Power Purchase Agreements and Corporate Energy Goals: A Performance Assessment

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***Abstract*—In the face of growing pressure to decarbonize operations, companies are increasingly turning to renewable electricity procurement through corporate power purchase agreements (CPPAs). These agreements are effective in driving investments in renewable energy, providing competitive electricity prices, and ensuring a green supply. However, CPPAs expose companies to market and contractual risks, particularly during periods of price cannibalization driven by increasing penetration of renewables like solar and wind into the wholesale electricity market. By employing a Data Envelopment Analysis model, this study aims to evaluate the performance of different CPPA types, focusing on their ability to balance financial performance and risk exposure while meeting sustainability goals. Results indicate that baseload contracts consistently outperform other structures during periods of price cannibalization, offering the best equilibrium between risk mitigation and performance. Variable-price contracts show high potential to mitigate cannibalization effects, but their success depends critically on the negotiation of floor and cap prices.**

***Index Terms*--Corporate Power Purchase Agreements, Electricity Markets, Electricity Procurement Strategy, Renewable Generation, Risk Mitigation**

I. Introduction

The global push by companies to achieve sustainability and meet climate objectives is gaining momentum. Among the prominent initiatives supporting this transition is the Renewable Energy 100% (RE100) program, which has united over four hundred major corporations dedicated to sourcing all their electricity from renewable energy [1]. To achieve these ambitious goals while keeping electricity costs competitive, companies have increasingly turned to Corporate Power Purchase Agreements (CPPA) in recent years. Data from Bloomberg New Energy Finance (BNEF) indicates that between 2008 and 2023, companies globally secured a total of 198 GW of solar and wind capacity through CPPAs [2]. In Europe alone, CPPA contracts accounted for a cumulative 36.2 GW of capacity between 2013 and 2023, with an exceptional 24.8 GW added between 2021 and 2023 [3].

CPPAs are long-term contracts established directly between renewable energy developers and corporate buyers, or off-takers [4]. These agreements enable companies to purchase part, or all of the energy generated by renewable projects at a pre-agreed price. By locking in electricity costs for an extended period, CPPAs act as a financial hedge, shielding companies from the volatility of wholesale electricity markets. Lee et al. [5] highlighted that CPPAs are among the most cost-effective strategies for companies to secure renewable energy over the long term.

Despite these advantages, CPPAs expose companies to certain risks, primarily price risk, volume risk, and profile risk [6]. Price risk occurs when wholesale market prices fall below the contracted rates, resulting in excess financial obligations for the off-takers. Volume risk is associated with the variability in renewable energy output, where actual generation may deviate from projections, potentially disrupting a company's energy supply. Profile risk arises due to the "cannibalization effect," a phenomenon unique to renewable energy sources. Given that renewable energy generation is non-dispatchable and has negligible marginal costs, periods of high renewable output tend to drive wholesale electricity prices significantly lower [7], [8]. As the penetration of renewables increases, this risk becomes more pronounced, potentially leading companies to purchase higher volumes of electricity at elevated prices compared to what they could secure directly in the spot market.

While many studies have explored strategies to mitigate these risks, such as long-term generation modelling [9], energy storage solutions [10], [11], and geographically diversified technology portfolios [12], there is limited research focusing on how the design of CPPA contracts, specifically the combination of various pricing and electricity profile structures, can reduce corporate risk exposure, a research gap emphasized by Brindley et al. [13] and Jimenez et al. [9].

Building on this idea and following previous research [14], this article aims to evaluate the performance of different CPPA designs during a period of solar energy cannibalization. With the increasing penetration of renewables into the energy market, the frequency and magnitude of price cannibalization are expected to rise [8]. Therefore, assessing how companies can effectively mitigate this risk through CPPA design is a critical step. To achieve this objective, the study employs Data Envelopment Analysis (DEA) methodology to evaluate the efficiency of various CPPA designs.

The following text is organized as follows: Section 2 details the methodology and the data used, Section 3 discusses the results, and Section 4 provides the main conclusions.

II. DATA & METHODS

A. DEA Model

Data Envelopment Analysis (DEA) is a widely used mathematical linear programming method for assessing the performance of Decision-Making Units (DMUs) [15]. By analyzing the efficiency with which each DMU converts inputs into outputs, DEA identifies relative efficiency scores and benchmarks, i.e., efficient DMUs operating on the "efficiency frontier" [16]. These benchmarks highlight best practices and provide actionable insights for improving inefficiencies [17].

