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***Abstract*— Decarbonation of urban districts would be critical for reducing carbon footprints. In this sense, Renewable Energy Communities (RECs) support this transition through collective self-consumption, yet their local generation rarely meets the local demand, still requiring grid-supplied residual energy. Power Purchase Agreements (PPAs) could bridge this gap by providing off-site renewable energy to RECs, but their associated risks often limit access for non-corporate buyers. Therefore, this paper proposes a PPA portfolio optimization tool to enable RECs to participate in PPAs as buyers and partially cover their residual demand. The methodology is based on a bi-objective optimization using the Pareto front to maximise both Net Present Value (NPV) and Conditional Value-at-Risk (CVaR) such that both economic returns and risk mitigation are balanced. The optimization tool is tested on a 15-years PPA (2026-2040). Uncertainty over the long-term is addressed by considering input data across 10 scenarios, ranging from high to low penetration of renewable energy scenarios. The results indicate that the contractual configuration varies according to whether the economic return or risk mitigation is prioritised, leaving the portfolio choice to the buyer.**

Keywords*— *pay-as-consumed, portfolio optimization, power purchase agreement, renewable energy community, renewable energy support, risk management.

NOMENCLATURE

Sets

J	Scenarios
Y	Years
H	Hours
G	Generators
S	Storage systems

Parameters

n_j	Number of scenarios
n_{points}	Number of points in the Pareto front
p_g^{PPA}	PPA price for generator g
p_s^{PPA}	PPA price for storage system s
C_g^{MAX}	Maximum size allowed for generator g
C_s^{MAX}	Maximum size allowed for storage system s
K	Synthetic curtailment penalty
r	Discount rate
α	Buyer confidence level

Scenario data

$p_{j,y,h}$	Day-ahead electricity price in scenario j, year y and hour h
$g_{j,g,y,h}$	Generation profile in p.u. of generator g in scenario j, year y and hour h
$i_{j,s,y,h}$	Injection profile in p.u. of storage s in scenario j, year y and hour h
$d_{j,y,h}$	Energy community demand profile in scenario j, year y and hour h

Variables

C_g	Contractual capacity of generator g
C_s	Contractual capacity of storage system s

$c_{j,g,y,h}$	Curtailment profile for generator g in scenario j, year y and hour h
$r_{j,y,h}$	Market residual demand profile in scenario j, year y and hour h
VaR	Value-at-Risk with confidence level α
z_j	Auxiliary variable for CVaR computation in scenario j

I. INTRODUCTION

According to the IEA, urban districts are responsible for about 28% of global CO_2 emissions related to the energy sector [1]. These emissions arise not only from electricity use within buildings, but mainly from heating, cooking and transportation consumptions, which nowadays still rely on fossil fuels. Therefore, two fundamental elements are needed to reduce the carbon footprint of these areas: first, the supply of clean energy, based on renewable energy sources (RES); then, the electrification of fossil-fuels consumptions. In this sense, the Renewable Energy Community (REC) paradigm, introduced by the RED II Directive [2], has recently emerged as a promising solution to facilitate the supply of clean and affordable energy in urban areas. Indeed, they allow community members to share RES-based and locally produced electricity, therefore enhancing collective self-consumption and reducing higher-voltage grid import. However, as the production is usually mainly based on rooftop photovoltaic (PV) plants, the generation potential is often not enough to fully meet the local demand. This may happen especially in urban areas where the high energy demand density faces the challenge of limited rooftop area availability, resulting in a residual demand not locally satisfied and thus supplied from the grid [3]. Moreover, even if on one hand the electrification of energy consumptions in urban areas would represent a fundamental step towards their decarbonization, it would also cause a significant increase in their electricity consumption, meaning that this phenomenon will worsen as well. For these reasons, a hybrid decarbonization approach should be implemented in urban areas by coupling the on-site collective self-consumption allowed by RECs with the off-site procurement of RES-based electricity. One way to achieve this could be through Power Purchased Agreements (PPAs). PPAs represent a type of contract in which two actors, a buyer and seller, agree to buy and sell electricity at a contracted price for a generally long period of time [4]. This allows the securement of cheap electricity to the buyer and guarantees stable cash flows to the seller, allowing the finance of the capital-intensive RE projects. However, these contracts have been traditionally limited to large users due to their contractual complexity and associated investment risk [5]. Particularly, three main risks are associated with PPAs: price risk, volume risk and shape risk [6]. Price risk arises from the market price variability with respect to the contractual PPA price, which may be higher or lower. Conversely, volume risk relates to the uncertainty in supplying a predetermined quantity of energy. Finally, the shape risk concerns the delivery profile, distinguishing PPAs into pay-as-consumed (in which the supplier bears the risk) or pay-as-produced (in which the risk falls on the buyer).

