# Advanced Quantitative Assessment Methodology for Power Purchase Agreements Contracts


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***Abstract*—Power Purchase Agreements (PPAs) are essential for financing renewable energy projects, providing revenue stability while exposing investors to market volatility and operational risks. Assessing their financial performance requires a structured approach that considers market evolution, price volatility, production variability, and contract design. Thus, a quantitative framework for evaluating solar PPAs under different market conditions is proposed through Monte Carlo simulations and risk assessment techniques. The model analyzes key contract types, such as Pay-as-Produced and Baseload types, quantifying their financial performance through indicators like Internal Rate of Return, Value at Risk, and Expected Shortfall. A case study on the Italian market illustrates how geography, pricing structures, and coverage levels influence PPA outcomes. The findings provide key insights for investors and developers, supporting data-driven decision-making in structuring renewable energy contracts.**



***Index Terms*—Monte Carlo simulations, power purchase agreements, renewable energy resources, risk management.**


## I. Introduction

In recent years, the reduction of the Levelized Cost of Electricity (LCOE) of Renewable Energy Sources (RES) has made them increasingly competitive, providing market operators with the opportunity to complement regulated support mechanisms with the possibility to sell energy through private contracts [1]. RES projects require substantial capital investments, and market price volatility creates significant financing risks in purely merchant settings, constraining their growth. Hence, to ensure stable revenues and increase financing opportunities, RES producers explore alternative market mechanisms. At the same time, growing consumer awareness of environmental impact is driving more companies to commit to 100% renewable energy. These dynamics, coupled with the increasing penetration of decentralized energy resources, require advanced flexibility management strategies to balance grid stability and economic efficiency [2], [3], including coupling RES with electrochemical battery storage to compensate their uncertainty in production [4]. Like RES developers, these companies seek hedging tools against electricity price fluctuations, especially after the recent energy crisis [5].

Corporate Power Purchase Agreements (PPAs) have emerged as a key solution to these challenges [6]. These contracts establish a fixed-price structure between a seller and a buyer, typically in a multi-year scheme. By committing to purchase a share of produced energy at a predetermined price, buyers mitigate market risks while ensuring compliance with renewable energy targets and acquiring Renewable Energy Certificates (RECs). Meanwhile, developers transfer part of their investment risk to corporate buyers, making RES projects easier to finance. The emergence of PPAs demonstrates their appeal, with increasing volumes signed in recent years [7]. Diversified PPA portfolios, including multiple locations, technologies, and storage, can further reduce risk compared to single-project agreements, making them even more attractive to corporate buyers. However, their adoption is still challenged by the complexity of assessing financial performance and associated risks, particularly in bundled portfolios where interactions between contracts must be carefully evaluated [8].

To address these challenges, this study develops a framework for evaluating the financial viability of PPAs under different market conditions using Monte Carlo simulations (MCS) and quantitative risk assessment. While the model focuses on solar power plants (PV), it can be easily adapted to other RES types, integrating key contractual structures, such as Pay-as-Produced (PaP) and Baseload agreements, to better manage financial risks associated with market fluctuations.

## II. Methodology

The proposed algorithm consists of a series of modules, see Fig. 1, each representing specific aspects of the project's financial performance to provide stakeholders with a solid framework for making informed decisions on PPA contracts.

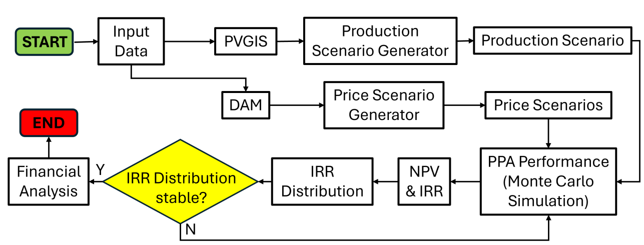



Fig. 1: Flowchart of the proposed algorithm.