This study employs the Slack-Based Measure (SBM) DEA model, introduced by Tone [18]. The SBM model offers a more detailed efficiency analysis than the Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models [19], [20], as it directly incorporates slacks into efficiency calculations. Unlike radial models, the SBM model accounts for disproportionate variations in inputs and outputs.

To enhance evaluation accuracy, the SBM model is combined with clustering techniques to group DMUs based on shared characteristics [21]. For this study, each CPPA design under analysis represents a distinct cluster. This clustering approach enables efficiency evaluations within homogenous groups, reducing the impact of heterogeneity across DMUs.

To apply this methodology effectively, it is essential to define a set of contracts and corresponding performance indicators that quantify the efficiency of each contract over a predetermined period.

B. CPPA Simulation

Due to limited access to real CPPA data, contract designs were simulated using a Monte Carlo approach, incorporating six contract structures derived from combinations of price and electricity profile configurations identified in the literature.

According to Dominy and Zubair [22], CPPA price structures can be categorized into Fixed Price (FP) and Variable Price (VP). Under an FP structure, the electricity price remains constant throughout the contract duration. In contrast, the VP structure ties the electricity price to wholesale market rates, incorporating mechanisms such as floor and cap prices to ensure minimum revenue for the developer and limit costs for the off-taker. Regarding electricity profile structures, Brindley et al. [13] classify electricity profile structures into three types. The first is Pay-as-Produced (PAP), where the off-taker purchases all electricity generated by the renewable power plant. The second is Monthly Baseload (BLM), where a fixed hourly volume of electricity is procured monthly. The third, Annual Baseload (BLA), involves a consistent fixed volume of electricity procured annually.

In total, the CPPA simulation was carried out for six different CPPA, Table 1.

Table 1 *– CPPA Types - Price and Profile Structure Combinations*

Contract Types	Price Structure	Electricity Profile
1	FP	PAP
2	VP	PAP
3	FP	BLM
4	VP	BLM
5	FP	BLA
6	VP	BLA

The simulation inputs were derived from a database with CPPA reference prices in the Iberian market for CPPA with a duration of 10 years [23]. Contract prices were randomly generated for each CPPA type using a normal distribution. For generation profiles, the solar profile followed the standard profile defined by MIBEL for its solar financial futures product [24]. All profiles were standardized to represent projects with an installed capacity of 20 MW.

C. Indicators

To evaluate the relative efficiency of the CPPAs under analysis, three indicators were selected to measure the performance of each contract: Net Present Value (NPV), Contract Performance Deviation (CPD), and Demand Residual (DR).

The NPV indicator quantifies the financial performance of the CPPA by assessing the corporate benefit of purchasing electricity at the CPPA price compared to the wholesale electricity market price [12]. Higher NPV values indicate superior financial performance and greater benefits for the company. This indicator is calculated daily using the following formula:

$$NPV = \sum_{d=1}^{D} \sum_{t=1}^{T} \frac{(p_{d,t} - k_{d,t}) S_{d,t}}{(1+\frac{r}{365})^{d}} \quad (1)$$

Where D represents the contract duration in days, T refers to the 24-hour daily cycle, $p_{d,t}$ represents the hourly price in the wholesale electricity market for a given day, $k_{d,t}$ corresponds to the hourly CPPA price, and $S_{d,t}$ indicates the hourly supply of renewable electricity based on the contract terms. The discount rate (r) is assumed to be 6% per year, as outlined in [23].

The CPD indicator, presented in Eq. (2) is adapted from the Semi-Absolute Mean Deviation (SAMD) metric introduced by Speranza [24] to measure the risk of financial assets. The goal of this indicator is to measure the volatility of contract returns, given by Eq. (1).

$$CPD = \sum_{d=1}^{D} \sum_{t=1}^{T} \frac{|(NPV_{d,t} - NPV_e)| + (NPV_e - NPV_{d,t})}{2(T \times D)} \quad (2)$$

Here, $NPV_{d,t}$ is the hourly CPPA return, NPV_e is the average hourly return and $(T \times D)$ represents the total periods under analysis. Higher contract returns volatility represents higher risks for companies.