In literature, most research focuses on pay-as-produced PPA, while pay-as-consumed logics remain unexplored. However, this PPA model prevents small users from participating in such contracts due to the high risks borne by the buyers. For instance, the work of [7] develops a tool for optimising PPA portfolios under a pay-as-produced framework. In this study, while volume risk is partially shared among buyer and seller, as the seller is asked to supply at least a predefined cumulative demand, the buyer bears the full price and shape risks. A step towards the opening of PPA frameworks to non-corporate participants is represented by the work of [8]. This study proposes a risk mitigation tool to facilitate the sale of electricity generated within an energy community to an external off-taker. While this work introduces an important innovation by extending the PPA framework to energy communities, it positions them as sellers rather than buyers. This approach can surely help energy communities to monetise their energy surplus, but it does not support them in securing electricity supply when local RES generation is insufficient—a scenario that is significantly more likely to occur, as previously highlighted. Additionally, the PPA structure remains pay-as-produced, meaning that the buyer continues to bear the associated risks. While research in this direction facilitates participation for non-corporate sellers in PPAs, it still limits the involvement of non-corporate buyers. In this sense, the work of [9] seeks to mitigate PPA risks for energy communities when they act as buyers. Indeed, it explores the integration of a physical battery within an energy community to purchase more PV-generated electricity under a pay-as-produced PPA, offering a partial protection against profile and price risks.

Since the majority of existing research focuses on corporate pay-as-consumed PPAs, this paper aims to address the literature gap by developing a PPA portfolio optimization tool for energy communities as non-corporate buyers. This approach seeks to extend access to cheap, zero-carbon and stable electricity prices to small users, while simultaneously contributing to the financing of off-site RE projects.

The rest of this paper is organised as follows. Section II introduces the methodology implemented for the tool development. Section III illustrates the case study adopted for the analysis and the obtained results. Finally, Section IV summarises the main implications of the work.

II. METHODOLOGY

This section presents the optimisation problem formulated by the authors to implement the PPA portfolio optimisation in energy communities. The proposed methodology is built upon the work of [7], which focuses on corporate pay-as-produced PPAs.

As in the original work, the portfolio optimisation follows a bi-objective optimisation, aiming to maximise both the Net Present Value (NPV) and the Conditional Value-at-Risk at confidence level α (α-CVaR). In the context of this analysis, the α -CVaR serves a risk measure for the portfolio optimization. Particularly, it represents the expected NPV for values in the NPV distribution that fall below the threshold indicated by the α-VaR, which corresponds to the NPV value with probability α of realisation. In this sense, α reflects the confidence level the buyer is willing to accept. A graphical representation of these concepts is illustrated in Figure 1. For the sake of simplicity, the acronyms VaR and CVaR will be adopted throughout this paper to refer to the α-VaR and α-CVaR concepts, respectively.

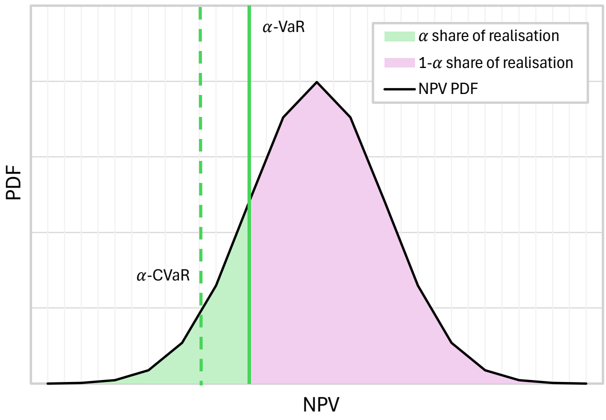

Figure 1. Graphical representation of α-VaR and α-CVaR concepts.