The first step is the *Input Data* of the historical irradiance, energy price and PPA contract type; based on them a set of future *Production Scenarios* of solar energy plants in the geographical location selected, and a set of future *Electricity Price*

*Scenarios*, which incorporate both regular market fluctuations and the potential impact of catastrophic events of variable magnitude are generated. Next, MCS are carried out by randomly picking a production scenario and a price scenario and evaluate the PPA contract by calculating the Net Present Value (NPV) and Internal Rate of Return (IRR) financial metrics. They are aggregated together with the previous results into proper distributions. The simulation process iterates until the statistical properties of the distributions stabilize. Finally, the obtained results are subject to the *Financial Analysis* that calculates Value at Risk (VaR), Expected Shortfall (ES), and Sharpe Ratios (SR) economic performance indexes.

### A. Price Scenario Generator

The market model simulates future trends in electricity prices by considering a wide range of possible market conditions, including both normal fluctuations and the impact of extraordinary events. The following steps are carried out:

1) **Day-Ahead Market (DAM) yearly price estimation**. A forecast of long-term DAM price evolution is obtained considering key factors such as future commodity prices (natural gas, coal, etc.), renewable generation production, electricity demand evolution, transmission system capacity expansion, and market participation of storage plants. As this step is very complex, it regards the input data, and it was obtained based on reserved information using Edera [9] - Elemens proprietary software, only the final result is shown: Fig. 2a shows the three yearly long-term DAM price evolution curves -central (expected value), high (worst case), and low (best case)- obtained for the Italian DAM starting from the historical Italian market results [10] (see Fig. 2b). The curves, shown in thick and green, yellow and blue colors, respectively, depict the so called "Prezzo Unico Nazionale" (PUN, the reference energy price for the Italian DAM [11]) yearly trends until year 2050. This data is considered part of a normal distribution defined as

$$PUN_{yr} \sim \mathcal{N}(\mu_{yr}, \sigma^2_{yr}) \tag{1}$$

where $\mu_{yr}$ and $\sigma^2_{yr}$ are the mean and variance derived from considering the central curve the mean and the high and low curves the 95th and 5th percentiles, respectively.

2) **Hourly prices scenario generation**. For each year considered, a value is sampled from the annual probabilistic distribution, representing the mean annual PUN:

$$PUN_{sample,yr} \sim PUN_{yr} \tag{2}$$

The light gray and the red curves in Fig. 2a are examples of scenarios obtained through such sampling. Next, the sampled annual mean PUN values must be refined into hourly time series. First it is reasonable to assume that, since the daily DAM prices relative shape is strongly influenced by the demand trend of which shape is cyclical and predictable in long term, the daily DAM prices relative shape is conserved over long periods of time. Thus, the historical hourly series is used as reference for trend characterization and it is first segmented into three yearly periods (January-April, May-August, and September-December). For each period the hourly values within are normalized by dividing them to the average of the period. This approach preserves the relative variation within the period, allowing for the reconstruction of the profile at a different scale.

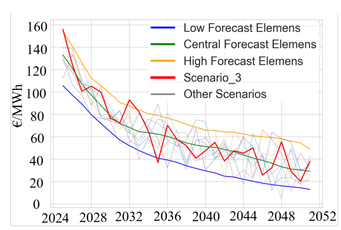
Next, the percentage change in the average between consecutive quarters ($\Delta^{\%}_{qt,i}$) is evaluated as:

$$\Delta^{\%}_{qt,i} = \frac{PUN_{end,i} - PUN_{start,i}}{PUN_{start,i}} \times 100 \tag{3}$$

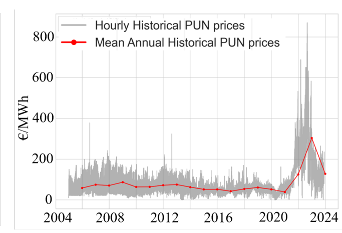
together with the percentage change of yearly PUN between consecutive years:

$$\Delta^{\%}_{yr} = \frac{PUN_t - PUN_{t-1}}{PUN_{t-1}} \times 100 \tag{4}$$

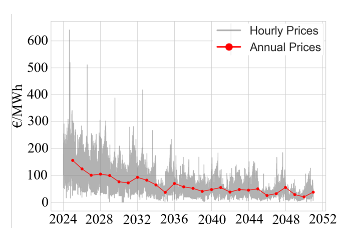
Finally, for the considered year, normalized DAM hourly prices profiles are randomly selected for each period of the year and a large number of possible normalized hourly price profiles are generated. Among them, the one for which the sum of $\Delta^{\%}_{qt,i}$ quantities is the nearest to $\Delta^{\%}_{yr}$ is selected to represent the sample year. The resulting normalized hourly price profile for the considered year is scaled by the corresponding $PUN_{sample,yr}$. Fig. 2c shows the outcome of this last step for the annual sampled scenario shown in red in Fig. 2a.



