demand facing other participants. These actions can raise or reshape spot prices, change dispatch patterns and increase price volatility in certain hours. Among these possible strategic behaviours, this work focuses on the role of long term contracting decisions through PPAs, examining how different levels of contracted participation may influence both producer incentives and market outcomes.

From a modeling perspective, analysing this type of strategic behaviour requires accounting for interactions in which a producer anticipates how market outcomes respond to its contracting decisions. Rather than treating market prices as independent of producer actions, a strategic framework captures the feedback between PPA participation and market clearing outcomes. This is particularly relevant when contracted generation represents a meaningful share of supply, as changes in participation levels may deeply the market clearing process outcome.

For regulators and system operators, understanding these interactions is important because contracting decisions may have effects beyond the individual producer, influencing market outcomes and participant incentives. In particular, studying how contracted volumes affect spot market participation can help assess whether PPAs are primarily serving their intended role of reducing risk and supporting investment or whether, under certain conditions, they may contribute to reducing effective supply available to the spot market in ways that resemble strategic withdrawal [22]. Including strategic behaviour in optimization studies therefore provides a way to quantify how increasing PPA participation may reshape electricity market performance and support the evaluation of contracting patterns from a market monitoring perspective.

2.2 Relevant Techniques and Models

2.2.1 Optimization formulations

Linear programming (LP) formulations of the clearing problem are common when unit commitment and other discrete operational constraints can be relaxed: LPs scale well, have strong duality properties, and yield clear economic interpretations (dual variables correspond to marginal prices). A standard LP clearing model enforces power balance, capacity and ramping limits, and may include simple cost curves or piecewise-linear bids.

When realistic operational limits must be respected (start-ups, minimum up/down times, integer unit commitment decisions, minimum stable generation), mixed integer formulations (MIP/MILP) are required. These increase model fidelity but also computational complexity: MILPs are harder to solve to optimality and may require decomposition, relaxations, or heuristics for large systems.

Common practical approaches include convex relaxations and linearizations to keep problems tractable while preserving price interpretation; decomposition methods to split the problem by time or by components; and piecewise linear cost representations to approximate non-linearities while keeping LP/MIP structure.

Choice of formulation is a trade-off between realism and solvability: for studies that require endogenous prices (dual variables), convex LP based formulations are attractive because they preserve economically meaningful marginal prices and allow reformulations used in bilevel to single level conversions.

2.2.2 Bilevel optimization

Bilevel modeling represents hierarchical decision making: the upper level models a strategic agent (for example, a producer choosing PPA volumes or bids) and the lower level represents market clearing by the system operator [7]. The lower level clearing returns dispatch decisions and marginal prices that the upper level anticipates when optimizing its contract and market participation.

Solution approaches depend on the structure of the lower level problem. If the lower level is convex and satisfies regularity conditions, a common technique is to replace it by its Karush-Kuhn-Tucker (KKT) optimality conditions or by the primal-dual pair together with strong duality. Doing this converts the bilevel problem into a single level program, but it introduces complementarity conditions (products of primal and dual variables that must equal zero). Those complementarity conditions are nonconvex and typically require special treatment: they can be linearized using big-M formulations, which often leads to mixed integer models, or handled with nonlinear solvers or disjunctive constraints, all of which increase computational complexity.

An alternative is to keep the equilibrium structure explicit and formulate a mathematical program with equilibrium constraints (MPEC). MPECs let you state the market clearing optimality conditions directly, but they are numerically delicate and usually require specialized solvers or regularization techniques. When the upper level has only a few discrete options, a straightforward approach is enumeration: try each candidate upper level decision, solve the lower level market clearing for each, and compare outcomes. Alternatively, decompose the problem across time periods or scenarios so each subproblem is smaller and easier to solve.

Finally, when exact reformulations are impractical for realistic instances, practitioners often use simulation coupled with heuristic search. This means simulating the market response for candidate upper level decisions and using heuristic optimization to explore promising regions of the decision space. This approach scales better but does not provide optimality guarantees.

KKT reformulation is the approach adopted in this study for the lower level market clearing problem. This choice is motivated by three practical considerations: first, replacing the convex lower level with its KKT or primal-dual conditions preserves the economic interpretation of dual variables as marginal prices, which is central to our analysis of price impacts from PPA decisions; second, the single-level reformulation makes it straightforward to embed market clearing conditions within the upper level optimization and to apply standard mixed-integer or linear solvers after appropriate linearizations of complementarity conditions; and third, compared with MPEC formulations or fully heuristic simulation methods, the KKT route gives a controllable trade-off between fidelity and solvability for the case studies considered here.

2.3 Related Works

The literature spans studies focused on market bidding, PPA valuation, contract portfolio optimization, and bilevel models that include market clearing. Representative works address these topics from different perspectives. For example, [11] presents a bilevel formulation for cooperative virtual power plants optimizing bidding strategies, emphasizing strategic market participation rather than long term contracting. Similarly, [10] develops a bilevel model for revenue maximization subject to constraints that ensure renewable energy clears the market, including network considerations in some formulations.

Other contributions focus more directly on long term contracting and portfolio optimization.

In this context, [15] investigates the optimization of long term contract portfolios, including PPAs, while treating market prices as exogenous inputs to evaluate risk and net present value. Related studies, such as [14, 16, 17], address procurement and scheduling problems involving PPA like contracts, often from the perspective of buyers or system planners. In addition, [19, 20, 18] explore bilevel and mixed integer linear programming formulations for distributed generation contract pricing and location decisions, highlighting leader follower interactions at different levels of market granularity.

The table 2.2 groups representative optimisation studies by their primary objective and indicates whether they explicitly model PPAs or use a bilevel structure. It shows a recurring pattern: many works that analyse PPAs treat market prices as exogenous or use single level procurement formulations, while many bilevel studies focus on strategic bidding without explicitly modelling long term contracts. This contrast highlights the target of the proposed model, which combines both features to study feedback effects between contracting decisions and short term price formation.

Model	**Problem**	**PPA**	**Bilevel**	**Summary**
[11]	Revenue maximization		✓	Optimizes bidding for cooperative virtual power plants
[10]	Revenue maximization		✓	Strategy for producers ensuring renewable clearing
[15]	Revenue maximization	✓		Maximizes net present value of long term contract portfolios
[14]	Cost minimization	✓		Bicriteria lot sizing and scheduling considering PPAs and storage
[16]	Cost minimization	✓		Electricity procurement of large consumers considering PPAs
[17]	Cost minimization	✓		Examines PPA structures for firm renewable supply
[19]	Revenue maximization		✓	Bilevel model for distributed generation contract pricing
[20]	Revenue maximization		✓	Detailed bilevel optimization for distributed generation contract pricing
[18]	Revenue maximization		✓	Optimizes distributed generation location and contract pricing using bilevel MILP
Proposed	Revenue maximization	✓	✓	Bilevel model of renewable producer optimizing PPA share and market clearing

Table 2.2: Optimization models.

2.4 Limitations of revised literature

Several limitations emerge from the surveyed literature. Many PPA and procurement studies rely on an exogenous pricing assumption, treating spot prices as externally forecast variables, which prevents analysis of feedback effects arising from contracting decisions. A further limitation concerns the trade-off between scalability and realism, as bilevel models can become computationally intensive and therefore often require linearization or aggregation of units to remain solvable. Finally, relatively few studies assess broader market impacts, such as system-level welfare, price volatility, or market power implications, particularly when large PPA portfolios remove significant supply from the spot market.

These gaps motivate modelling approaches that integrate long-term contracting decisions with market-clearing mechanisms while maintaining computational tractability.

2.5 Justification of the project

The reviewed literature provides strong foundations in market-clearing formulations, bilevel modelling, stochastic optimization, and a broad set of applications to bidding and procurement. However, a clear gap remains in the joint treatment of PPA portfolio design from the producer's perspective and short-term price formation within a tractable bilevel framework capable of analysing both firm revenues and market-level consequences. In addition, much of the existing literature focuses primarily on model formulation and methodological development, with comparatively limited emphasis on using these models to derive broader strategic, economic, or policy-relevant conclusions. The proposed project seeks to address these gaps by embedding PPA decision variables in the upper level of a bilevel model while employing a market-clearing optimization in the lower level to determine spot prices endogenously. Furthermore, the approach incorporates sufficient operational detail to capture economically meaningful effects while applying reformulations that preserve computational tractability for realistic problem instances, enabling not only model development but also the extraction of insights regarding market behaviour, producer revenues, and system-level impacts.

Chapter 3

Developed Model

3.1 Problem Statement

3.1.1 Formal Problem Definition

This project studies the interaction between long-term Power Purchase Agreements (PPAs) and short-term electricity market operation. The objective is to understand how the contracting decisions of a renewable energy producer influence its own profitability and affect broader market outcomes such as electricity prices, dispatch decisions, and market efficiency.

The model represents a simplified electricity market in which electricity producers and consumers participate through a centralized market clearing mechanism. Producers offer electricity generation to the market, specifying the amount of energy available and the price at which they are willing to sell it. Consumers submit demand bids indicating the quantity of electricity they wish to purchase and the value they assign to that energy. Based on these offers, the market determines which transactions take place and establishes the corresponding spot market price.

A key feature of the model is the presence of a strategic renewable producer that can allocate part of its generation to a long-term PPA while selling the remaining energy through the spot market. The producer therefore faces a trade-off between the revenue stability provided by long-term contracts and the potential gains associated with market participation. Unlike the strategic producer, all other market participants are assumed to behave competitively and do not actively optimize their market influence.

The model requires information describing both the market participants and the contractual environment. Input data include electricity demand profiles, generation availability, production costs, generation capacities, market offer prices, and PPA characteristics such as the contract price and contracted energy share. Renewable generation profiles are also required to represent the variability of the strategic producer's output throughout the year.

The market is simulated over a one-year horizon with hourly resolution. Each hour represents a separate market clearing interval in which electricity supply and demand must be balanced. For every hour, the model determines which generation offers are accepted, which demand bids are satisfied, the quantity of electricity produced and consumed, and the resulting market price. While market outcomes are calculated for each individual hour, the PPA decision is made from a long-term perspective. Rather than choosing a different contract level for each period, the strategic producer selects a single PPA coverage level that applies throughout the entire simulation horizon.

The model produces both operational and strategic outputs. Operational outputs include hourly dispatch quantities, accepted market offers, electricity production levels, energy consumption levels, and spot market prices. Strategic outputs include the optimal PPA coverage level, revenues obtained from PPA contracts and spot market participation, total producer profits, and indicators describing the economic performance of the market.

The purpose of the model is not only to reproduce market dispatch outcomes but also to evaluate the economic consequences of different contracting strategies. By comparing scenarios with different levels of PPA participation, the model can be used to analyse the trade-off between revenue stability and market exposure, assess the impact of PPAs on electricity prices and social welfare, and identify contracting strategies that are beneficial for the strategic producer while considering their broader market effects.

The problem is implemented through a bilevel optimization framework that simultaneously represents the producer's contracting decision and the market response. The mathematical formulation of this framework is presented in detail in Section 3.2.3.

3.1.2 Analysis Metrics

The impact of different PPA contracting strategies is evaluated through a set of economic and market indicators that capture both the performance of the strategic producer and the broader effects on the electricity market.

Strategic profit is the primary indicator used to assess the attractiveness of a given contracting strategy from the perspective of the renewable producer. It includes revenues obtained through PPA contracts and spot market participation, net of production costs, and reflects the trade-off between revenue stability and market exposure.

Spot market prices are analysed to evaluate how different levels of PPA participation influence price formation in the electricity market. Since market prices affect both producer revenues and consumer costs, they provide an important measure of the broader market impact of contracting decisions.

Production quantities and generation allocation are used to examine how the strategic producer distributes its energy between PPA commitments and spot market sales, as well as how this decision affects overall market dispatch. These indicators provide insights into the operational consequences of different contracting strategies.

Social welfare is used as a measure of overall market efficiency. It reflects the total economic value created in the market by comparing the benefits obtained by consumers with the costs incurred by producers. Changes in social welfare help identify whether strategic contracting decisions improve or reduce the efficiency of market outcomes.

The distribution of economic surplus among market participants is also analysed. In particular, consumer surplus, producer surplus, and the surplus obtained by the strategic producer are examined to understand how the benefits and costs associated with different PPA penetration levels are shared across the market.

Together, these metrics provide a comprehensive framework for evaluating the economic implications of long-term contracting decisions and for identifying the trade-offs between producer profitability, market performance, and overall welfare.

3.2 Solution Design

3.2.1 Hypothesis

Fixed-Price PPA Structure

The primary objective is to analyse the interaction between long-term contracting decisions, strategic bidding behaviour, and spot market price formation. Adopting a fixed-price PPA avoids the additional complexity associated with market-indexed or hybrid pricing mechanisms, making the results easier to interpret and reducing computational requirements. Furthermore, linking the PPA price to market prices could strengthen the strategic producer's incentive to influence spot prices, potentially amplifying market impacts. By using a fixed price, the model demonstrates that significant market price effects can emerge even without these additional incentives, providing a more conservative assessment of the influence of PPAs on market outcomes.