Therefore, three analyses are conducted:

1) NPV maximisation The first optimisation problem aims to maximise the expected NPV in absence of risk, therefore the highest achievable expected NPV. In this sense, the objective is shifting the centre of the NPV distribution to higher values without accounting for its variability. Then, the risk in the optimised portfolio is evaluated by computing the corresponding CVaR, based on the optimisation results. Since this value represents the lowest achievable NPV with confidence α, it provides a measure of the portfolio risk. A detailed description of this optimisation problem is provided in Section II.A.

2) CVaR maximisation The second optimisation problem aims to maximise the CVaR, representing the expected NPV reachable with confidence level α. In this case, the objective is moving the left tail of the NPV distribution towards higher values on the right. Therefore, maximising the CVaR is somehow equivalent to minimising the portfolio risk, as it leads to a maximisation of the expected NPV in the worst cases. This optimisation problem is further described in Section II.B.

3) Pareto front The bi-objective optimisation is finally performed by building a Pareto front. Indeed, the NPV maximisation problem is repeatedly solved while constraining the CVaR value at predefined points. These points span from the minimum CVaR value obtained from the NPV maximisation problem (Step 1) to the maximum CVaR value derived from the CVaR maximisation problem (Step 2). A detailed description of the front construction is provided in Section II.C.

A. NPV Maximisation

The formulation of the NPV maximisation problem is presented in this section. In this case, the optimisation problem aims to maximise the expected NPV, as shown in eq. (A.1), by considering several input variables scenarios. The NPV in each scenario is determined from the buyer point-of-view by accounting for three components, as illustrated in eq. (A.2) and described below.

$$\max_{C_g, C_s} \frac{1}{n_j} \cdot \sum_{j \in J} NPV_j \tag{A.1}$$

$$NPV_j = \sum_{g \in G} \sum_{y \in Y} \sum_{h \in H} \left(C^{Avoid}_{j,g,y,h} - C^{curt}_{j,g,y,h} \right) + \sum_{s \in S} \sum_{y \in Y} \sum_{h \in H} R^{proxy}_{j,s,y,h} \tag{A.2}$$

1) Avoided costs due to pay-as-consumed PPA The first NPV component represents the avoided costs from purchasing energy at the contractual PPA price instead of the market price, as shown in eq. (A.3). Note that the price difference, that represents the buyer's benefit, does not apply to all energy produced by the RES plants, as would be the case in a pay-as-produced PPA. Instead, it applies only to the energy actually needed to meet the demand, which is represented by the energy produced minus any curtailment.

$$C^{Avoid}_{j,g,y,h} = \frac{\left(p_{j,y,h} - p^{PPA}_{g}\right) \cdot \left(g_{j,g,y,h} \cdot C_g - c_{j.g,y,h}\right)}{(1+r)^{y-y_0}} \tag{A.3}$$

2) Penalty curtailment The penalty illustrated in eq. (A.4) has been introduced for generator curtailment to discourage the selection of higher contractual capacities that would reduce the market residual demand, i.e. the demand still supplied at the market price. In fact, such higher capacities expose the sellers to higher price risks in cases where the hourly energy production exceeds the demand and cannot be sold at the contractual PPA price. Indeed, any flexibility or physical storage system has not been considered in this phase of the work, meaning that buyers can only purchase energy when it is actually needed. Therefore, this penalty accounts for the potential risk the seller faces when the contracted energy is not sold at the agreed PPA price, but at the market price, which can be either higher or lower. However, this is an artificial penalty introduced to discourage such behaviour, but it does not correspond to an actual cost. The risk exposure is tied to the value of K, which should be defined as a trade-off between the contractual PPA price and the market price.

$$C^{curt}_{j,g,y,h} = \frac{K \cdot c_{j.g,y,h}}{(1+r)^{y-y_0}} \tag{A.4}$$

3) Revenues from proxy-storage PPA A proxy-storage PPA is introduced to mitigate the investment risk of the portfolio, as shown in eq. (A.5). In this agreement, the buyer somehow virtually rents a storage system. The buyer receives revenues from the virtual injection of the storage system, with an injection profile computed through predefined rules, while paying the energy virtually discharged by the storage, with a discharging profile derived through predefined agreements as well. In the context of this analysis, the storage virtual injection profile is determined as the optimal behaviour of the storage system on the day-ahead market to maximise the storage revenues. Moreover, the agreed virtual discharging profile is assumed to completely discharge the storage capacity in 24h at a constant rate. As everything is merely virtual, the buyer does not actually operate the storage, leaving the seller free to independently operate the assets on the markets.