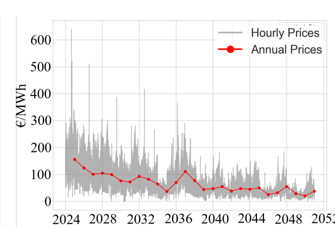

(a) Elemens' curves (2025-2050).




(b) Historical PUN data [10].




(c) Hourly reconstruction (2025-2050).




(d) Crisis addition (2025-2050).

Fig. 2: *Price Generator* curves.

3) **Crisis events overlap**. Crisis, like COVID pandemic, can significantly impact market prices. To account for such events, a crisis ($\zeta$) is artificially introduced into a selected subset of scenarios by adjusting price trajectories based on predefined crisis parameters: start year,

duration in months, and a target percentage increase in prices. The process starts by randomly selecting scenarios to apply the crisis. Once chosen, prices during the crisis period are adjusted upward according to:

$$P_{\zeta,yr} = P_{yr} \times (1 + \frac{\tau^{\zeta}}{100}) \tag{5}$$

where $\tau^{\zeta}$ range is derived from historical time series data, identifying annual price changes that exceed two standard deviations from the mean. Crisis duration, expressed in months, is based on the distribution of past market crises, while the start year is randomly chosen from the scenario time series. Fig. 2d shows a crisis overlap on the hourly price scenario of Fig. 2c.

### B. Production Scenario Generator

For an analyzed PV plant site, the procedure builds a multi-year forecasted hourly production scenario in two steps:

1) PVlib [12] is used to emulate the historical hourly PV production based on the following input: the plant's location atmospheric data according to the PVGIS database [13], defined PV model through parameters such as the tilt and orientation of solar panels, the number of modules per string and strings per inverter, and the types of modules and inverters used [14], [15] and the PV plant's installed capacity.
2) The historical production time series such that each entry is labeled according to the ISO week number and a database of historical profiles is obtained for each week. Then, for each week of each considered future year a historical profile is randomly selected from the database and the multi-year forecasted hourly production scenario is obtained. In this way, short-term patterns are preserved, while variability is introduced through random selection.

### C. Monte Carlo Simulations

The MCS iterative process consists of the following steps:

In the **first step**, one *production* and one *price scenario* are randomly selected.

In the **second step** the energy sold and income received through the PPA is calculated. The quantity exchanged through PPA is defined considering two PPA configurations:

- **PaP:** the agreed quantity is the actual hourly production.
- **Baseload:** The quantity agreed is fixed for the entire duration of the PPA. For this, the average hourly production over the entire PPA duration is calculated and adjusted according to the agreed coverage percentage to obtain the final value.

In both configurations, a fixed price for the energy exchanged through PPA is defined for the entire contract period and only a portion of the quantity agreed is paid at this price, while the remaining is allocated to the DAM market. The quantity of energy sold under the PPA, $Q_{ppa}$, for any given configuration is calculated as follows:

$$Q_{ppa} = Q_{production} \times \text{Coverage } \% \tag{6}$$

where $Q_{production}$ is the total quantity of energy agreed in the PPA and Coverage % is the agreed coverage percentage. In this way, the cash flow for every hour t during the PPA contract, i.e. $CF_t$ (which also includes taxes), is determined.