No Demand Reduction from PPA Contracting

The model assumes that increasing the volume of energy contracted through PPAs does not reduce the demand participating in the spot market. In practice, some PPA arrangements may involve consumers that would otherwise purchase electricity through the market, creating a feedback between contracted volumes and market demand. This effect is deliberately excluded from the analysis.

Instead, PPAs are assumed to supply demand originating outside the modeled market demand, such as new industrial electrification projects, green hydrogen production facilities, or other forms of additional electricity consumption. This assumption allows the study to isolate the supply-side effects of PPAs on strategic behaviour and market outcomes without introducing demand-side feedback mechanisms.

Hourly Market Representation

An hourly resolution provides a balance between model tractability and temporal detail. It substantially reduces computational burden while still capturing the main dynamics relevant to the study. This level of aggregation is particularly suitable for solar generation, whose production profile is strongly driven by hourly variations. Consequently, the hourly representation retains the most relevant operational information while keeping the model manageable.

Single PPA Percentage for the Entire Horizon

This assumption reflects the long-term nature of PPAs, which are typically negotiated as multi-year agreements rather than being adjusted frequently on a daily, weekly, or monthly basis. Maintaining a constant contracted share allows the model to focus on the fundamental trade-off between revenue stability provided by the PPA and participation in the spot market, which is one of the key questions of interest in the analysis.

One-Year Simulation Horizon

Limiting the analysis to one year simplifies the formulation and computational requirements while still capturing seasonal variations in demand, renewable generation, and market conditions. The modelling framework could be extended to multiple years without major structural changes. However, the current formulation assumes a single PPA coverage percentage across the entire horizon and is therefore not designed to represent year-specific contracting decisions.

Single Strategic Producer

The inclusion of multiple strategic agents would significantly increase the complexity of the problem, requiring the analysis of strategic interactions among several market participants. By focusing on a single strategic producer, the model remains tractable while allowing a clear assessment of how PPA commitments influence the bidding behaviour and market impact of a strategic market participant.

No Network Constraints

The purpose of the study is to investigate the relationship between PPAs, strategic bidding, and market price formation rather than the influence of transmission limitations. Excluding network constraints simplifies the market-clearing process and allows the analysis to focus directly on the economic effects of contracting decisions without introducing additional spatial and operational complexities.

Perfect Information (No Uncertainty)

The model adopts a deterministic framework in which all demand and production values are perfectly forecasted. This assumption eliminates the need to model forecast errors and stochastic processes, allowing the analysis to isolate the fundamental effects of PPAs on producer behaviour and market outcomes. Consequently, the results can be interpreted without the confounding influence of uncertainty, providing a clearer understanding of the mechanisms under investigation.

3.2.2 Proposed Approach

The solution employs a linear programming approach to solve the bilevel optimization problem by reformulating it as a single-level Mixed Integer Linear Programming (MILP) problem. The key insight is to replace the lower-level problem with their KKT conditions and linearize them.

The approach consists of two main components:

1. **Market Clearing Solver (Lower Level):** Solves a competitive electricity market without strategic behavior to establish a baseline and provide a mechanism for extracting market-clearing prices. The market clering mechanism is simple and does not take into account the network distribution or other technical factors.

2. **Bilevel Strategic Solver (Upper + Lower Levels):** Embeds the KKT conditions of the market clearing problem into the upper-level optimization, allowing the strategic agent to simultaneously decide its PPA percentage and account for the market's equilibrium response.

3.2.3 Mathematical formulation

Market Clearing Model (Lower Level)

The market clearing problem is a linear optimization program that maximizes total social welfare (consumer utility minus production costs):

Sets:

- $j \in J$: Set of generators (producers)
- $l \in L$: Set of consumers (demand nodes)
- $t \in T$: Set of time periods (hours)

Parameters:

- $\alpha_{j,t}$: Marginal production cost (or offer price) of generator j at hour t [€/MWh]
- $\beta_{l,t}$: Maximum willingness to pay (demand utility) for consumer l at hour t [€/MWh]
- $Q_{j,t}$: Maximum production capacity of generator j at hour t [MW]
- $D_{l,t}$: Maximum demand that can be served to consumer l at hour t [MW]

Variables:

- $q_{j,t}$: Production quantity of generator j at hour t [MW]
- $d_{l,t}$: Consumption quantity of consumer l at hour t [MW]

Objective function and constraints:

$$\max_{q,d} \quad \sum_{l,t} \beta_{l,t} d_{l,t} - \sum_{j,t} \alpha_{j,t} q_{j,t} \tag{3.1}$$

$$\text{s.t.} \quad \sum_{j} q_{j,t} = \sum_{l} d_{l,t} \quad (\perp \lambda_t) \quad \forall t \tag{3.2}$$

$$q_{j,t} \geq 0 \quad (\perp \omega_{j,t}^{q,\min}) \quad \forall j, t \tag{3.3}$$

$$q_{j,t} \leq Q_{j,t} \quad (\perp \omega_{j,t}^{q,\max}) \quad \forall j, t \tag{3.4}$$

$$d_{l,t} \geq 0 \quad (\perp \omega_{l,t}^{d,\min}) \quad \forall l, t \tag{3.5}$$

$$d_{l,t} \leq D_{l,t} \quad (\perp \omega_{l,t}^{d,\max}) \quad \forall l, t \tag{3.6}$$

The notation $\perp$ indicates the dual variable associated with each constraint:

The dual variable λ_t of the power balance constraint (3.2) represents the marginal cost of energy at hour t, which is the market-clearing price for that hour. So this price emerges from the equilibrium condition, which will be useful when formulating the bilevel problem.

Similarly, $\omega_{j,t}^{q,\min}$, $\omega_{j,t}^{q,\max}$, $\omega_{l,t}^{d,\min}$, and $\omega_{l,t}^{d,\max}$ are the shadow prices capturing how much the social welfare would improve if capacity or demand limits were relaxed.

Bilevel Strategic Optimization with KKT Reformulation (Upper level)

The strategic agent maximizes its own profit by deciding the PPA fraction x_i through a combination of three benefit components. Spot market revenue is generated from selling the remaining production at the market-clearing price: $\sum_t \lambda_t \cdot q_{i,t}$. PPA revenue comes from the long-term contracts at fixed prices: $\sum_t \gamma \cdot x_i \cdot Q_{i,t}$. Finally, production costs reduce the total benefit: $\sum_t \alpha_{i,t} \cdot (q_{i,t} + x_i Q_{i,t})$, where costs apply to both the spot and PPA portions. The key variables and parameters are the market price λ_t which depends on the choice of x_i through market equilibrium, spot production $q_{i,t}$ (which is equal to $(1 - x_i)Q_{i,t}$ if fully dispatched), the fixed PPA price γ, and the production cost $\alpha_{i,t}$.

The fundamental challenge is that the market price λ_t is not exogenous, meaning it is not given or fixed from outside the model. Instead, it is endogenous: it depends on the strategic agent's choice of x_i and is determined as part of the solution. When the agent increases its PPA percentage x_i, three effects emerge. First, available spot capacity decreases according to $Q'_{i,t} = (1 - x_i)Q_{i,t}$, thus reducing supply. Second, the market price likely increases due to fewer sellers in the spot market. Third, the agent's spot revenue may increase or decrease depending on whether the price increase outweighs the reduction in quantities sold. In summary, it creates a complex optimization problem because committing capacity to the PPA changes both the guaranteed contract revenues and the profits that could otherwise be earned in the spot market. In order to capture this feedback loop, the market's equilibrium conditions (KKT) must be embedded into the upper-level problem as constraints, creating a single optimization that simultaneously determines the strategic decision and the market equilibrium.

The formulation is as follows:

Additional Sets:

- i: The strategic renewable energy producer (upper-level agent)

Additional Parameters:

- γ: Fixed PPA (Power Purchase Agreement) price [€/MWh]

Additional Variables:

- x_i: PPA fraction (percentage of capacity committed to long-term contracts) for strategic agent i [dimensionless, $0 \leq x_i \leq 1$]

- λ_t: Market-clearing price (dual variable of power balance constraint) at hour t [€/MWh]
- $\omega^{q,\min}_{j,t}$: Shadow price for lower production bound of generator j at hour t [€/MWh]
- $\omega^{q,\max}_{j,t}$: Shadow price for upper production bound of generator j at hour t [€/MWh]
- $\omega^{d,\min}_{l,t}$: Shadow price for lower demand bound of consumer l at hour t [€/MWh]
- $\omega^{d,\max}_{l,t}$: Shadow price for upper demand bound of consumer l at hour t [€/MWh]

Objective function and constraints:

$$\begin{aligned}
\max_{x,q,d,\omega,\lambda} \quad & \sum_t \left[(\lambda_t - \alpha_{i,t})q_{i,t} + (\gamma - \alpha_{i,t})x_i Q_{i,t}\right] && (3.7)\\
\text{s.t.} \quad & 0 \le x_i \le 1 && (3.8)\\
& Q_{i,t}(1 - x_i) - q_{i,t} \ge 0 && (3.9)\\
& \textbf{KKT Conditions of the Lower Level:} && (3.10)\\
& \quad \text{(1) Primal Feasibility: Market constraints} && (3.11)\\
& \quad \text{(2) Dual Feasibility: } \omega \ge 0, \quad \lambda \in \mathbb{R} && (3.12)\\
& \quad \text{(3) Complementarity: } \omega \perp \text{(slack of capacity constraints)} && (3.13)\\
& \quad \text{(4) Stationarity: First-Order Conditions (FOCs) of market Lagrangian} && (3.14)
\end{aligned}$$

KKT Conditions of the Lower Level

For the bilevel formulation to be valid, the strategic agent must solve the lower-level market clearing problem optimally. Since the lower-level problem is a linear program, its optimality is characterized by the Karush-Kuhn-Tucker (KKT) conditions. These conditions are embedded as constraints in the upper-level bilevel problem.

(1) Primal Feasibility:

The primal feasibility constraints are the market clearing constraints themselves:

$$\text{Equations (3.2), (3.3), (3.4), (3.5), (3.6)} \tag{3.15}$$

(2) Dual Feasibility:

All dual variables associated with inequality constraints must be non-negative. A distinction is made between dual variables for lower and upper bound constraints:

Production constraints:

$$\begin{aligned}
\omega^{q,\min}_{j,t} &\ge 0 \quad \forall j,t \quad \text{(dual for lower bound: } q_{j,t} \ge 0) && (3.16)\\
\omega^{q,\max}_{j,t} &\ge 0 \quad \forall j,t \quad \text{(dual for upper bound: } q_{j,t} \le Q_{j,t}) && (3.17)
\end{aligned}$$

Demand constraints:

$$\begin{aligned}
\omega^{d,\min}_{l,t} &\ge 0 \quad \forall l,t \quad \text{(dual for lower bound: } d_{l,t} \ge 0) && (3.18)\\
\omega^{d,\max}_{l,t} &\ge 0 \quad \forall l,t \quad \text{(dual for upper bound: } d_{l,t} \le D_{l,t}) && (3.19)
\end{aligned}$$

The dual variable λ_t associated with the equality constraint (power balance) is unrestricted in sign: $\lambda_t \in \mathbb{R}$.

(3) Complementary Slackness:

For each constraint, either the constraint is binding (tight) or its dual variable is zero:

$$\omega_{j,t}^{q,\max}(Q_{j,t} - q_{j,t}) = 0 \quad \forall j, t \tag{3.20}$$

$$\omega_{j,t}^{q,\min} \cdot q_{j,t} = 0 \quad \forall j, t \tag{3.21}$$

$$\omega_{l,t}^{d,\max}(D_{l,t} - d_{l,t}) = 0 \quad \forall l, t \tag{3.22}$$

$$\omega_{l,t}^{d,\min} \cdot d_{l,t} = 0 \quad \forall l, t \tag{3.23}$$

These conditions encode the logic: if a constraint is not binding (has slack), its dual variable must be zero; conversely, only binding constraints can have nonzero dual variables.

(4) Stationarity (First-Order Optimality Conditions):

The gradient of the Lagrangian with respect to the primal variables must equal zero at optimality:

$$\alpha_{j,t} - \lambda_t - \omega_{j,t}^{q,\min} + \omega_{j,t}^{q,\max} = 0 \quad \forall j, t \tag{3.24}$$

$$-\beta_{l,t} + \lambda_t - \omega_{l,t}^{d,\min} + \omega_{l,t}^{d,\max} = 0 \quad \forall l, t \tag{3.25}$$

These can be rearranged to express the market-clearing price λ_t in equilibrium:

$$\lambda_t = \alpha_{j,t} - \omega_{j,t}^{q,\min} + \omega_{j,t}^{q,\max} \quad \forall j, t \tag{3.26}$$

$$\lambda_t = \beta_{l,t} + \omega_{l,t}^{d,\min} - \omega_{l,t}^{d,\max} \quad \forall l, t \tag{3.27}$$

The interpretation is that the market price must equal the marginal cost (for producers) and marginal utility (for consumers), adjusted by the shadow prices of capacity and demand constraints. This will be useful when linearizing the objective function.