$$R_{j,s,y,h}^{proxy} = \frac{p_{j,y,h} \cdot i_{j,s,y,h} \cdot C_s - p_s^{PPA} \cdot \frac{C_s}{24}}{(1+r)^{y-y_0}} \tag{A.5}$$

The objective function is subject to several constraints. Constraint (A.6) introduces an hourly energy balance among the market residual demand, the energy community demand, the supply from off-site RES plants and the plant curtailment. It may be noted that this balance equation considers an hourly energy demand, in contrast to the cumulative demand considered in [7]. This approach aims to mitigate the buyer's volume risk by making the problem aware of the hourly variability, thereby facilitating diversified PPA portfolios with a mix of technologies—an approach recommended by [6] as a strategy for managing volume risk. Constraint (A.7) limits the hourly curtailment of each generator to be always lower than its production. Finally, constraint (A.8) and (A.9) impose a limit to the capacity of the generators and storage systems, respectively.

$$r_{j,y,h} = d_{j,y,h} - \sum_{g \in G} \left(g_{j,g,y,h} \cdot C_g - c_{j,g,y,h} \right) \quad \forall j \in J \quad \forall y \in Y \quad \forall h \in H \tag{A.6}$$

$$c_{j,g,y,h} \leq g_{j,g,y,h} \cdot C_g \quad \forall g \in G \tag{A.7}$$

$$C_g \leq C_g^{MAX} \quad \forall g \in G \tag{A.8}$$

$$C_s \leq C_s^{MAX} \quad \forall s \in S \tag{A.9}$$

The optimisation variables include the capacities of the generators C_g and storage systems C_s. Once the optimisation is performed, the CVaR for the selected capacities can be determined as the average NPV of the worst-performing scenarios with α probability of realization. This value represents the minimum expected NPV with confidence level α for the chosen capacities, therefore it provides a measure of the selected portfolio associated risk.

B. CVaR maximisation

The CVaR maximisation problem is formulated as follows. In this case, the objective is the maximisation of the CVaR as shown in the objective function presented in eq. (B.1). Particularly, it can be observed that this representation follows a linear formulation derived using the auxiliary variable z_j [10].

$$\max_{C_g, C_s} VaR - \frac{1}{\alpha} \cdot \frac{1}{n_j} \sum_{j \in J} z_j \tag{B.1}$$

The objective function is subjected to several constraints. Constraints (A.6)-(A.9) still hold. Moreover, constraints (B.2) and (B.3) are also included.

$$z_j \geq VaR - NPV_j \quad \forall j \in J \tag{B.2}$$

$$z_j \geq 0 \quad \forall j \in J \tag{B.3}$$

The optimisation variables are still represented by the capacities of the generators C_g and storage systems C_s. Once the optimization is performed, the expected NPV for the selected capacities can be determined using the same expressions presented in eq. (A.1) and (A.2).

C. Pareto front

In this section, the building of the Pareto front for the bi-objective optimization is described. Particularly, the NPV maximisation problem introduced in Section II.A is solved over n_{points} iterations. Therefore, the objective function remains as defined in eq. (A.1) and the constraints (A.6)-(A.9) still hold. However, additional constraints are introduced. Indeed, the range between the minimum CVaR (from Section II.A) and the maximum CVaR (from Section II.B) is uniformly divided in n_{points} values. At each iteration i, the CVaR is constrained to the corresponding value in this range, introducing the new constraint presented in eq. (C.1). Furthermore, constraints (B.2) and (B.3) are also included, following the same formulation used in the CVaR maximisation problem of Section II.B.

$$VaR - \frac{1}{\alpha} \cdot \frac{1}{n_j} \sum_{j \in J} z_j = CVaR[i] \tag{C.1}$$

III. CASE STUDY AND RESULTS

The case study adopted for the portfolio optimisation is illustrated in the following. The optimisation models can determine the capacities of generators and storage systems from a predefined list of available projects, as shown in TABLE I for generators and in TABLE II for storage systems. Each project is associated with a PPA price. For generators, this corresponds to the Levelized Cost of Energy (LCOE) of the power plant; for storage systems, it corresponds to the Levelized Cost of Storage (LCOS) of the technology, assuming a decline in storage costs over the coming years [11]. The selected PPA prices are presented in TABLE I and TABLE II as well.