Finally, the Demand Residual (DR) aims to assess the company's exposure to electricity profile risk by quantifying the additional costs incurred to fulfil its electricity demand [6]. At each hour, if the supplied electricity $S_{d,t}$ is less than the company's consumption ($C_{d,t}$), the company must purchase the shortfall from the wholesale market at the price $p_{y,t}$. Conversely, if $S_{d,t}$ exceeds $C_{d,t}$, the company generates a surplus that can be sold on the wholesale market at the price $p_{d,t}$. This surplus may lead to revenue if the market price ($p_{d,t}$) is higher than the contracted CPPA price ($k_{d,t}$), otherwise, selling the surplus may result in a financial loss. Consequently, a lower DR value indicates a higher level of exposure to profile risk. The DR indicator is mathematically defined in Eq. (3):

$$DR = \begin{cases} \sum_{d=1}^{D}\sum_{t=1}^{T_d} \frac{(S_{d,t}-C_{d,t})*p_{d,t}}{(1+\frac{r}{365})^{d}}, (S_{d,t}-C_{d,t}) \leq 0 \\ \sum_{d=1}^{D}\sum_{t=1}^{T_d} \frac{(S_{d,t}-C_{d,t})*(p_{d,t}-k_{d,t})}{(1+\frac{r}{365})^{d}}, (S_{d,t}-C_{d,t}) > 0 \end{cases}$$
(3)

In the DEA model, the NPV indicator will be treated as an output, while the CMD and DR indicators will serve as inputs.

D. Solar Price Cannibalization

In the context of the energy markets, two indicators are commonly used to quantify the economic efficiency of solar energy technology, the captured price and the capture rate. The captured price measures the average price at which electricity from a determined technology is sold in the market and is calculated using the following equation [25]:

$$Captured\ Price = \frac{\sum_{d=1}^{D}\sum_{t=1}^{T} G_{d,t}*p_{d,t}}{\sum_{d=1}^{D}\sum_{t=1}^{T} G_{d,t}} \quad (4)$$

Here, $G_{d,t}$ represents the total solar generation in the market for day d at hour t.

The capture ratio quantifies how much of the market price a renewable energy project can capture compared to the average market price of electricity. It is calculated as follows [25]:

$$Captured\ Ratio = \frac{Captured\ Price}{Average\ Market\ Price} \quad (5)$$

where the Average Market price is given by the following equation:

$$Average\ Market\ Price = \frac{\sum_{d=1}^{D}\sum_{t=1}^{T} p_{d,t}}{D*T} \quad (6)$$

As price cannibalization directly impacts the captured price of solar energy projects, according to the definition of cannibalization, it is valid to consider that a lower capture rate corresponds to a greater exposure to cannibalization of solar technology.

Using the previously defined formulas, the month with the highest price cannibalization for solar technology in 2024 was identified. The analysis revealed that April experienced the most pronounced price cannibalization, with a captured ratio of 34%, which is nearly half of the 2024 annual average captured ratio of 64%. In light of this analysis and the objectives of this study, the impact of price cannibalization on the performance of solar CPPAs was evaluated using wholesale market prices of April 2024.

III. Results and Discussion

A. Meta-frontier Efficiency Score

The following boxplots illustrate the distribution of meta-frontier efficiency scores for simulated contracts across different contract types, based on both input-oriented and output-oriented models. In an output-oriented model, higher efficiency scores on the meta-frontier reflect contracts that maximize outputs (NPV) while maintaining the same level of inputs (CPD and DR). Conversely, in an input-oriented model, higher efficiency scores indicate contracts that minimize inputs (CPD and DR) while achieving a consistent level of outputs (NPV). As shown in Figure 1, for the output-oriented model, fixed-price contracts achieve higher median efficiency scores. However, among all electricity profile structures, only BLA VP and BLM VP include at least one contract classified as efficient.

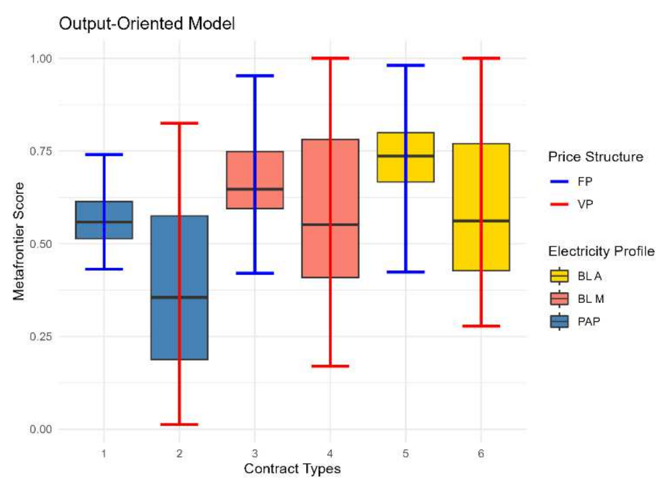

Figure 1 - Output-Oriented Model – Meta-frontier Efficiency Score distribution by contract type.