When both shadow prices are inactive ($\omega_{j,t}^{q,\min} = 0$ and $\omega_{j,t}^{q,\max} = 0$), the stationarity condition simplifies to $\lambda_t = \alpha_{j,t}$, meaning the market price equals the marginal cost of that generator. This occurs when the generator is neither hitting its lower bound (production is positive) nor its upper capacity bound (it could produce more if needed). In a competitive market context, this aligns with the marginal generator, which is the one with the highest production cost that is still needed to satisfy demand. Similarly, for consumers with both shadow prices at zero, the price equals their willingness to pay, reflecting the marginal consumer in demand.

Big-M Linearization of Complementarity Conditions

Complementarity conditions express the fundamental trade-off in optimization: for each constraint, either the constraint is binding (tight) or the dual variable is zero. Mathematically, this is expressed as $\omega \cdot (Q - q) = 0$, which reads: "Either the generator is producing at full capacity ($Q - q = 0$), OR the shadow price is zero ($\omega = 0$), or both." The product $\omega \cdot (Q - q) = 0$ cannot be directly included in a linear solver because it is inherently nonlinear. To overcome this, complementarity conditions are linearized using binary variables and the big-M technique. For each complementarity condition, a binary variable $z \in \{0, 1\}$ is introduced and the condition reformulated as: $\omega \leq M \cdot (1 - z)$ and $(Q - q) \leq M \cdot z$. This encodes the same logic: either $z = 0$ (allowing $\omega > 0$ but forcing $Q = q$) or $z = 1$ (forcing $\omega = 0$ but allowing slack in $Q - q$).

This linearization is applied separately to each bound of each constraint. For generators and consumers, four complementarity conditions must be linearized: lower bound and upper bound constraints for both primal feasibility and dual variables. The implementation introduces binary variables $z_{j,t}^{q,\min}$, $z_{j,t}^{q,\max}$, $z_{l,t}^{d,\min}$, and $z_{l,t}^{d,\max}$ for production and demand, respectively. For each pair of bounds (lower and upper), two big-M constraints are created: one for the dual variable and one for the slack of the primal constraint.

Selection of Big-M Values

The parameter M must be chosen carefully to balance two competing objectives. It must be sufficiently large to avoid artificially restricting the feasible region and cutting off valid solutions, yet not so large that it causes numerical instability and poor linear programming relaxations that slow solver convergence. Eventough th strategy that is explained below looks for a solid bound, a $m_{\text{multiplier}}$ is set to give extra room for numerical stability.

For primal constraints involving capacities and demand, the value is set as $M^{\text{primal}} = \max_t(Q_{j,t}) \times m_{\text{multiplier}}$ and $M^{\text{primal}} = \max_t(D_{l,t}) \times m_{\text{multiplier}}$. The upper bound of any production or consumption variable is naturally the maximum capacity or demand, so using this as M ensures that the constraint $(Q - q) \leq M \Rightarrow q \geq Q - M$ is automatically satisfied for non-negative production. A multiplier of 1.2 is applied to add a 20% margin that accounts for numerical solver tolerances and rounding, preventing edge cases where constraints might be violated due to floating-point arithmetic.

For dual constraints involving shadow prices, the value is $M^{\text{dual}} = \max(\text{all offers}) \times m_{\text{multiplier}}$, where offers include both generator marginal costs $\alpha_{j,t}$ and consumer willingness-to-pay values $\beta_{l,t}$. Shadow prices ω represent the value of relaxing a constraint, and economically this cannot exceed the maximum price in the system (otherwise the system would imply unlimited willingness to pay for energy, which is economically irrational). Using $M^{\text{dual}} = \max(\text{prices}) \times 1.2$ ensures this bound is respected while adding numerical safety margin.

Big-M Formulation in the Bilevel Solver

The implementation linearizes four complementarity conditions for each generator and consumer at each hour:

For generators (production constraints):

- **Lower bound ($q_{j,t} \geq 0$):** Introduces binary variable $z_{j,t}^{q,\min}$ with constraints:

$$\omega_{j,t}^{q,\min} \leq M^{\text{dual}} \cdot (1 - z_{j,t}^{q,\min}) \tag{3.28}$$

$$q_{j,t} \leq M^{\text{primal}} \cdot z_{j,t}^{q,\min} \tag{3.29}$$

- **Upper bound ($q_{j,t} \leq Q_{j,t}$):** Introduces binary variable $z_{j,t}^{q,\max}$ with constraints:

$$\omega_{j,t}^{q,\max} \leq M^{\text{dual}} \cdot (1 - z_{j,t}^{q,\max}) \tag{3.30}$$

$$Q_{j,t} - q_{j,t} \leq M^{\text{primal}} \cdot z_{j,t}^{q,\max} \tag{3.31}$$

  where $Q_{j,t}$ is adjusted to $Q_{j,t}(1 - x_i)$ for the strategic agent i when solving the bilevel problem with a PPA percentage.

For consumers (demand constraints):

- **Lower bound ($d_{l,t} \geq 0$):** Introduces binary variable $z_{l,t}^{d,\min}$ with constraints:

$$\omega_{l,t}^{d,\min} \leq M^{\text{dual}} \cdot (1 - z_{l,t}^{d,\min}) \tag{3.32}$$

$$d_{l,t} \leq M^{\text{primal}} \cdot z_{l,t}^{d,\min} \tag{3.33}$$

- **Upper bound ($d_{l,t} \leq D_{l,t}$):** Introduces binary variable $z_{l,t}^{d,\max}$ with constraints:

$$\omega_{l,t}^{d,\max} \leq M^{\text{dual}} \cdot (1 - z_{l,t}^{d,\max}) \tag{3.34}$$

$$D_{l,t} - d_{l,t} \leq M^{\text{primal}} \cdot z_{l,t}^{d,\max} \tag{3.35}$$

The big-M parameters are computed dynamically in the solver following the strategy explained before:

- $M^{\text{dual}} = \max(\text{all offers}) \times m_{\text{multiplier}}$, where $m_{\text{multiplier}} = 1.2$

- $M^{\text{primal}} = \max_t(Q_{j,t}) \times m_{\text{multiplier}}$ for generators and $M^{\text{primal}} = \max_t(D_{l,t}) \times m_{\text{multiplier}}$ for consumers

This linearization introduces a total of $4 \times |J| \times |T| + 4 \times |L| \times |T|$ binary variables and an equal number of constraint pairs. With typical problem sizes (7 generators, 3 consumers, 8,760 hours), this results in approximately $8,760 \times (4 \times 7 + 4 \times 3) = 414,720$ binary variables, representing the primary source of computational complexity. The MILP solver handles these through branch-and-bound algorithms, while the data driven estimation of big-M parameters helps maintain computational efficiency and convergence.

Linearization of the Objective Function

The bilevel objective function contains a non-linear term: $(\lambda_t - \alpha_{i,t})q_{i,t}$, where both λ_t (market price) and $q_{i,t}$ (quantity) are variables. To convert this into a linear program solvable by MILP solvers, the KKT conditions are exploited.

Step 1: Original Objective Function

The original upper-level objective is:

$$\max_{x,q,d,\omega,\lambda} \quad \sum_t [(\lambda_t - \alpha_{i,t})q_{i,t} + (\gamma - \alpha_{i,t})x_i Q_{i,t}] \tag{3.36}$$

And the non-linear term is:

$$(\lambda_t - \alpha_{i,t})q_{i,t} \tag{3.37}$$

Step 2: Apply Stationarity Condition from KKT

The stationarity (first-order optimality) condition for the strategic agent i is given by equation (3.24):

$$\alpha_{i,t} - \lambda_t - \omega_{i,t}^{q,\min} + \omega_{i,t}^{q,\max} = 0 \tag{3.38}$$

Rearranging to isolate λ_t:

$$\lambda_t = \alpha_{i,t} - \omega_{i,t}^{q,\min} + \omega_{i,t}^{q,\max} \tag{3.39}$$

Step 3: Substitute λ_t into the Objective

Replacing λ_t in the non-linear term:

$$(\lambda_t - \alpha_{i,t})q_{i,t} = \left(\alpha_{i,t} - \omega_{i,t}^{q,\min} + \omega_{i,t}^{q,\max} - \alpha_{i,t}\right) \cdot q_{i,t} \tag{3.40}$$

$$= -\omega_{i,t}^{q,\min} q_{i,t} + \omega_{i,t}^{q,\max} q_{i,t} \tag{3.41}$$

The production cost term $\alpha_{i,t}q_{i,t}$ cancels out completely.

Step 4: Apply Complementarity Conditions

Two complementarity conditions are now applied:

From equation (3.21), the complementarity condition for the lower production bound states:

$$\omega_{i,t}^{q,\min} \cdot q_{i,t} = 0 \tag{3.42}$$

This means the product is always zero; therefore: $-\omega_{i,t}^{q,\min} q_{i,t} = 0$.

From equation (3.20), the complementarity condition for the upper production bound states:

$$\omega_{i,t}^{q,\max}(Q_{i,t} - q_{i,t}) = 0 \tag{3.43}$$

Expanding and rearranging:

$$\omega_{i,t}^{q,\max} Q_{i,t} - \omega_{i,t}^{q,\max} q_{i,t} = 0 \tag{3.44}$$

$$\omega_{i,t}^{q,\max} q_{i,t} = \omega_{i,t}^{q,\max} Q_{i,t} \tag{3.45}$$

Step 5: Substitute Complementarity Results
Inserting the complementarity results into the expression:

$$\lambda_t \cdot q_{i,t} = \alpha_{i,t} q_{i,t} - 0 + \omega_{i,t}^{q,\max} Q_{i,t} \tag{3.46}$$

$$= \alpha_{i,t} q_{i,t} + \omega_{i,t}^{q,\max} Q_{i,t} \tag{3.47}$$

$$(\lambda_t - \alpha_{i,t}) q_{i,t} = -\omega_{i,t}^{q,\min} q_{i,t} + \omega_{i,t}^{q,\max} q_{i,t} \tag{3.48}$$

$$= \omega_{i,t}^{q,\max} Q_{i,t} \tag{3.49}$$

Step 6: Final Linear Objective
The complete objective function becomes:

$$\max \quad \sum_t \left[\omega_{i,t}^{q,\max} Q_{i,t} + (\gamma - \alpha_{i,t}) x_i Q_{i,t} \right] \tag{3.50}$$

This can be rewritten as:

$$\max \quad \sum_t Q_{i,t} \left[\omega_{i,t}^{q,\max} + (\gamma - \alpha_{i,t}) x_i \right] \tag{3.51}$$

Interpretation of the Linearized Form
The linearization reveals two key insights:

1. **Shadow Price Effect:** The first term $\omega_{i,t}^{q,\max} Q_{i,t}$ is the total value of the upper production bound constraint for the strategic agent. When the capacity constraint is binding ($Q_{i,t} = q_{i,t}$), the shadow price $\omega_{i,t}^{q,\max}$ represents how much additional profit would result from relaxing this constraint (producing one more unit).

2. **PPA Revenue Effect:** The second term $(\gamma - \alpha_{i,t}) x_i Q_{i,t}$ is the direct profit from PPA contracts. The difference $(\gamma - \alpha_{i,t})$ is the margin between the PPA price and production cost, scaled by the PPA fraction x_i and capacity.

3. **Spot Market Implicit in Shadow Prices:** The non-linear term $\lambda_t \cdot q_{i,t}$ (spot market revenue) does not appear explicitly in the final objective. Instead, its effect is encoded through the shadow price $\omega_{i,t}^{q,\max}$, which measures the opportunity cost of capacity committed to the PPA. This is economically intuitive: higher capacity prices (higher $\omega_{i,t}^{q,\max}$) mean the spot market is more valuable, creating an incentive to reduce the PPA percentage x_i.

This linearization is the key mechanism that transforms the bilevel problem (which contains the KKT conditions of the lower level) from a nonconvex, nonlinear formulation into a Mixed Integer Linear Program solvable by commercial solvers like Gurobi.

3.2.4 System Architecture

The software is organized using a modular layered architecture to promote maintainability, extensibility, and separation of concerns. The system is divided into four primary components: data management, market clearing optimization, bilevel strategic optimization, and result visualization.

The Data Module (`data.py`) is responsible for loading, preprocessing, and storing market and profile data. It provides standardized data structures used throughout the optimization workflow.

The Market Solver Module (`market/solver.py`) implements the lower-level market-clearing problem and computes equilibrium quantities and prices under different PPA configurations.