TABLE I. LIST OF GENERATORS PROJECTS.

id	**Technology**	**Location**	**PPA price [€/MWh]**
PV South	PV	South of Italy	52
PV Sicily	PV	Sicily	51
PV Sardinia	PV	Sardinia	51
PV North	PV	North of Italy	53
O-WIND South 1	On-shore wind	South of Italy	73
O-WIND South 2	On-shore wind	South of Italy	70
OF-WIND Sardinia	Off-shore wind	Sardinia	91
OF-WIND Sicily	Off-shore wind	Sicily	92

TABLE II. LIST OF STORAGE SYSTEMS PROJECTS.

id	**Technology**	**EPR [h]**	**Cycles [1/day]**	**PPA price [€/MWh]**
Li-ion 4h 2 cycles	Li-Ion	4	2	27
Li-ion 8h 1 cycle	Li-Ion	8	1	35
Hydro 8h 1 cycle	Pumped Hydro	8	1	80

The portfolio optimisation requires two types of input data, as shown in Figure 2, namely scenario data and parameters.

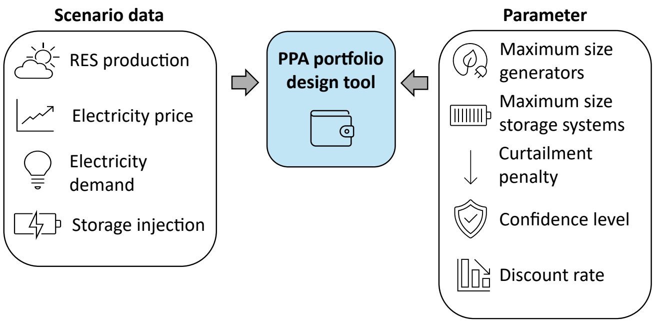

Figure 2. Input data for PPA portfolio optimisation.

a) Scenario data They represent future predictions of selected variables, generated across multiple scenarios to account for their uncertainty over the long-term. In this analysis, projections span the period from 2026 to 2040, covering 10 scenarios. Particularly, each variable is defined with hourly resolution for every year across all scenarios. RES production, electricity price and storage injections are generated with the methodology detailed in [7], which lies beyond the scope of this work. However, it is important to highlight that their generation is based on input variables uniformly distributed between a worst-case scenario, representing a delayed transition to green energy [12], and a best-case scenario, aligned with the FF55 target [12]. In contrast, the community electricity demand is assumed as a constant base load of 3 MWh per hour, across all years and scenarios.

b) Parameters They represent input data that remain consistent across all years and scenarios. In this analysis, the values of these variables have been assumed and are listed in TABLE III. Particularly, the synthetic curtailment penalty K has been set to 150 €/MWh to balance the risk exposure of the sellers, aiming to provide a trade-off between the PPA prices of generators and the market price.

TABLE III. ASSUMED PARAMETERS FOR PORTFOLIO OPTIMIZATION.

Parameter	Value		
C_g^{MAX}	10	MW	$\forall g \in G$
C_s^{MAX}	10	MWh	$\forall s \in S$
K	150	€/MWh	
r	4	%	
α	10	%	

B. Results and Discussion

The results of the bi-objective optimisation are presented in this section. Particularly, Figure 3 shows the Pareto front obtained when considering only two points, namely the maximum NPV and the maximum CVaR. As observed, the portfolio in the max CVaR case is more diversified compared to the max NPV case, introducing contractual capacities in new RES plants. Additionally, the contractual capacity of the proxy-storage decreases when transitioning from the max NPV to the max CVaR case.

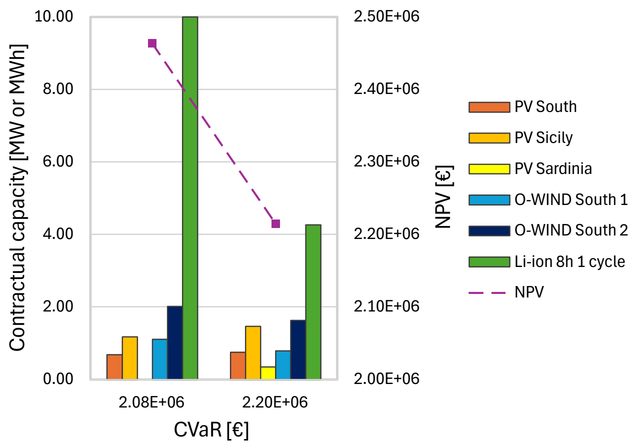

Figure 3. Two-points Pareto front of PPA portfolio.