On the other hand, Figure 2 shows that, in the input-oriented model, the performance of PAP contracts is not comparable to that of BLA and BLM contracts. Furthermore, although the median efficiency score of fixed-price contracts is higher compared to variable-price contracts, only BLA and BLM with VP structure include at least one contract classified as efficient.

B. Technology Gap Ratio

The facet plots in this subsection illustrate the comparison between the meta-frontier efficiency scores and the cluster-frontier scores for each contract type, evaluated using both output-oriented and input-oriented models. Each subplot corresponds to a specific contract type, as outlined in Table 1. Since efficiency within the cluster frontier is assessed by comparing contracts with similar characteristics and structural combinations, the efficiency scores are consistently higher than those observed in the meta-frontier, where contract performance is compared across all contracts in the dataset. The ratio of the meta-frontier efficiency scores to the cluster-frontier scores defines the TGR, which quantifies the disparity between the cluster and meta-frontiers.

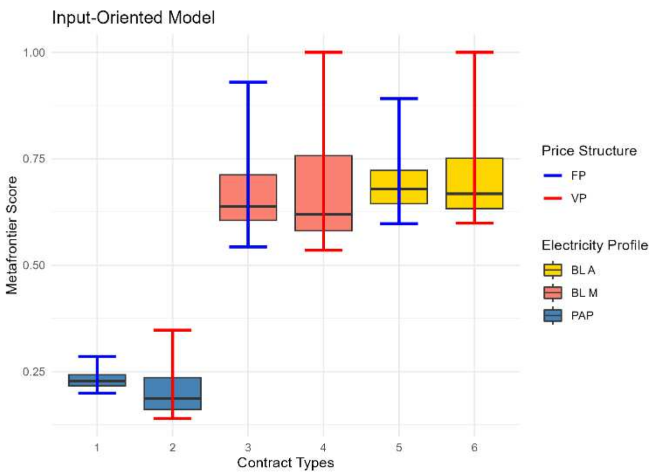

Figure 2 - Input-Oriented Model – Meta-frontier Efficiency Score distribution by contract type.

For the output-oriented model, Figure 3, contracts with the highest TGR are PAP contracts in both FP and VP structures. Conversely, contracts with the lowest TGR are BLA and BLM contracts, both in the VP structure (see Table A1 in Appendix A).

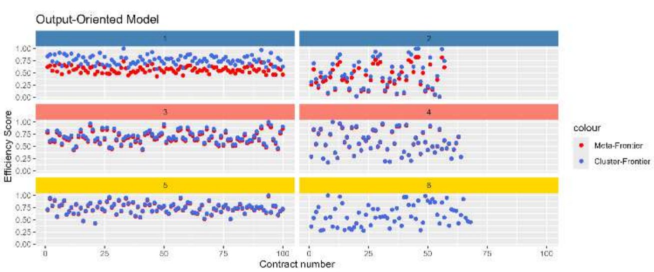

Figure 3 - Output-Oriented Model – Efficiency Score on Cluster and Meta-frontier by contract type.

In the input-oriented model, Figure 4, the TGR results are similar to those of the output-oriented model. The key difference is that the contract types with the lowest TGR are both BLA contracts, with VP and FP structures (see Table A2 in Appendix A).

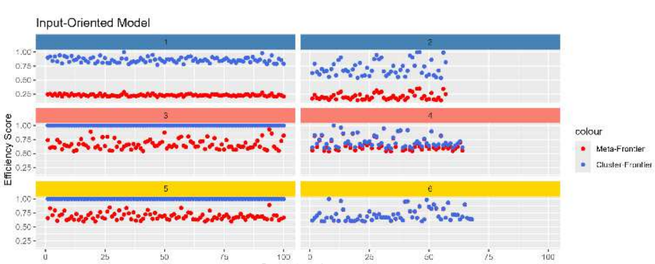

Figure 4 - Input-Oriented Model – Efficiency Score on Cluster and Meta-frontier by contract type.

C. Benchmark Contract Type

Figure 5 presents the frequency of contract types used as benchmarks for inefficient contracts on the meta-frontier, evaluated using both input- and output-oriented models. In both models, contract types 4 (BLM with a VP) and 6 (BLA with a VP) are used as benchmarks, but contract type 6 appears more frequently in both cases. These results suggest that during periods of price cannibalization in solar technology, CPPA with a baseload structure and a variable price offer the most effective approach to balancing financial performance with risk exposure.