In the **third step** the hourly cash flow $CF_t$ is used to calculate the NPV and IRR financial metrics, both from an unlevered and levered perspective. NPV quantifies the net benefit or cost associated with an investment by calculating the difference between the present value of cash inflows and outflows over time, adjusted for the time value of money; on the other hand, IRR is defined as the discount rate that sets the NPV of all cash flows from a project to zero [16]. Equation (7) describe the NPV formula, while (8) refers to the IRR calculation:

$$NPV = \sum_{t=0}^{n} \frac{CF_t}{(1+r)^t} - C_0 \tag{7}$$

$$0 = \sum_{t=0}^{n} \frac{CF_t}{(1+IRR)^t} - C_0 \tag{8}$$

where $r$ is the discount rate, $n$ is the number of analyzed periods, and $C_0$ is the initial investment cost.

In the **forth step** the simulation aggregates the results by building or updating the IRR and NPV distributions.

In the **fifth step** the change with respect to the previous iteration in the IRR/NPV distribution parameters is checked. If they are below a defined threshold, meaning that the distributions are stabilized and addition of new information would be trivial, the MCS stops. Otherwise, a new iteration of MCS is executed.

### D. Financial Analysis: performance indexes calculation

At the end of MCS the stable NPV and IRR distributions are known and the financial feasibility of the PPA can be evaluated through the calculation of performance indexes:

- VaR: the indicator quantifies potential losses in adverse scenarios, aggregating multiple risks into a single parameter. In the context of PPAs, VaR captures financial vulnerabilities arising from energy price volatility, production inconsistencies, enabling a clear evaluation of the IRR distribution and an understanding of the likelihood of achieving specific financial returns. VaR can be evaluated through historical simulations, variance-covariance method, and MCS [17]; it is calculated as [18]:

$$VaR_{\alpha}(y) = q(\alpha) = F^{-1}(\alpha) \tag{9}$$

where $\alpha$ is the confidence level, $y$ represents the portfolio under test, and $F^{-1}(\alpha)$ is the inverse of the cumulative distribution function at the quantile $\alpha$. Equation (9) states that there is a probability $\varrho = \alpha$ that the IRR falls below the VaR, indicating the level of risk or the maximum potential loss for the investment under normal market conditions up to the $\alpha^{th}$ percentile of the IRR distribution. As a downside, VaR does not quantify tail risks, therefore other metrics must be considered to have a more comprehensive view.

- ES: the indicator estimates the expected loss in the worst-case scenario of a given confidence level, focusing on the tail of the IRR distribution; ES measures the expected loss in cases where losses exceed the VaR threshold, offering insight into potential extreme losses in the tail of the distribution [19]. ES is calculated as [18]:

$$ES_\alpha = \frac{1}{\alpha}\int_0^\alpha VaR_\gamma(y)d\gamma \tag{10}$$

where $\gamma$ is the integration range.
- SR: the indicator assess the performance of an investment with respect to its risk. SR can be expressed as [20]:

$$SR = \frac{R_p - R_f}{\sigma_p} \tag{11}$$

where $R_p$ is the return of the portfolio (in this context it represents the mean value derived from the calculated IRR distribution), $R_f$ is the risk-free rate of return (typically that of a government bond considered free of risk for the specific investment period), and $\sigma_p$ is the standard deviation of the portfolio's excess return.

## III. Simulations and Results

### A. Input Data

The methodology is used to evaluate solar PPA contracts across Italian territory. As detailed in II-A, the *Price scenarios* were generated for the period 2025-2050 considering the Italian DAM market framework. Examples of obtained *Price scenarios* are shown in Fig. 2c and Fig. 2d, respectively. For the generation of the *Production scenarios*, three key locations in Italy were selected: the cities of Milan, Rome, and Palermo; these cities, representing northern, central, and southern Italy, provide a comprehensive view of how solar potential and market conditions vary across regions - Table I summarizes their geographical information. For each of them, a set of *Production scenarios* has been generated.

TABLE I: Geographical information for selected cities.

| City | Latitude [°] | Longitude [°] | Altitude [m] |
|---|---|---|---|
| Milan | 45.4642 | 9.1900 | 20 |
| Rome | 41.9028 | 12.4964 | 21 |
| Palermo | 38.1157 | 13.3615 | 14 |

The analysis focuses on the two fixed-pricing PPA models (PaP and Baseload), each with different coverage levels, as detailed in II-C. Their financial performance is evaluated across the three cities, with the corresponding configurations shown in Table II. Each PPA contract is specific, so there is no benchmark available in terms of energy covered by the contract and of energy sold on the spot markets. The authors have decided to adopt two values of practical relevance: (i) 80%, since it is usually the minimum threshold required by lenders to provide debt, and (ii) 50%, since it is the maximum amount covered by a regulated support system available in Italy (energy release), therefore, the remaining 50% of the energy generated is the maximum quantity that can be traded through PPA. The PPA prices in the table are estimated as average risk or low risk values with respect to the average of the obtained *price scenarios*.