The first result can be explained by considering that introducing additional RE projects may lower the expected NPV, due to factors such as additional payments or penalty curtailments, but it simultaneously reduces the NPV variability. In this way, buyers are protected against very low NPV values, even if very high NPV values cannot be reached. Indeed, Figure 4 shows the NPV distribution across the 10 scenarios for both the max NPV and max CVaR cases. As expected, the NPV distribution in the max CVaR case has a lower expected NPV but also a reduced variability, making it more predictable. In contrast, the max NPV case shows a higher expected NPV but also greater variability, making it more uncertain.

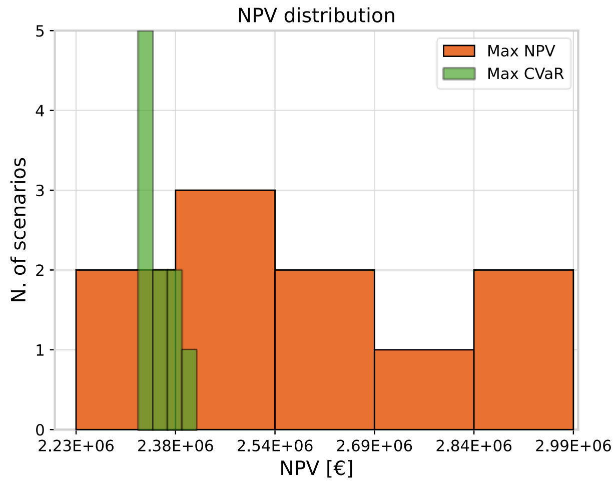

Figure 4. NPV distribution across the 10 scenarios in both max NPV and max CVaR cases.

The second result, concerning the contractual capacities of the proxy-storage, is more unexpected. Indeed, a previous study [7] suggests that the proxy-storage may play a risk-mitigating role, meaning that its contractual capacity would be expected to increase in the max CVaR case rather than decrease. However, the obtained outcome can be explained by examining the yearly expected revenues from proxy-storage PPA (Figure 5) and their variability compared to those of RES plants PPA (TABLE IV). As observed, the proxy-storage revenues become positive after 2029, indicating that introducing a storage capacity in the portfolio is highly profitable as the revenues after 2029 outweigh prior losses. Therefore, storage is introduced in the max NPV case. However, the distribution of proxy-storage revenues reveals greater variability, compared to the avoided costs of RES plants. This happens because the proxy-storage revenues are tied to the variability of the predicted price, whose volatility increases over time, especially between the worst and best scenarios due to the growing penetration of RES. As a result, the proxy-storage is perceived as the most uncertain asset, leading to a reduction in its contractual capacity when maximising the CVaR to lower the risk.

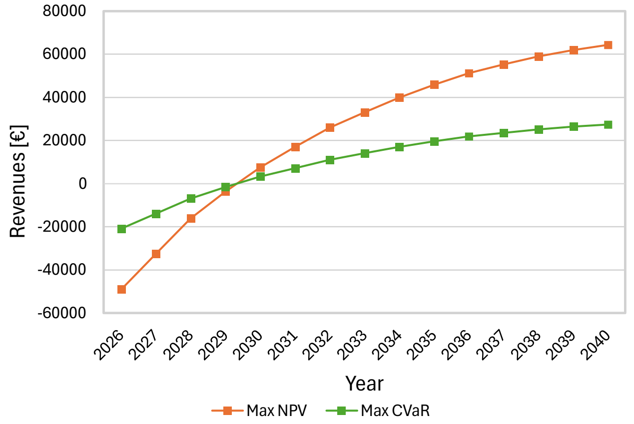

Figure 5. Yearly expected revenues from proxy-storage PPA in both max NPV and max CVaR cases.

TABLE IV. STANDARD DEVIATION OF REVENUES IN EACH SINGLE PPA COMPONENT.