The Bilevel Solver Module (`bilevel/solver.py`) implements the strategic optimization model using a KKT reformulation of the lower-level market equilibrium problem.

Visualization and reporting functionalities are separated into dedicated modules (`market/visualizer.py`, `bilevel/visualizer.py`, and `latex_gen.py`), which generate plots and formatted result tables for scenario comparison and analysis.

Finally, the Configuration Module (`configuration.py`) stores the main settings of the project, such as directory paths and solver parameters, making it easy to change experiments without modifying the core code. The `main.py` module manages the execution flow of the project, including data generation, solver execution, visualization, and result export.

3.2.5 Data Sets

The implementation processes electricity market data from two complementary sources. Market Estimations (`market_data.json`) provide base data containing generator and demand specifications with profiles and price ranges that define the market structure. Historical Profiles (`esios_profiles_processed2023.csv`) provide hourly generation and demand profiles used to normalize and scale the base estimations, ensuring realistic temporal variability. These data were provided by the IIT and are based on information obtained from ESIOS, the electricity system information platform operated by Red Eléctrica de España (REE) (`https://www.esios.ree.es/es`).

The data pipeline creates multiple estimation sets for different solar percentages (0%, 1%, 5%, 10%, 20%, 50%, 100%) managed by the strategic agent, facilitating a thorough analysis of how increasing market power influences market outcomes. Furthermore, there are additional test sets designed to facilitate explanation of the methodology and verification of the correct behaviour of the model.

3.2.6 Technical Justification

Choice of Bilevel Formulation

The bilevel approach is chosen because it captures the strategic behavior of a renewable generator in a market context. The resulting framework can also be interpreted as a Stackelberg game, where the strategic renewable producer acts as the leader by selecting the optimal PPA percentage, while the market-clearing process represented in the lower level acts as the follower and responds through equilibrium prices and dispatch decisions. The lower level ensures market-clearing prices reflect true equilibrium conditions rather than exogenous assumptions, while the upper level allows the strategic agent to exploit this equilibrium by choosing optimal PPA percentages. This formulation avoids assuming fixed prices and explicitly captures the bidirectional interaction between the strategic decision and market outcomes: when the agent changes its PPA percentage, market prices adjust, which in turn affects the agent's profits. Therefore, the solution corresponds to a Stackelberg equilibrium in which the leader anticipates the follower's optimal response.

Use of KKT Reformulation

The KKT reformulation is employed to solve the bilevel optimization problem for several compelling reasons. The KKT approach embeds the lower-level optimality conditions directly into the upper level, enabling a single integrated solve rather than iterative sequential optimization. From a mathematical perspective, this approach is well justified because the lower-level problem is a convex linear program, for which the KKT conditions are both necessary and sufficient for global optimality. Therefore, enforcing the primal constraints together with the KKT conditions guarantees that the lower level is solved optimally for any choice of upper-level variables.

Additionally, the KKT formulation captures equilibrium effects by allowing the upper-level agent to optimize while simultaneously respecting market-clearing conditions. Strategic decisions such as increasing x_i automatically account for their impact on market prices λ_t through the embedded KKT conditions. In this sense, the reformulation provides the mathematical framework required to compute the Stackelberg equilibrium between the strategic producer and the market-clearing mechanism. Finally, solving both levels simultaneously within the same MILP framework can improve computational efficiency compared to sequential approaches by avoiding repeated lower-level solves.

Big-M Linearization

Modern MILP solvers like Gurobi are highly optimized for mixed-integer programming, but they cannot directly handle nonlinear complementarity constraints. By converting complementarity conditions into linear big-M constraints through binary variables, the problem becomes compatible with well-established MILP solution techniques. This allows the use of commercial solvers that have benefited from decades of algorithmic development in branch-and-cut, presolve, and heuristic methods, avoiding the need for custom algorithm design. In addition, MILP solvers can provide certificates of global optimality within specified tolerances, unlike heuristic approaches that may converge only to local solutions. The reformulation also enables the exploitation of parallel branch-and-bound capabilities and facilitates the extraction of economically meaningful dual variables and shadow prices from the final solution.

The main trade-off associated with this reformulation is the increase in problem size. For each complementarity condition, the linearization introduces one binary variable z and two additional linear inequality constraints. In the case study considered in this project, with 7 generators, 3 consumers, and 8,760 hourly market intervals, the reformulation results in approximately $8,760 \times (4 \times 7 + 4 \times 3) = 350,400$ binary variables. While this increases model size substantially, modern MILP solvers are generally capable of handling problems of this scale. Nevertheless, the introduced binary variables constitute the primary source of computational complexity and are a key determinant of solution time as system size increases.

Despite this increase in complexity, the big-M MILP reformulation remains a standard and well-established approach in bilevel optimization when the lower-level problem is a convex linear program. One of its main advantages is that it preserves the theoretical guarantees provided by the KKT framework, including consistency with lower-level optimality and equilibrium conditions. Alternative approaches, such as heuristic or decomposition-based methods, may reduce computational burden in some cases but generally do not provide the same guarantees of global optimality or equilibrium consistency.

Solver Selection

Gurobi is selected as the MILP solver for several well-justified reasons. It implements state-of-the-art algorithms using advanced branch-and-cut, presolve, and cutting plane generation techniques, establishing it as one of the fastest commercial MILP solvers available. Gurobi provides native dual variable extraction after solving, directly returning all dual variables (shadow prices), which is essential for this application since λ_t represents the market price needed for the agent to optimize its PPA decision. The big-M reformulation with 1000+ binary variables and tight constraints is numerically challenging, but Gurobi's robust presolve and scaling techniques handle such difficult formulations well. Configuration flexibility is extensive: Gurobi allows users to set solver timeouts (crucial for large instances), specify optimality gaps (e.g., stop if within 1% of best bound), control parallel thread usage, and adjust numerical tolerances. Finally, an academic license is available free of charge for students and academic research, making Gurobi accessible for this thesis project.

Numerical Validation and Verification Strategy

To ensure solutions are mathematically correct and economically meaningful, a comprehensive verification strategy is employed. Complementarity Satisfaction is verified by checking that binary variables z align with primal/dual activity: if $z = 0$ then $\omega \approx 0$ (tolerance: 10^{-6}), and if $z = 1$ then $(Q - q) \approx 0$ (tolerance: 10^{-6}). Violations indicate numerical issues or big-M parameters that are too tight.

KKT Conditions are verified after solving by checking power balance ($\sum_j q_{j,t} = \sum_l d_{l,t}$ for all t), verifying stationarity conditions ($-\alpha_j + \lambda_t - \omega_j^q + \omega_j^q = 0$ with tolerance), and confirming dual feasibility ($\omega \geq 0, \lambda \in \mathbb{R}$). Economic Reasonableness is ensured by verifying that prices λ_t are bounded by $[\min(\alpha), \max(\beta)]$.

In addition to formal mathematical verification, the model is validated through inspection of small test cases where expected market outcomes can be interpreted manually. In these simplified instances, outputs are checked to confirm that market clearing results are economically coherent, including accepted supply and demand offers, dispatched quantities, and resulting market prices. Furthermore, graphical inspection of market clearing results is used as a qualitative validation tool, allowing visual confirmation that dispatch and price patterns behave consistently with expected market dynamics.

3.3 Implementation

3.3.1 Technologies Used

The implementation is developed in Python 3, chosen for its extensive scientific computing ecosystem and rapid prototyping capabilities. Pyomo (Python Optimization Modeling Objects) provides the optimization modeling framework, enabling declarative problem specification that is both readable and maintainable. Gurobi serves as the commercial MILP solver, selected for its state-of-the-art algorithms and robust handling of large-scale mixed-integer problems. Data processing leverages Pandas for efficient manipulation of tabular market data and NumPy for numerical computations involving array operations. Visualization of results is handled through Matplotlib, which provides quality plotting capabilities. Version control is managed with Git, ensuring reproducibility and collaborative development.

Gurobi Optimizer requires a valid license; however, academic licenses are available free of charge through Gurobi's website for educational institutions. All other software dependencies are free and open-source.

3.3.2 Requirements

The implementation requires a multi-core CPU with at least 4 cores to leverage Gurobi's parallel branch-and-bound algorithm for efficient computation. A minimum of 16 GB RAM is necessary, with 32 GB recommended for large instances. At least 5 GB of disk space should be allocated for data, results, and solver logs. Depending on the problem size and Gurobi timeout settings, computation time varies significantly: market clearing solves are typically very fast (seconds to minutes), while bilevel optimization problems can require up to 1 hour.

In practice, this implementation was successfully executed on an 11th Gen Intel Core i7-1165G7 laptop with 4 cores (8 logical threads), 16 GB RAM, and 475 GB disk space to solve the complete problem instance: one full year of hourly data (8,760 hours) with 7 generators and 3 demand nodes. Market clearing operations on this hardware execute in seconds regardless of instance size. Bilevel optimization solves occasionally reached computational times of approximately 1 hour, depending on solver timeout settings and problem configuration. While more powerful hardware with 8+ cores and higher clock speeds will provide faster execution times, the framework is demonstrably feasible on standard laptop specifications for realistic problem instances.

3.3.3 Code Structure

The codebase is organized as follows:

```
bilevel-optm/
|-- src/
|   |-- __init__.py
|   |-- main.py               # Orchestrates execution pipeline
|   |-- configuration.py      # Solver and path configuration
|   |-- data.py               # Data loading and processing
|   |-- market/
|   |   |-- __init__.py
|   |   |-- solver.py         # Market clearing implementation
|   |   |-- visualizer.py     # Market analysis plots
|   |-- bilevel/
|   |   |-- __init__.py
|   |   |-- solver.py         # Bilevel strategic optimization
|   |   |-- visualizer.py     # Bilevel analysis plots
|   |   |-- latex_gen.py      # Bilevel latex tables generator
|-- data/
|   |-- base_estimations/     # JSON market data
|   |-- profiles/             # CSV historical profiles
|   |-- estimations/          # Processed input files
|   |-- solved_estimations/   # Solution outputs
|-- images/                   # Generated plots
|-- requirements.txt
|-- README.md
```

3.3.4 Key Implementation Details

This section summarises how the mathematical models are implemented using Pyomo and Gurobi, focusing on data handling, model construction, and result processing.

Data Processing (`data.py`)

The `DataProcessor` class loads market inputs from JSON files and historical profiles from CSV files. Hourly profiles are normalised to match annual energy values and then split into owned and non-owned solar components based on the specified ownership share. The resulting structured dataframes contain all inputs required by the optimisation models, including capacities, demand profiles, and offer data.

Market Clearing Solver (`market/solver.py`)

The market-clearing model is implemented as a Pyomo `ConcreteModel` with standard sets, variables, and constraints for production, consumption, and power balance. The objective maximises social welfare.

For PPA scenarios, the available capacity of the strategic generator is adjusted before solving. After optimisation, dual variables from the power balance constraint are extracted and used as market prices.

Bilevel Strategic Solver (`bilevel/solver.py`)

The bilevel model is implemented as a single MILP in Pyomo. It includes primal and dual variables and uses a big-M formulation with binary variables to handle complementarity conditions.

All optimality conditions are encoded directly as algebraic constraints, and the resulting model is solved using Gurobi with a configurable time limit.

Visualization and Result Export

Results are automatically collected by scanning the output directory structure of solved scenarios. Visualization modules generate comparison plots across cases, while the `LatexTableGenerator` produces summary tables of key metrics such as profits, runtimes, and optimal decisions.

3.3.5 Processing Pipeline

The execution pipeline consists of four main stages.

First, input data is prepared by loading and normalising market and profile data, and generating scenarios with different strategic solar market shares.

Second, the market-clearing model is solved for each scenario to obtain equilibrium prices and quantities.

Third, the bilevel optimisation model is solved for selected scenarios and PPA values to determine optimal strategic decisions and resulting market outcomes.

Finally, results are post-processed to generate plots, comparisons, and summary tables for analysis.

3.3.6 Reproducibility

To reproduce all results:

```
# Install dependencies
pip install -r requirements.txt

# Ensure Gurobi is installed and licensed
# (see Gurobi documentation for installation and licensing)

# Run the complete pipeline
python -m src.main

# To configure solver parameters, edit:
# src/configuration.py
# - ExecutionConfiguration.SOLVER_TIMEOUT_SECONDS
# - ExecutionConfiguration.M_MARGIN_MULTIPLIER

# You can change the execution flow by modifying the function calls in:
# src/main.py
# For example, you can replace or reorder the calls to different "main"
# functions from other modules/files to run specific parts of the pipeline.

# Results are saved to:
# data/solved_estimations/   # Solution data
# images/                    # Generated plots
```

Chapter 4

Results

This chapter presents the validation of the model and the main results obtained from the different scenarios considered in the study. The objective is not only to report the numerical results, but also to explain their economic implications and the mechanisms that drive the observed behaviour. In particular, the chapter analyses how the strategic producer's share of total solar generation and different PPA pricing levels affect profitability, market prices, social welfare, and computational performance. A key aspect of the analysis is the influence that the strategic producer can exert on market outcomes. As the share of total solar generation controlled by the strategic producer increases, its ability to affect market prices and dispatch decisions also grows, which explains much of the nonlinear behaviour observed in the results.