TABLE II: Configuration details for profiles, coverage percentages and fixed PPA prices.

| Profile Type | Coverage [%] | PPA Price [€/MWh] |
|---|---|---|
| PaP | 50 | 60 |
| | 80 | 60 |
| | 50 | 75 |
| | 80 | 75 |
| Baseload | 50 | 60 |
| | 80 | 60 |
| | 50 | 75 |
| | 80 | 75 |

Lastly, since the analysis has been conducted in Italy, in this work it has been assumed $R_f = 4\%$, a value that reflects the return of 10-year Italian bonds at the time of writing [21].

### B. Sensitivity Analysis

Evaluating solar energy projects requires a clear understanding of the key factors that influence returns and risks. This analysis explores how location, contractual profile, financial leverage, coverage percentage, and price level shape the performance of PPAs, highlighting their direct impact on returns and risk profiles.

*1) Location:* Table III summarizes the average over all configurations considered of the financial metrics for PPAs in the selected cities. VaR and ES metrics are evaluated for a 5% quintile. Palermo and Rome exhibit higher average IRRs compared to Milan due to their greater solar irradiance. Based on their $VaR_{95\%}$, these cities have higher returns in the worst-case scenarios but, according to $ES_{95\%}$, also face higher financial risks beyond that threshold. However, the SR indicates that investments in Palermo and Rome offer better risk-adjusted returns than those in Milan.

TABLE III: Average financial metrics by city.

| City | $\boldsymbol{IRR}$[%] | $\boldsymbol{VaR_{95\%}}$ | $\boldsymbol{ES_{95\%}}$ | $\boldsymbol{SR}$ |
|---|---|---|---|---|
| Milan | 11.60 | 7.97 | 6.23 | 8.59 |
| Palermo | 21.14 | 14.31 | 4.99 | 12.32 |
| Rome | 20.24 | 13.49 | 3.63 | 11.94 |

*2) Contract Type:* Table IV outlines the financial metrics associated with each contract type. The Baseload contract shows a higher average IRR, suggesting greater profitability; however, its negative average $ES_{95\%}$ indicates a higher exposure to extreme losses. On the other hand, the PaP profile, while having a lower average IRR, offers a more balanced risk profile, with a positive $ES_{95\%}$ and a significantly higher SR and, therefore, better risk-adjusted returns. Investors can balance stability and efficiency by diversifying across both profiles, combining the steady income of Baseload agreements with the risk-adjusted benefits of PaP contracts. The choice of contract type significantly impacts the financial performance and risk exposure of solar PPAs. While Baseload contracts may offer higher returns, they also come with greater risks, especially in extreme conditions. In contrast, PaP contracts take a more balanced approach, prioritizing risk management without significantly reducing returns.

TABLE IV: Average financial metrics by contractual profile.

| Profile | $IRR[\%]$ | $VaR_{95\%}$ | $ES_{95\%}$ | $SR$ |
|---|---|---|---|---|
| Baseload | 21.64 | 12.59 | -0.98 | 7.47 |
| PaP | 13.68 | 11.26 | 10.88 | 14.44 |

*3) Leverage:* Table V presents the financial metrics for PPAs based on their leverage status. Leverage can significantly increase profitability, with levered PPAs showing a 15.09% higher average IRR. It also increases returns in the worst-case scenarios, as reflected in the higher $VaR_{95\%}$. At the same time, levered PPAs have a lower $ES_{95\%}$, indicating that while extreme financial losses are less likely, their severity is higher compared to unleveraged PPAs. The SR is higher for unlevered PPAs, suggesting that although leverage can enhance returns, it also introduces greater risk and may lead to less efficient investments.