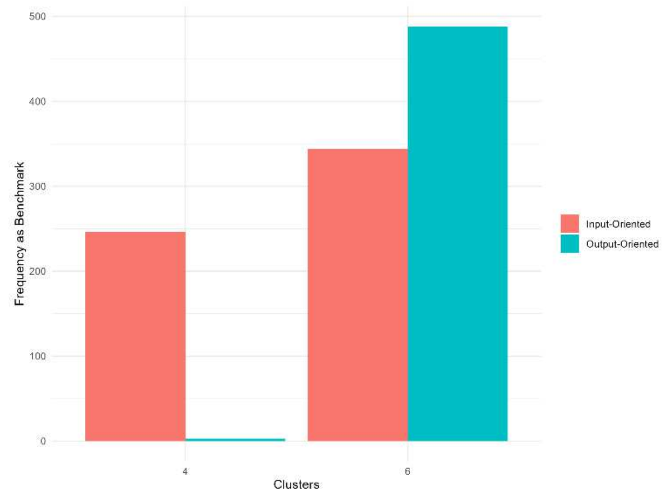

Figure 5 - Times as Benchmark by contract type.

These results indicates that, although fixed-price structures remain the most commonly adopted option for CPPAs, companies should consider negotiating variable-price (VP) structures. By setting the floor price close to the project's levelized cost of energy (LCOE), companies can benefit from periods of price cannibalization while minimizing risk. Recent trends in the wholesale electricity market have shown increasing price volatility, driven by the growing penetration of renewable energy sources. During periods of abundant renewable generation, price cannibalization becomes highly prevalent, and its frequency is expected to rise in the future [8]. Conversely, during periods of renewable shortages, the reliance on gas-fired power plants to maintain system stability leads to significant price increases, with monthly average electricity prices often reaching around 100 €/MWh.

Given this emerging paradigm, companies that limit their exposure to price volatility through VP structures and mitigate profile risk with baseload agreements (BLA or BLM) can effectively capitalize on periods of price cannibalization while protecting themselves against electricity price spikes. This dual benefit positions baseload CPPAs with VP structures as an attractive option in an increasingly volatile electricity market.

IV. CONCLUSIONS

This study aims to assist companies in preparing for a future wholesale electricity market dominated by renewable energy sources, many of which have near-zero marginal costs. The focus is on identifying the most efficient CPPA contract types during periods of solar price cannibalization. As the penetration of renewable technologies increases, particularly solar and wind, the occurrence of price cannibalization is expected to rise due to their unique generation profiles and lower marginal costs [8].

Furthermore, as corporate interest in CPPAs grows, the responsibility for managing price cannibalization risk has shifted from developers to companies. To mitigate this risk within the evolving market paradigm created by the energy transition, it is essential for companies to develop strategies that balance financial performance and risk exposure without compromising their carbon neutrality goals.

Using a DEA SBM model, this study analyzed three key indicators, NPV, CPD, and DR, to evaluate the performance of various CPPA contract types during April 2024, a period marked by pronounced price cannibalization. The results indicate that the most effective contracts for balancing risk and financial performance during such periods are baseload contracts (BLM or BLA) with variable price (VP) structures. However, the study highlights that the definition of floor and cap prices in VP contracts is critical for ensuring their effectiveness. Companies are advised to negotiate floor prices closer to the Levelized Cost of Energy (LCOE) of renewable projects, enabling them to benefit from lower wholesale electricity prices without jeopardizing the financial viability of renewable energy investments.

While this article focuses on evaluating CPPA performance during price cannibalization, it is important to consider that future market dynamics may shift with the introduction of new technologies, such as energy storage systems, or increased demand-side flexibility [26], [27]. These developments could counteract current trends in the medium to long term. Nevertheless, given the prevailing uncertainty, companies may benefit from adopting shorter-duration contracts, which provide flexibility to adapt to evolving market conditions while still leveraging the opportunities presented by the current market paradigm.

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APPENDIX A

Table A1 - Output-oriented Model - TGR Values

Cluster	Median	Standard Deviation	Min	Max	Count
1	0.27	0.01	0.26	0.29	100
2	0.28	0.02	0.26	0.35	57
3	0.64	0.08	0.54	0.93	100
4	0.91	0.03	0.91	1.00	64
5	0.68	0.06	0.60	0.89	100
6	1.00	0.00	0.99	1.00	68

Table A2 - Input-oriented Model - TGR Values

Cluster	Median	Standard Deviation	Min	Max	Count
1	0.74	0.74	0.00	0.74	0.74
2	0.83	0.83	0.00	0.83	0.83
3	0.95	0.95	0.00	0.95	0.95
4	0.98	0.98	0.00	0.98	1.00
5	0.98	0.98	0.00	0.98	0.98
6	1.00	1.00	0.00	1.00	1.00