4.1 Case Study

Input data comprise a set of generators and demand sources. The case study considers four deterministic scenarios that differ only in the proportion of the system's total Solar PV generation assigned to the strategic producer. Specifically, the strategic producer controls 1%, 5%, 10%, or 20% of the total Solar PV generation available in the system, while the remaining Solar PV generation is owned by non-strategic producers. The total Solar PV generation capacity in the system remains unchanged across all scenarios; only its ownership distribution is modified. Demand, generation capacities, production cost assumptions, offer and bid prices, and temporal generation profiles remain identical across all scenarios, allowing the impact of increasing concentration of Solar PV ownership to be isolated. Tables 4.1 and 4.2 present the input data corresponding to the representative 20% ownership scenario used throughout the chapter for illustration purposes.

Each generator is described by its technology type, an annual energy estimate (`annual_gwh`), a price range (`min_price / max_price`), and a temporal profile key. For both producers and consumers, the offer or bid price used in the market-clearing process is set equal to the midpoint of the specified price range, in other words the average of `min_price` and `max_price`. Historical hourly profiles (`esios_profiles_processed2023.csv`) are used to transform annual energy estimates into hourly availability: the chosen profile is scaled so that its yearly sum equals the entity's `annual_gwh`. The peak hourly values reported in the tables are therefore the maximum instantaneous hourly generation after scaling, expressed in MW.

Table 4.1: Demand input data for 2030.

Source	Commodity	Annual (GWh)	Peak (MW)	Profile
Direct Market	Elec	51250.00	7777	DemandDirect
H2 production	Elec	10000.00	1500	gas_pipeline_norm
Retailer	Elec	231909.00	49503	DemandCommercial

Table 4.2: Generators input data for 2030 (20% own solar).

Entity	Type	Annual (GWh)	Peak (MW)	Profile	Strategic
Biomass/Biogas	Thermal	8000.91	913	flat	No
CCGT	Thermal	20155.30	2301	flat	No
Nuclear	Nuclear	35176.02	4015	flat	No
Reservoir Hydro	Hydro	11001.26	1256	flat	No
Run-of-river Hydro	RES	16500.00	15718	hydro	No
Solar PV	RES	90729.39	36452	solar_pv	No
Solar PV (Own)	RES	22682.35	9113	solar_pv	Yes
Wind (On+Offshore)	RES	113188.74	32094	wind_onshore	No

The strategic agent considered in the experiments is a Solar PV producer, represented in the model by the entity `Solar PV (Own)`. In each scenario, this producer may commit part of its available generation to Power Purchase Agreements (PPAs), while the remaining generation is offered in the spot market. The four ownership-share scenarios (1%, 5%, 10%, and 20% of total Solar PV generation) represent increasing levels of market concentration and, consequently, increasing ability of the strategic producer to influence market outcomes.

As a reference point, a baseline case is defined by setting the PPA allocation to 0%, meaning that all generation is sold through the spot market. This represents the situation in which the producer does not participate in the PPA market. Under these conditions, the bilevel formulation reduces to the lower level market clearing problem, which is solved independently. Results from the strategic scenarios are compared against this baseline to isolate the impact of strategic PPA contracting on market outcomes.

Figure 4.1 shows the scaled Solar PV generation profile during the first week of the year. The figure highlights the strong diurnal pattern of solar production, with generation concentrated during daylight hours and falling to zero overnight. This temporal variability implies that the economic value of generation depends not only on the total amount of energy produced but also on when it is available. Consequently, the timing of generation plays an important role in determining the profitability of different contracting strategies, motivating the analysis of PPA allocation while considering an hourly market.

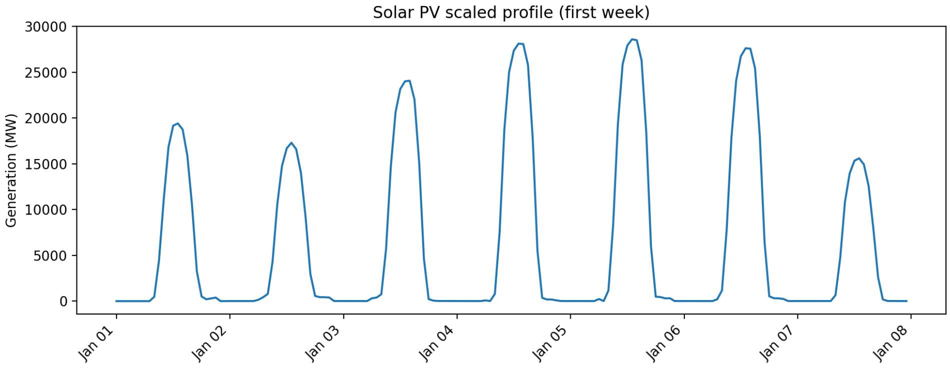


Figure 4.1: Solar PV production profile during the first week of the year

4.2 Solution Validation

4.2.1 Experimental Configuration

The model was implemented in Pyomo and solved using Gurobi. Simulations were performed using hourly demand and generation profiles over a full year horizon, allowing both seasonal effects and short term variability to be captured. All experiments use the input data described in the previous section.

4.2.2 Evaluation Protocol

The experiments are designed as a deterministic sensitivity analysis rather than as a stochastic or Monte Carlo study. The objective is to isolate and quantify the impact of changes in Solar PV ownership concentration and PPA contracting decisions while keeping all other model inputs fixed.

The results are evaluated relative to the baseline case defined in the previous section. Producer profit, market prices, social welfare, and computational performance are used as the main performance indicators. By comparing outcomes across the different test cases, it is possible to assess how sensitive market outcomes are to variations in Solar PV ownership concentration and PPA contracting conditions.

4.3 Results Analysis

4.3.1 Main Results

Figure 4.2 provides a useful overview of the strategic producer's optimal contracting behaviour across all scenarios. The figure shows how the optimal PPA share changes as the PPA price increases for different levels of strategic ownership of the solar fleet. Note that the PPA price range considered is not identical for all ownership levels. For each scenario, the analysis was focused on the range of PPA prices over which the optimal PPA allocation changes. Once the optimal solution reached either 0% or 100% PPA allocation and remained unchanged, additional PPA price values outside that range were not evaluated.

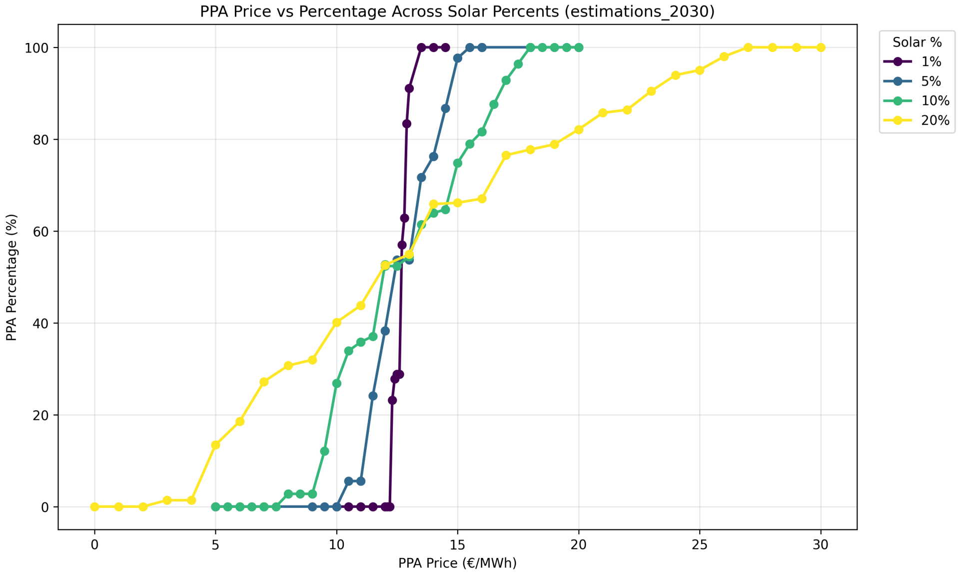


Figure 4.2: PPA percentage as a function of PPA price for all solar penetration scenarios.

For producers with a small market share, the response is almost binary: the optimal solution remains close to either 0% or 100% PPA participation, with only a narrow transition region between the two extremes. In contrast, larger strategic producers exhibit a much wider transition range. As the share of solar generation controlled by the strategic producer increases, the producer gains greater influence over market outcomes and therefore faces a more complex trade-off between selling energy through PPAs and retaining exposure to the spot market. Instead of switching abruptly between contracting and market participation, the producer gradually adjusts the contracted share over a broader range of PPA prices.

An important observation is that, for all strategic ownership levels considered in this study, a PPA price of 0 €/MWh never leads to a positive PPA allocation. In other words, the producer does not benefit from withdrawing generation from the market solely to increase spot prices. This suggests that, within the range of ownership shares analysed, the market power of the strategic producer is insufficient to make pure output withholding profitable. Although such behaviour could theoretically emerge for substantially larger ownership shares, these cases would likely be unrealistic in practice. The widening transition region observed for larger producers therefore reflects increasing market influence rather than outright market manipulation.

Figure 4.3 shows the average revenue obtained from electricity sold in the spot market as a function of the PPA price. For each strategic ownership scenario, market revenue remains approximately constant while the optimal PPA allocation is zero. Once the PPA price becomes sufficiently attractive and the producer begins allocating generation to PPAs, the realised market revenue per MWh increases.

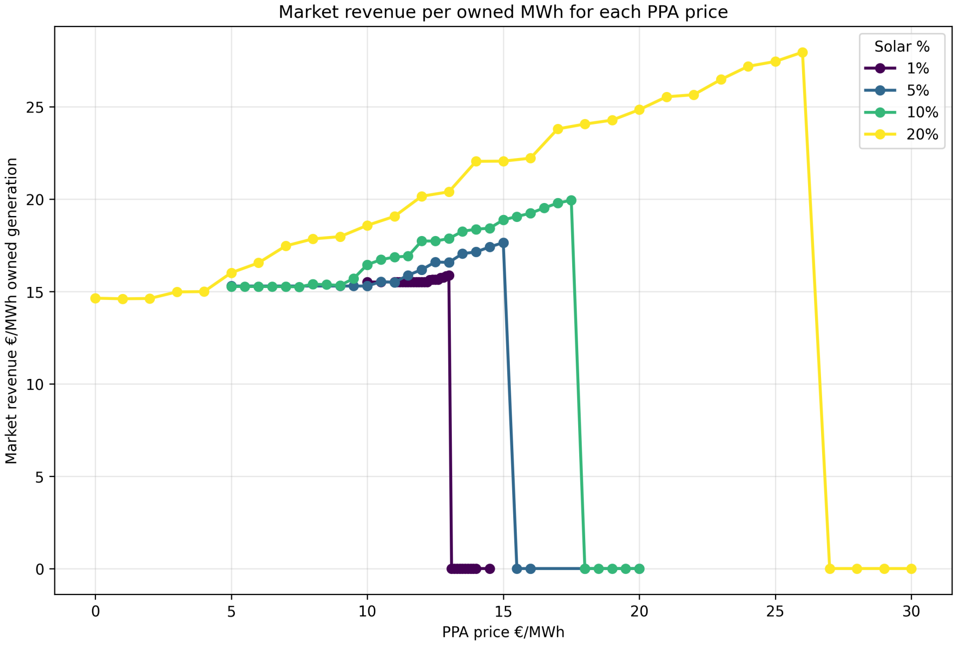


Figure 4.3: Means market price vs PPA price

This increase occurs because the energy remaining in the spot market is sold only when its expected revenue exceeds the revenue available through the PPA. As a result, the average revenue obtained from market sales tends to approach the PPA price from above. However, the two values never coincide while market participation remains positive. If the revenue available in the market were lower than the PPA price, the producer would simply allocate that energy to the PPA instead. Consequently, the market revenue curves approach the line corresponding to equal PPA and market revenues before abruptly collapsing to zero when all available generation is contracted through PPAs.

Revenue rather than profit is reported in this figure because it provides a direct comparison with the PPA price. Since production costs are identical regardless of whether energy is sold through the market or through a PPA, comparing revenues isolates the effect of the contracting decision itself.

Figure 4.4 compares the total profit of the strategic producer with the profit obtained exclusively from spot market participation. The market profit curves are monotonic non-increasing with respect to the PPA price. This behaviour is a direct consequence of the optimization process. For each PPA price, the model selects the allocation between market sales and PPAs that maximizes total profit. Therefore, if withholding additional energy from the market were beneficial for increasing market profits, the optimization would already have chosen to do so at a lower PPA price.