TABLE V: Average financial metrics by leverage status.

| Leverage Status | $IRR[\%]$ | $VaR_{95\%}$ | $ES_{95\%}$ | $SR$ |
|---|---|---|---|---|
| Levered | 25.20 | 14.77 | 1.04 | 5.92 |
| Unlevered | 10.11 | 9.08 | 8.86 | 15.98 |

*4) Coverage Percentage:* In this article, PPAs are classified into two main categories based on their coverage percentage: 50% and 80%. This classification is intended to represent a medium level versus a high level of coverage, following the market trends that, based on Elemens' experience, are typically observed. Table VI shows the average financial metrics for the two categories. The analysis shows that projects with 80% coverage tend to have a lower average IRR compared to those with 50% coverage, suggesting that higher coverage level offers greater revenue stability, but also limits potential returns. At the same time, higher coverage generally reduces financial risk, as indicated by $VaR_{95\%}$ and $ES_{95\%}$; however, negative $ES_{95\%}$ at 50% coverage highlights concerns about extreme financial loss scenarios. On the other hand, the increase in SR from 50% to 80% coverage suggests a more favorable risk-return balance at higher coverage levels, meaning that greater revenue stability can improve investment efficiency.

TABLE VI: Average financial metrics by coverage percentage.

| Coverage Percentage | $IRR[\%]$ | $VaR_{95\%}$ | $ES_{95\%}$ | $SR$ |
|---|---|---|---|---|
| 50% | 22.07 | 12.82 | -0.82 | 7.47 |
| 80% | 13.25 | 11.03 | 10.71 | 14.44 |

*5) Price:* Table VII summarizes the main financial metrics for PPAs at different PPA price levels. The pricing structure plays an important role in shaping the financial and risk profile of solar energy investments: This analysis shows that PPAs with higher price levels offer greater profitability, as reflected in a higher IRR and this is also associated with reduced financial risk, as indicated by higher $VaR_{95\%}$ and $ES_{95\%}$. The higher SR at the 75 €/MWh price level indicates a more favorable risk-adjusted return, suggesting that a higher price level can improve investment efficiency.

TABLE VII: Average financial metrics by price level.

| Price Level | $IRR[\%]$ | $VaR_{95\%}$ | $ES_{95\%}$ | $SR$ |
|---|---|---|---|---|
| 60 | 14.34 | 8.89 | 2.88 | 8.86 |
| 75 | 20.97 | 14.96 | 7.02 | 13.04 |

### C. Summary of the Sensitivity Analysis

The analysis examines how key factors impact the financial performance and risk profile of solar PPAs:

- **Contract Types:** Baseload contracts have higher average IRRs, while PaPs have better risk-adjusted returns (higher SR), balancing revenue stability and return variability.
- **Price Sensitivity:** Higher PPA prices boost profitability but increase financial risk. A good pricing strategy is key to maximizing returns while managing exposure.
- **Leverage:** Levered PPAs enhance returns but elevate risk, as indicated by higher IRRs and $VaR_{95\%}$ values. Unlevered PPAs, with better risk-adjusted returns, may be preferable for risk-averse investors.
- **Coverage Percentage:** Higher coverage improves revenue predictability but caps upside potential during high solar output periods. Selecting an optimal coverage level is crucial for aligning risk tolerance with financial goals.
- **Geographical Influence:** Solar irradiance and market conditions impact performance, with sunnier cities like Palermo and Rome showing higher IRRs than Milan.

## IV. Conclusions

The work examined solar PPAs in the Italian electricity market, focusing on risk, pricing, and profitability. Using theoretical analysis and empirical data, it provides a practical framework for evaluating PPA structures and managing risk. The results highlight the trade-offs between PaP and Baseload contracts: the former offers greater risk mitigation, while the latter can yield higher returns in favorable conditions.

This research provides investors and project developers with concrete tools to structure PPAs, refine risk management strategies, and optimize financial planning. By offering a structured approach to navigate market uncertainties, it reinforces the role of advanced analytics in improving decision-making within the renewable energy sector.

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## References


[1] IEA, "Renewable energy market update-june 2023," IEA, Tech. Rep., 2023.