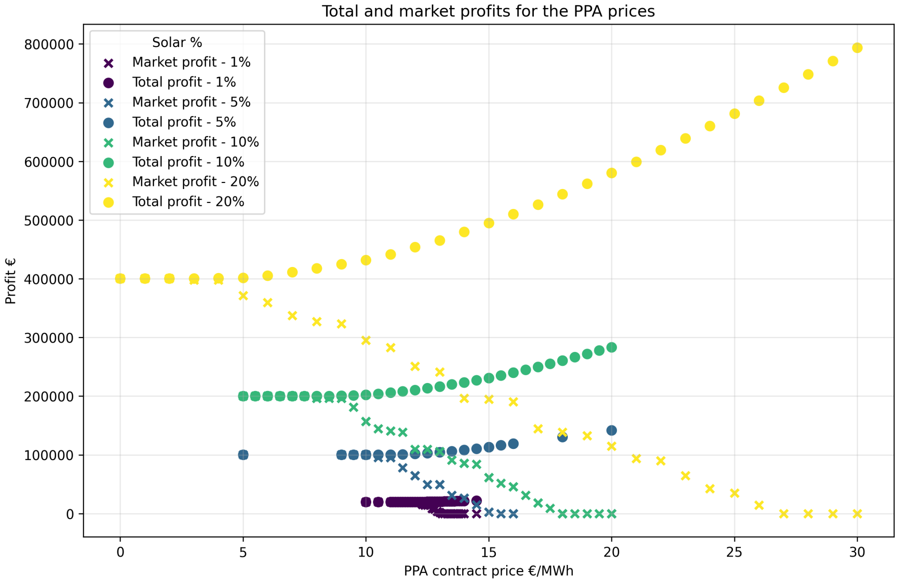


Figure 4.4: Total and market profit

As the PPA price increases, the producer gains access to increasingly attractive contractual revenues and therefore shifts generation away from the spot market. Market profits either remain unchanged or decline, while total profits continue to increase due to growing revenues from PPAs. The difference between the total profit curve and the market profit curve therefore represents the contribution of PPA revenues to the producer's overall profitability.

Figure 4.5 illustrates the profitability improvement achieved by the optimal contracting strategy relative to a baseline scenario without PPAs. The reported ratio is obtained by dividing the optimal profit at each PPA price by the profit obtained when the PPA share is fixed at zero.

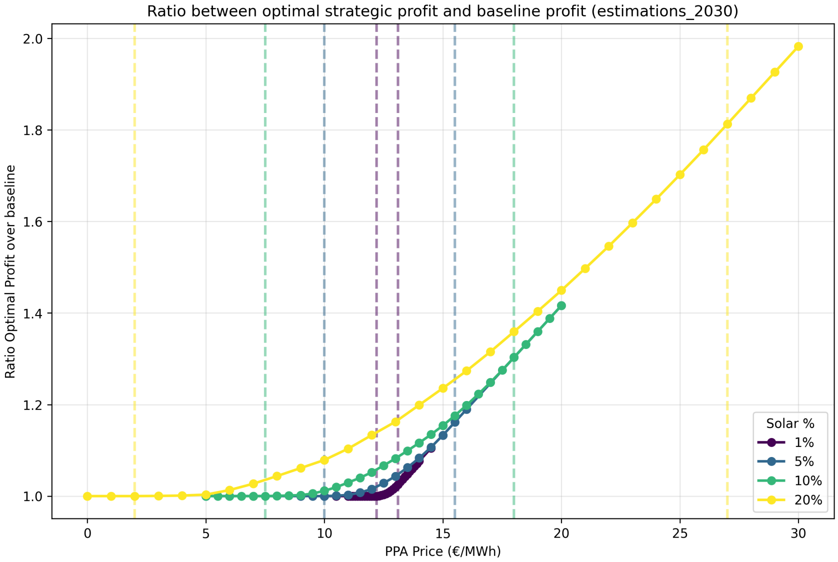
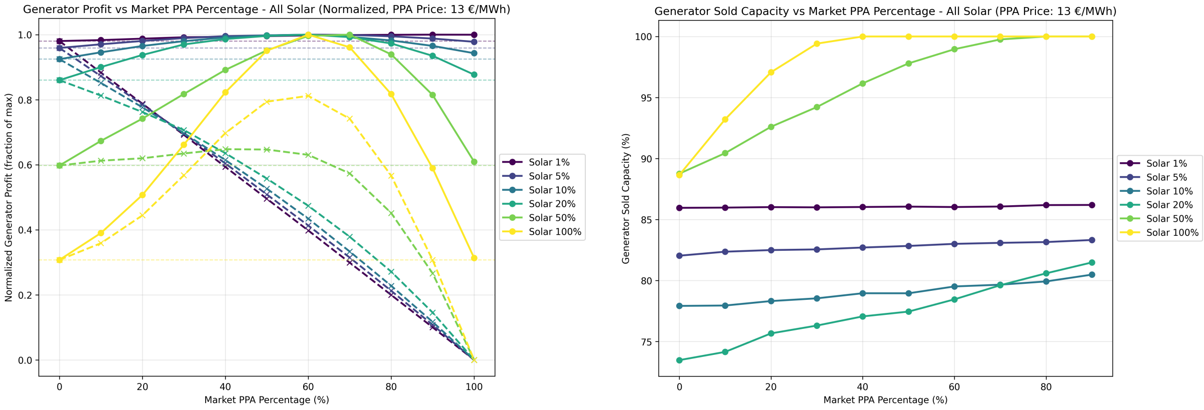


Figure 4.5: Ratio of the optimal profit over the baseline profit for each PPA price

The vertical dashed lines indicate the PPA prices at which the optimal solution reaches full PPA participation for each strategic ownership scenario. Beyond these points, all generation controlled by the strategic producer is contracted through PPAs and further profit increases are driven exclusively by increases in the contract price rather than by changes in market behaviour.

The figure highlights a significant opportunity cost associated with ignoring PPAs. For larger strategic producers, the profitability gains available through optimal contracting can be substantial. For example, the scenarios with higher strategic ownership shares achieve considerably larger profit improvements before reaching full PPA participation. This reflects the additional flexibility available to larger producers, which can balance market participation and contractual sales over a wider range of PPA prices.

The smooth and nonlinear transition observed for larger ownership shares is consistent with the behaviour already identified in Figure 4.2. While small producers tend to switch rapidly from market participation to full contracting once a threshold price is reached, larger producers move progressively through intermediate PPA levels, reflecting their greater ability to influence market outcomes and exploit the trade-off between spot market revenues and contractual revenues.



(a) Total and market profit for each PPA percent.

(b) Sold capacity for each PPA percent.

Figure 4.6: Results for different PPA percentages.

Figures 4.6a and 4.6b are best interpreted together, as they illustrate the relationship between market participation and profitability as the PPA share increases.

Figure 4.6b shows that the amount of energy sold by the strategic producer in the spot market decreases monotonically as the PPA allocation increases. This behaviour is expected because a larger fraction of the available generation is committed to long-term contracts, leaving less energy available for market participation. Consequently, the percentage of the offered generation that is successfully sold in the market can only remain unchanged or increase, as a smaller quantity is being exposed to the same market conditions.

Figure 4.6a reveals a more interesting effect. For the scenarios in which the strategic producer controls a significant share of the solar fleet, market profits remain approximately constant or even increase over part of the PPA allocation range despite the reduction in market sales observed in Figure 4.6b. Since less energy is being sold in the market, this increase in market profit cannot be explained by larger sales volumes. Instead, it indicates that the energy remaining in the market is being sold under more favourable market conditions.

This result suggests that the strategic producer benefits not only from the revenues obtained through PPAs but also from the market impact of withdrawing low-cost solar generation from the spot market. By reducing the amount of renewable energy offered to the market, the producer can contribute to higher market prices, partially compensating for the reduction in sold volume. The effect becomes more visible as the strategic producer's share of the solar fleet increases, reflecting the greater influence that larger producers can exert on market outcomes.

The normalized profit curves exhibit the expected inverted U-shape, with each peak corresponding to the optimal PPA allocation identified by the model. Moving away from this optimum in either direction reduces total profitability. Low PPA allocations leave profitable contractual opportunities unexploited, while excessive contracting eventually reduces the benefits associated with market participation. The location and width of the peak vary across scenarios, illustrating how the balance between contractual revenues and market influence changes as the strategic producer's ownership share of the solar fleet increases.

4.3.2 Market Impact of Strategic Solar Share

To better understand the mechanisms behind the optimal solutions, additional analyses were performed in which the PPA allocation was fixed exogenously at different values and the corresponding lower level market clearing problem was solved. The resulting price duration curves therefore do not represent optimal solutions of the bilevel model. Instead, they are used to examine how different levels of PPA participation affect market prices and to explain the behaviour observed in the optimization results.

The figure presents price duration curves for the simulated market prices under different PPA allocation scenarios. A price duration curve is obtained by ranking all market price observations over the simulated year from highest to lowest and plotting them against their cumulative duration. The x-axis therefore shows the proportion of the year for which prices are at or above a given level, while the y-axis shows the corresponding market price. Price duration curves are widely used in electricity market analysis because they provide a concise summary of the price distribution, allowing comparisons of both the magnitude of prices and the frequency with which different price levels occur across scenarios.

Figure 4.7 compares the market price distributions obtained under different imposed PPA allocations when the strategic producer controls 5% of the total Solar PV generation. In this setting, the price duration curves are relatively similar, with only minor shifts across allocations. The differences that do appear are most noticeable in the lower-price region of the curves, while the remainder of the price distribution remains largely unchanged. This indicates that the overall market structure remains largely stable, and changes in the PPA share mainly affect the distribution of outcomes rather than fundamentally altering price formation. As a result, the impact of contracting decisions on profitability is smooth and gradual, reflecting the limited market influence of the strategic producer.

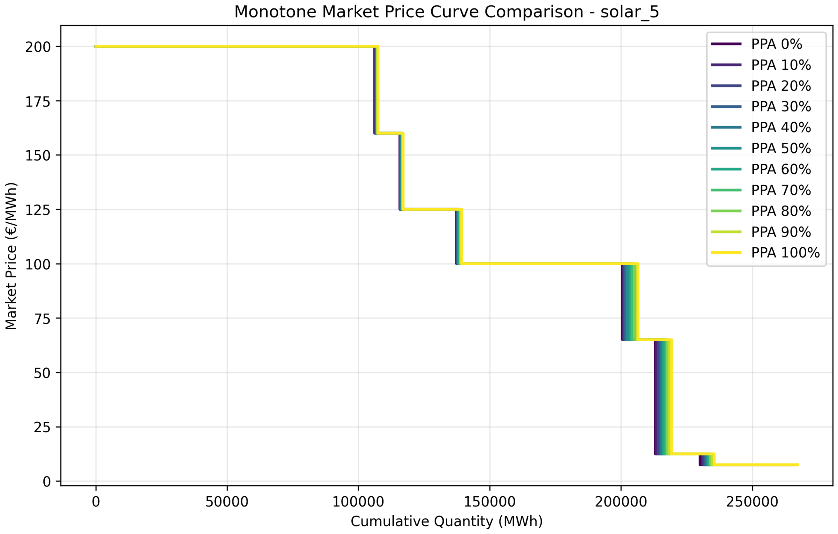


Figure 4.7: Monotone market price curves for the 5% strategic solar share scenario across PPA allocations.

The situation changes in Figure 4.8, where the strategic producer controls the entire Solar PV fleet. In this case, the price distributions become highly sensitive to the imposed PPA allocation, and substantial differences emerge across the entire price distribution, although the effect is particularly pronounced in the lower-price region of the curves. This indicates that PPA decisions are now able to materially reshape market outcomes rather than merely shift them. As the PPA allocation increases, a growing fraction of the available solar generation is committed through PPAs and is therefore no longer offered in the spot market. When the PPA allocation reaches 100%, the entire strategic solar production is withdrawn from the market, directly reducing the amount of energy available for market clearing and producing a significant impact on price formation.

In this high influence setting, the strategic producer affects not only its own revenue composition but also the timing and level of market prices. Certain PPA allocations improve the effective capture price, while higher allocations can reduce exposure to periods of elevated market prices, increasing the importance of timing and market composition effects. This helps explain why profitability no longer evolves monotonically with the PPA share, but instead exhibits an interior optimum. Increasing contractual coverage initially improves revenue stability and market positioning, but excessive contracting eventually reduces the benefits associated with favourable market conditions.

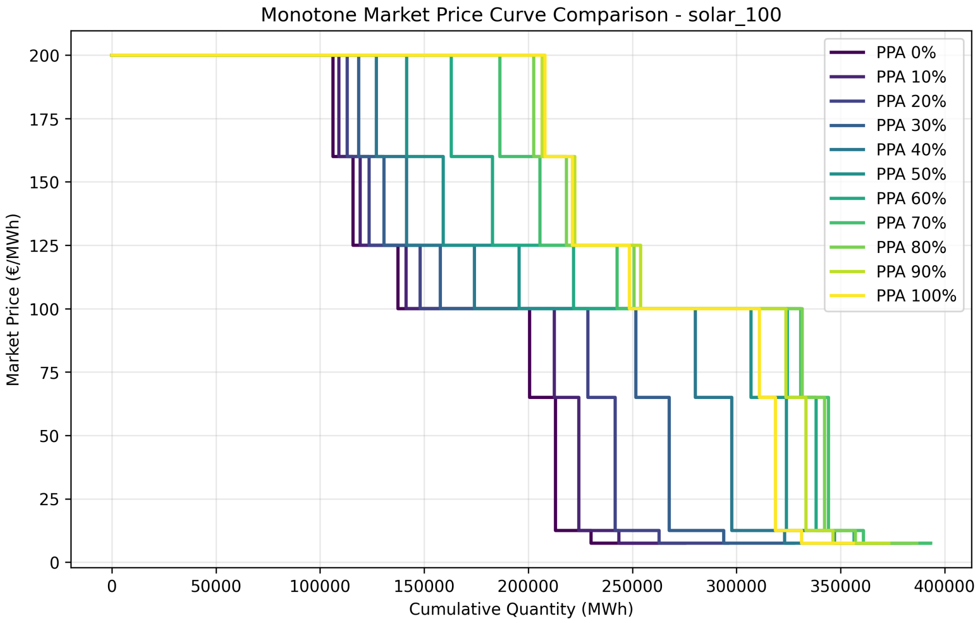


Figure 4.8: Monotone market price curves for the 100% strategic solar share scenario across PPA allocations.

4.3.3 Economic and Welfare Analysis

The increase in strategic profitability observed in previous sections is accompanied by a measurable but limited impact on overall market efficiency. Figure 4.9 illustrates the relationship between social welfare and strategic profit across different scenarios. The figure highlights a clear trade-off between the objectives of the strategic producer and aggregate market efficiency: higher levels of strategic profit are associated with only marginal changes in social welfare.

As the strategic solar share increases, the Pareto frontier shifts, indicating that the strategic producer is able to achieve higher levels of profit for a given level of social welfare. At the same time, the shape of the frontier becomes more pronounced, suggesting that the system becomes more sensitive to contracting decisions as the producer's influence over the market increases.

This reflects the growing ability of the strategic producer to affect price formation and surplus allocation as its share of solar generation expands.

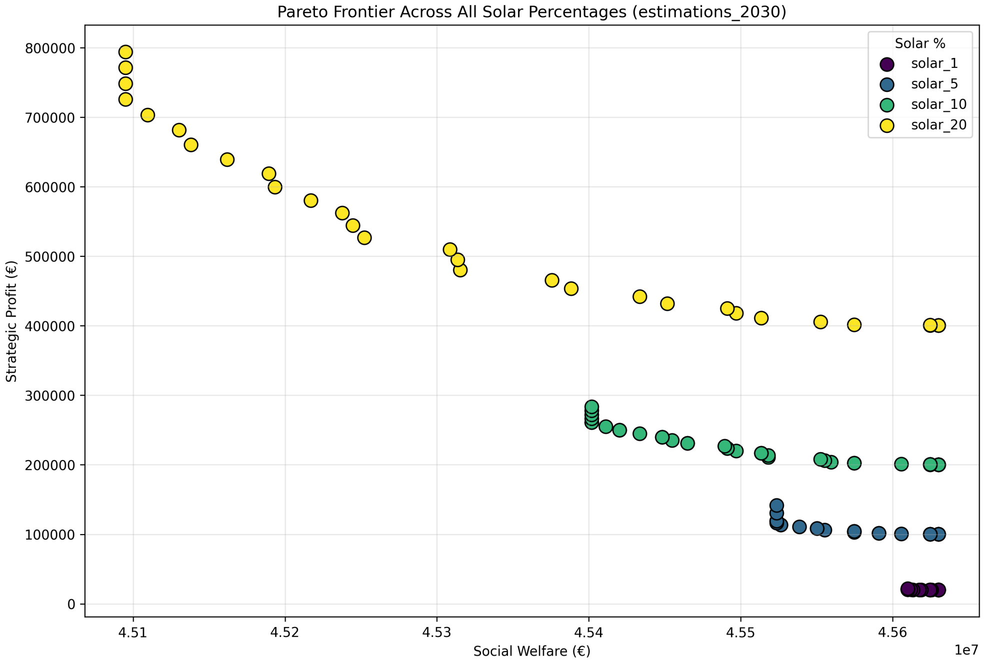


Figure 4.9: Pareto frontier between social welfare and strategic profit across strategic solar share scenarios.

The vertical segments observed in the frontier correspond to regions in which the producer increases the PPA price while already operating at full contractual allocation. In this regime, the allocation decision is saturated, meaning that additional changes in PPA price affect only the distribution of surplus without altering market dispatch outcomes. As a result, strategic profit continues to increase while social welfare remains unchanged.

This interpretation is consistent with the profit ratio analysis presented in the results section, where outcomes are normalised with respect to the no-PPA benchmark. The ratio highlights that profitability improvements vary significantly across strategic solar share scenarios, with larger shares achieving substantially higher gains before reaching saturation.

Overall, the results indicate that the primary effect of the strategic contracting mechanism is not a substantial change in aggregate social welfare, but rather a redistribution of surplus among market participants. While small variations in welfare are observed across scenarios, these changes are limited in magnitude compared to the shifts in strategic profit and surplus allocation. In contrast, higher strategic solar shares amplify the redistribution effects, allowing the strategic producer to capture a larger portion of the available surplus without materially affecting total system efficiency.

4.3.4 Stakeholder Perspectives

From the perspective of strategic generators, the results suggest that the model can be used as a screening tool to identify commercially attractive PPA price ranges under different levels of exposure to the solar market. At low strategic solar shares, the profitable region is relatively narrow and decision-making exhibits near-threshold behaviour, meaning that small changes in PPA price can lead to abrupt shifts between low and high contract participation. In this regime, timing and precise pricing of contract offers are therefore particularly important.

At higher strategic solar shares, the decision space becomes wider and more nonlinear. This implies that contract design cannot be based solely on average market prices, but must also account for how contracting decisions interact with market price formation and the resulting exposure to different market conditions. In practical terms, the model helps distinguish between PPA prices that primarily shift the allocation of energy between market and contract, and those that meaningfully improve overall revenue outcomes under uncertainty in market conditions.

From the perspective of regulators, the results provide a framework for analysing how market outcomes change under different levels of strategic exposure to solar generation. The observed shifts in price distributions and Pareto frontiers indicate how the influence of the strategic producer increases as its share of solar generation grows. This allows identification of scenarios in which contracting decisions have a stronger impact on price formation and surplus allocation, even if aggregate welfare effects remain limited in magnitude.

In this sense, the model is useful not only for describing equilibrium outcomes, but also for understanding when and how PPA-based strategies increase the strategic influence of market participants and reshape the distribution of economic surplus within the market.

4.3.5 Computational Performance

The final aspect of the results concerns the computational cost of solving the bilevel model. Table 4.3 shows a strong nonlinear increase in runtime as the strategic solar share increases. The mean execution time rises from 44.20 seconds in the lowest-share case to 2022.48 seconds in the highest-share case, while the maximum runtime reaches 5840.87 seconds in the most challenging instances. This increase is significantly larger than what would be expected from a purely linear growth in problem size.

Solar %	Overall %	Min Time (s)	Max Time (s)	Mean Time (s)
1	0.36	40.61	51.13	44.20
5	1.79	69.58	239.05	135.76
10	3.57	95.34	933.47	291.62
20	7.15	146.72	5840.87	2022.48

Table 4.3: Execution Time Statistics for estimations_2030

This behaviour indicates that the difficulty of the optimisation problem is driven not only by the number of variables, but also by the strength of the coupling between the upper-level contracting decision and the lower-level market equilibrium. As the strategic solar share increases, this coupling becomes stronger, leading to a more nonlinear and irregular optimisation landscape. This is reflected in the dispersion of solver runtimes: while performance is relatively stable at low strategic solar shares, higher shares produce a much wider spread between best and worst-case runtimes, indicating increased sensitivity to specific market configurations rather than uniform scaling.

Overall, the computational behaviour is consistent with the economic results, as scenarios with higher strategic influence exhibit both stronger nonlinearities in prices and profits and greater variability in solver performance, reflecting a system in which the interaction between contracting decisions and market outcomes becomes increasingly pronounced.

4.4 Limitations and Discussion

The model is based on a set of simplifying assumptions that allow the interaction between long-term contracting decisions and short-term market outcomes to be studied in a controlled setting. These assumptions are necessary to ensure tractability and interpretability of the bilevel structure, but they also define the scope within which the results should be interpreted.

A key assumption is the use of perfect information, where demand and generation profiles are assumed to be known in advance without uncertainty. This allows the model to isolate the direct relationship between PPA contracting decisions and market outcomes without introducing forecast errors or stochastic variability. As a consequence, the results should be interpreted as equilibrium responses under idealised conditions, rather than as forecasts of real-world market outcomes under uncertainty.

The model also considers only a single strategic producer. This design choice allows a clear identification of how PPA decisions affect market behaviour and price formation without introducing strategic interaction between multiple competing agents. In more realistic settings, competition among strategic producers could partially offset or amplify the effects observed here, particularly in terms of price formation and surplus redistribution.

Network constraints are not included in the market-clearing formulation. This abstraction removes spatial limitations and congestion effects, allowing the analysis to focus exclusively on economic interactions between supply, demand, and contracting decisions. While this improves interpretability, it also implies that local price differences and transmission-driven bottlenecks are not captured.

The assumption of a fixed PPA price in each scenario further simplifies the analysis by separating contract pricing decisions from market dynamics. This allows the study to focus on how the contracted volume responds to exogenous price signals and how this interacts with spot market participation. However, in real markets PPA pricing can be endogenous and linked to expected market conditions, which could strengthen feedback effects between contracting and price formation.

Another important assumption is that PPA contracting does not reduce the demand represented in the spot market. The model implicitly assumes that the energy committed through PPAs is consumed by additional demand sources that are not explicitly represented in the market-clearing process, such as new industrial loads or green hydrogen electrolysers. In reality, some PPAs may replace purchases that would otherwise occur in the spot market, creating a feedback between contracting decisions and market demand. In such cases, the reduction in spot-market supply would be partially offset by a reduction in spot-market demand, likely weakening the price effects observed in this study. Consequently, the nonlinear market responses identified for larger strategic solar shares may emerge at higher ownership levels or be less pronounced in markets where PPAs primarily substitute existing demand.

Despite these simplifications, the results provide robust insights into the mechanisms linking long-term contracting and market outcomes. Across all analysed scenarios, the model suggests that the primary impact of PPAs is the redistribution of surplus and the modification of price dynamics rather than substantial changes in aggregate social welfare. Furthermore, the results indicate that nonlinear behaviour emerges only when the strategic producer controls a sufficiently large share of solar generation, highlighting the importance of market influence as the main driver of the observed effects.

Finally, the computational results indicate that problem complexity increases with higher levels of strategic exposure to solar generation, particularly due to stronger coupling between contracting decisions and market outcomes. This suggests that extending the model with additional realism—such as uncertainty, multiple strategic agents, or network constraints—would likely increase computational difficulty and reduce interpretability. For this reason, the current formulation is best understood as a controlled framework for identifying fundamental mechanisms rather than as a fully operational market simulator.

Chapter 5

Conclusions and Future Works

5.1 Conclusions

5.1.1 Summary of Contributions

This thesis developed a bilevel optimization framework to study the interaction between Power Purchase Agreement (PPA) contracting decisions and electricity market outcomes. The framework models a strategic solar producer that determines the fraction of its generation allocated to fixed-price PPAs, while the remaining energy participates in an electricity market cleared through social welfare maximization.

The main contributions of this work are:

- The development and implementation of a bilevel optimization framework for strategic PPA allocation. The framework combines a market-clearing model with strategic contracting decisions and addresses the first two objectives of the thesis.
- The implementation of the proposed framework in Python using Pyomo and Gurobi, enabling the analysis of hourly market outcomes over an entire year.
- A systematic evaluation of the effects of strategic solar share and PPA prices on producer profitability, spot prices, social welfare, and computational performance. This analysis, together with the stakeholder-oriented interpretation of the results, addresses the third objective of the thesis and provides insights for both renewable generators and regulators.

5.1.2 Final Reflection

This thesis examined the interaction between long-term fixed-price Power Purchase Agreements (PPAs) and short-term electricity market outcomes. A bilevel optimization framework was developed in which a strategic solar producer determines the proportion of its generation allocated to PPAs, while the remaining energy participates in a welfare-maximizing electricity market. The objective was to study how contracting decisions influence producer profitability, spot-market outcomes, and social welfare under different strategic solar share scenarios.