[2] R. Nebuloni, V. Ilea, A. Berizzi, C. Bovo, C. Arrigoni, F. Corti, B. Conte, and R. Bonera, "Optimal management of flexibility services in lv distribution grids," in *27th International Conference on Electricity Distribution (CIRED 2023)*, 2023.

[3] V. Ilea, R. Nebuloni, C. Arrigoni, F. Re, C. Bovo, and R. Bonera, "A sensitivity-based linear model for optimal dispatch of local flexibility," in *2024 20th International Conference on the European Energy Market (EEM)*, 2024, pp. 1–6.

[4] R. Nebuloni, L. Meraldi, L. Moretti, V. Ilea, C. Bovo, A. Berizzi, and P. Raboni, "A real-time cycle counting method for battery degradation calculation in milp models," in *2023 IEEE International Conference on Environment and Electrical Engineering and 2023 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, 2023, pp. 1–6.

[5] Y. Ghiassi-Farrokhfal, W. Ketter, and J. Collins, "Making green power purchase agreements more predictable and reliable for companies," *Decision Support Systems*, vol. 144, p. 113514, 2021.

[6] L. Mendicino, D. Menniti, A. Pinnarelli, and N. Sorrentino, "Corporate power purchase agreement: Formulation of the related levelized cost of energy and its application to a real life case study," *Applied Energy*, vol. 253, p. 113577, 2019.

[7] S. Jain, "Exploring structures of power purchase agreements towards supplying 24x7 variable renewable electricity," *Energy*, vol. 244, p. 122609, 2022.

[8] C. Mittler, M. Bucksteeg, and P. Staudt, "Review and morphological analysis of renewable power purchasing agreement types," *Renewable and Sustainable Energy Reviews*, vol. 211, p. 115293, 2025.

[9] Elemens. (2024). [Online]. Available: https://www.elemens.it/price-revenues-scenarios-edera/

[10] Gestore Mercati Energetici. (2024). [Online]. Available: https://mercatoelettrico.org/it/

[11] L. H. Lam, V. Ilea, and C. Bovo, "A thorough comparison among various mathematical approaches to compute pun in italy," in *2018 15th International Conference on the European Energy Market (EEM)*, 2018, pp. 1–5.

[12] K. Anderson, C. Hansen, W. Holmgren, A. Jensen, M. Mikofski, and A. Driesse, "Pvlib python: 2023 project update." *Journal of Open Source Software*, vol. 8, 2023.

[13] European Commission. (2024) Sarah-2 solar radiation data. [Online]. Available: https://joint-research-centre.ec.europa.eu/photovoltaic-geographical-information-system-pvgis/pvgis-data-download/sarah-2-solar-radiation-data_en

[14] Sandia National Laboratories. (2023) Pv lifetime module characterization datasets. [Online]. Available: https://pvpmc.sandia.gov/datasets/pv-lifetime-module-datasets-clone/

[15] D. L. King, S. Gonzalez, G. M. Galbraith, , and W. E. Boyson. (2023) Performance model for grid-connected photovoltaic inverters. [Online]. Available: https://energy.sandia.gov/wp-content/gallery/uploads/Performance-Model-for-Grid-Connected-Photovoltaic-Inverters.pdf

[16] M. Sokolov, "Npv, irr, pi, pp, and dpp: a unified view," 02 2023.

[17] A. J. Patton, J. F. Ziegel, and R. Chen, "Dynamic semiparametric models for expected shortfall (and value-at-risk)," *Journal of Econometrics*, vol. 211, no. 2, pp. 388–413, 2019.

[18] J. M. Chen, "On exactitude in financial regulation: Value-at-risk, expected shortfall, and expectiles," *Risks*, vol. 6, no. 2, 2018.

[19] C. Acerbi and D. Tasche, "On the coherence of expected shortfall," *Journal of Banking & Finance*, vol. 26, no. 7, pp. 1487–1503, 2002.

[20] M. Debasri and U. Aman, "Nonparametric sharpe ratio," *Journal of Quantitative Economcis*, vol. 2, p. 172–185, 2004.

[21] Tradin Economics. (2024). [Online]. Available: https://tradingeconomics.com/italy/government-bond-yield