The proposed framework successfully represented the interaction between strategic contracting decisions and market-clearing outcomes. By linking the upper-level PPA allocation decision with the lower-level market equilibrium, the model was able to capture how changes in contracting behaviour affect market participation, dispatch decisions, prices, and revenues. The results therefore demonstrate that bilevel optimization provides a suitable framework for studying the mechanisms connecting long-term contracts and short-term market outcomes in a controlled setting.

The economic analysis showed that PPA participation can substantially increase the profitability of strategic renewable producers. Across all strategic solar share scenarios, higher PPA prices led to greater participation in PPAs and higher total profits. The results also revealed a significant opportunity cost associated with ignoring PPAs. Under the analyzed scenarios, the profit obtained with optimal PPA participation reached approximately 1.2 times, 1.3 times, and 1.8 times the profit obtained without PPAs for strategic solar shares of 5%, 10%, and 20%, respectively. These results highlight the growing importance of contracting decisions as larger shares of solar generation are controlled by a single strategic producer.

The behaviour of the optimal PPA allocation changed considerably across strategic solar share scenarios. For small strategic shares, the optimal decision resembled a threshold response, with very limited participation below a certain PPA price and almost complete participation above it. As the strategic solar share increased, this transition became progressively more gradual and a wider range of intermediate PPA allocations became optimal. This indicates that the interaction between contractual revenues and market participation becomes increasingly complex as the strategic producer controls a larger share of solar generation.

The results also showed that PPA participation affects market outcomes beyond the producer's own revenues. Changes in contracting levels modified the quantity of energy offered to the market, influencing spot prices and the distribution of surplus among market participants. However, the impact on aggregate social welfare was relatively small across all analyzed scenarios. Consequently, the primary effect of PPAs within the proposed framework was not a substantial change in overall market efficiency, but rather a redistribution of economic benefits between participants.

From a computational perspective, solution times increased significantly as the strategic solar share grew. Larger strategic shares produced stronger interactions between the upper-level and lower-level decisions, leading to longer runtimes and greater variability in computational performance. The same conditions that generated richer economic behaviour also increased the complexity of the optimization problem.

Overall, the results suggest that PPA participation can play an important role in determining both producer profitability and market outcomes. While aggregate welfare effects remained modest, profitability improvements were substantial, particularly for producers controlling larger shares of solar generation. The framework therefore provides a useful tool for studying how long-term contracting decisions interact with electricity market operation and how these interactions evolve as strategic ownership of renewable generation increases.

5.2 Future Works

5.2.1 Short-Term Improvements

Several short-term improvements could further strengthen the framework:

- **Uncertainty representation:** Incorporate stochastic or robust optimization approaches to account for uncertainty in renewable generation, demand, and market conditions.

- **Expanded sensitivity analysis:** Explore additional parameter ranges, including fuel prices, demand growth scenarios, and alternative PPA price structures, to better characterize threshold effects and nonlinearities.

- **Enhanced stakeholder metrics:** Develop additional performance indicators, such as risk-adjusted profitability measures for producers and market monitoring indicators for regulators.

5.2.2 Long-Term Extensions

Several extensions could significantly increase the realism and scope of the framework:

- **Multiple strategic producers:** Extend the model to include strategic interactions among several producers making simultaneous contracting and market participation decisions.
- **Network-constrained markets:** Incorporate transmission constraints, congestion effects, and nodal pricing mechanisms to capture spatial market dynamics.
- **Dynamic contracting decisions:** Replace the single annual PPA allocation with a dynamic contracting strategy that allows periodic adjustments over time.
- **Alternative PPA structures:** Analyze indexed, hybrid, or more complex PPA designs to evaluate how contract structures affect strategic incentives and market outcomes.
- **Demand-side contracting effects:** Relax the assumption that PPA demand is additional to existing market demand. Future work could explicitly model situations in which PPA demand partially substitutes spot-market demand, allowing the interaction between supply withdrawal and demand reduction to be quantified.

5.2.3 Potential Impact

The proposed framework has practical relevance for both strategic producers and regulators.

For renewable generators, the model can support contracting decisions by identifying PPA price ranges that justify participation, quantifying potential profitability gains, and evaluating the trade off between contractual revenue and market exposure. These insights become particularly valuable as strategic ownership of renewable generation increases and market influence becomes more significant.

For regulators and market designers, the framework can serve as a scenario-analysis tool to assess how ownership concentration may affect market outcomes. Rather than indicating substantial welfare losses, the results suggest that the primary effects arise through changes in price formation and surplus distribution. Consequently, the framework can help identify situations in which strategic influence becomes increasingly relevant and where market monitoring may be warranted.

More broadly, this work provides a structured methodology for studying the interaction between long-term contracting and electricity market operation. As renewable generation continues to expand and ownership structures evolve, understanding these interactions will become increasingly important for both private decision-making and public policy design.

Bibliography

[1] Vlassis, N.A.; Papakonstantinou, G.; Tsanakas, P. “Dynamic sensory probabilistic maps for mobile robot localization.” *Proceedings. 1998 IEEE / RSJ International Conference on Intelligent Robots and Systems.* New York, NY, USA: IEEE, 1998, pp. 718–23.

[2] Loeffler, B. “Cloud Computing: What is Infrastructure as a Service.” *Microsoft Technet Magazine*, October 2011. `https://technet.microsoft.com/en-us/magazine/hh509051.aspx`

[3] Herrero Alcántara, T. “Big Data: ¿Moda u oportunidad de negocio para el emprendedor?.” *Think Big*, Octubre 2014. `http://blogthinkbig.com/big-data-emprendedor/`

[4] Bendezu, K. “DIAGRAMA UML Y ARQUITECTURA DEL SISTEMA.” *Sistemas Distribuidos*, Febrero 2013. `http://comparape.blogspot.com.es/2013/02/diagrama-uml-y-arquitectura-del-sistema.html`

[5] EPEX SPOT. "Basics of the Power Market." EPEX SPOT, 2025. `https://www.epexspot.com/en/basicspowermarket`.

[6] D. I. Chatzigiannis, G. A. Dourbois, P. N. Biskas and A. G. Bakirtzis, "European day-ahead electricity market clearing model," *Electric Power Systems Research*, vol. 140, pp. 225–239, 2016. `https://doi.org/10.1016/j.epsr.2016.06.019`.

[7] V. V. Kalashnikov, S. Dempe, G. A. Pérez-Valdés et al., "Bilevel Programming and Applications," *Mathematical Problems in Engineering*, vol. 2015, 2015. `https://doi.org/10.1155/2015/310301`.

[8] World Economic Forum, "How Corporate PPAs can help drive Europe’s green recovery," World Economic Forum, 17 Jul. 2020. `https://www.weforum.org/stories/2020/07/corporate-power-purchase-agreements-europe-decarbonization/`.

[9] D. Brunnberg and J. Johnsen, "Power Purchase Agreements: A European Outlook," Aquila Capital, Whitepaper, 2019. `https://www.aquila-capital.de/fileadmin/user_upload/PDF_Files_Whitepaper-Insights/2019-11-15_Whitepaper_PPA_EN.pdf`.

[10] Q. He, Z. Lin, H. Chen et al., "Bi-level optimization based two-stage market clearing model considering guaranteed accommodation of renewable energy generation," *Protection and Control of Modern Power Systems*, vol. 7, 2022. `https://doi.org/10.1186/s41601-022-00253-y`.

[11] E. G. Kardakos, C. K. Simoglou and A. G. Bakirtzis, "Optimal Offering Strategy of a Virtual Power Plant: A Stochastic Bi-Level Approach," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 794–806, Mar. 2016. `https://doi.org/10.1109/TSG.2015.2419714`.

[12] I. Savelli, A. Giannitrapani, S. Paoletti and A. Vicino, "An Optimization Model for the Electricity Market Clearing Problem With Uniform Purchase Price and Zonal Selling Prices," *IEEE Transactions on Power Systems*, vol. 33, no. 3, pp. 2864–2873, May 2018. `https://doi.org/10.1109/TPWRS.2017.2751258`.

[13] United Nations, "THE 17 GOALS | Sustainable Development," UN Sustainable Development, https://sdgs.un.org/goals.

[14] M. Hilbert, A. Dellnitz and A. Kleine, "Production planning under RTP, TOU and PPA considering a redox flow battery storage system," *Annals of Operations Research*, vol. 328, pp. 1409–1436, 2023. https://doi.org/10.1007/s10479-023-05338-x.

[15] H. Yang, S. Xu, W. Gao et al., "Mitigating long-term financial risk for large customers via a hybrid procurement strategy considering power purchase agreements," *Energy*, vol. 295, 2024. https://doi.org/10.1016/j.energy.2024.131038.

[16] J. Arellano and M. Carrión, "Electricity procurement of large consumers considering power-purchase agreements," *Energy Reports*, vol. 9, pp. 5384–5396, 2023. https://doi.org/10.1016/j.egyr.2023.04.371.

[17] S. Jain, "Exploring structures of power purchase agreements towards supplying 24x7 variable renewable electricity," *Energy*, vol. 244, 2022. https://doi.org/10.1016/j.energy.2021.122609.

[18] M. J. Rider, J. M. López-Lezama, J. Contreras and A. Padilha-Feltrin, "Bilevel approach for optimal location and contract pricing of distributed generation in radial distribution systems using mixed-integer linear programming," *IET Generation, Transmission & Distribution*, vol. 7, no. 7, pp. 724–734, 2013. https://doi.org/10.1049/iet-gtd.2012.0369.

[19] J. M. Lopez-Lezama, A. Padilha-Feltrin, J. Contreras and J. I. Muñoz, "Optimal contract pricing of distributed generation under a competitive framework," in *IEEE PES T&D 2010*, 2010, pp. 1–6. https://doi.org/10.1109/TDC.2010.5484456.

[20] J. M. Lopez-Lezama, A. Padilha-Feltrin, J. Contreras and J. I. Muñoz, "Optimal Contract Pricing of Distributed Generation in Distribution Networks," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 128–136, 2011. https://doi.org/10.1109/TPWRS.2010.2048132.

[21] European Commission, "Electricity market design," European Commission — Energy, (no date). https://energy.ec.europa.eu/topics/markets-and-consumers/electricity-market-design_en.

[22] P. Tsangaris, *Capacity Withdrawals in the Electricity Wholesale Market: Between Competition Law and Regulation*, Springer, Berlin, Heidelberg, 2017. doi:10.1007/978-3-662-55513-2.

Appendix

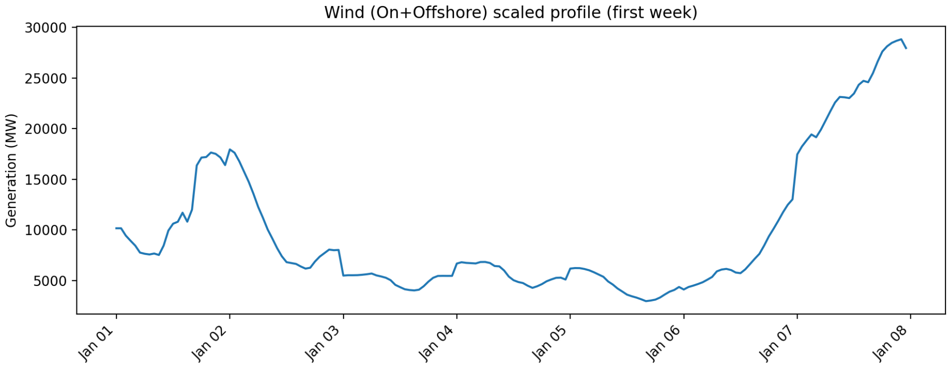


Figure 1: Wind production profile

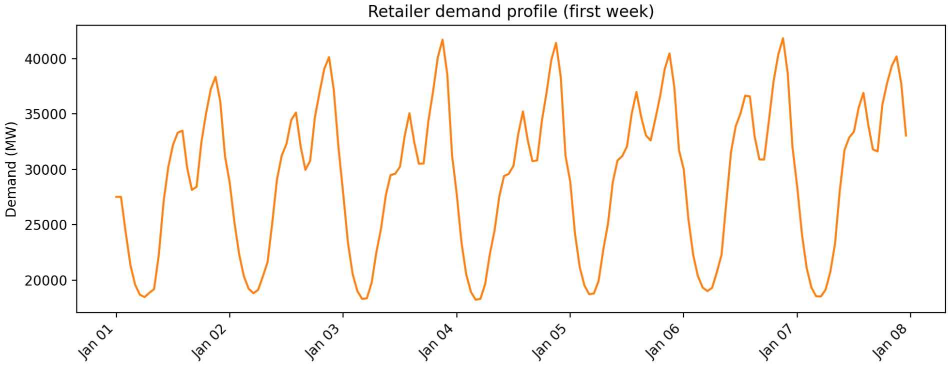


Figure 2: Retailer demand profile