PPA component	Standard deviation [k€]
RES plants	89.816
Proxy-storage	316.105

Additionally, the results also provide some insights about market residual demand. Indeed, Figure 6 illustrates the expected hourly market residual demand per year in both max NPV and max CVaR cases. As observed, it follows the same pattern across the contractual years for both cases, thus suggesting that the degree of market dependence remains unaffected by the chosen risk level. Moreover, it is also worth noting that the PPA agreement generally covers approximately half of the hourly community base load. This outcome is achieved through an hourly curtailment that averages 4.50 kWh in the max NPV case and 4.52 kWh in the max CVaR case. In this sense, integrating physical storage solutions could help bridge the gap between community demand and intermittent RES generation. Indeed, they could not only prevent curtailment penalties, but also enable additional purchases of surplus RES generation during periods of excess, which can be stored and later utilised when facing generation scarcity.

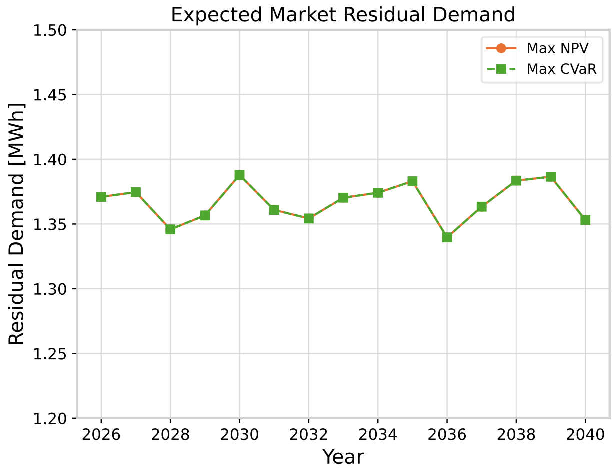

Figure 6. Expected hourly market residual demand per year in both max NPV and max CVaR cases.

Further insights into market residual demand can be inferred also from Figure 7, which shows the expected hourly residual market demand per hour in year 2026 in the max NPV case. Since the observed trend remains consistent across all other contractual years, only this particular year is shown for simplicity. As observed, the residual demand tends to remain lower during daylight hours, with values ranging between 0 and 1 MWh. This pattern is more visible during summer months, when the higher availability of daylight hours extend the period of reduced market residual demand. Moreover, higher residual demand values emerges during summer nights between May and October, suggesting that wind power production may be insufficient in these months due to the lower wind speeds as solar generation is absent. On the other hand, winter nights show lower residual demand values, probably due to higher wind power availability. Once again, these observations emphasise the need for physical storage solutions to manage the excess of renewable energy generation, especially during peak production hours, for demand compensation.

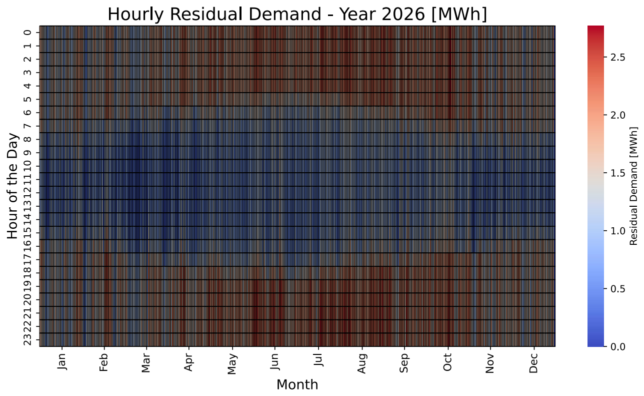

Figure 7. Expected hourly market residual demand per hour in year 2026 in max NPV case.

IV. CONCLUSIONS

This study analyses the optimization of Power Purchase Agreement (PPA) portfolios for renewable energy communities, focusing on the trade-off between economic performance and financial risk mitigation. By adopting a bi-objective optimization framework, the study evaluates how different contractual configurations impact the Net Present

Value (NPV) and Conditional Value-at-Risk (CVaR) over a 15-year period (2026–2040) across ten different energy market scenarios.

The results highlight that market residual demand remains significant across all cases, indicating that current PPA configurations alone are insufficient to ensure full energy self-sufficiency. The analysis of hourly trends reveals that residual demand is highest during summer nights, when solar production is absent and wind generation remains insufficient. This underscores the importance of a diversified renewable energy portfolio, integrating physical storage solutions to balance seasonal and intraday generation fluctuations while avoiding curtailment.

Beyond financial returns, the analysis reveals how PPA risk is distributed between buyers and sellers. Price risk is partially shared, as the buyer remains exposed to market prices in the presence of residual demand, while the seller faces this risk when production exceeds demand. However, the introduction of a curtailment penalty mitigates the seller's exposure. Profile risk is also shared, as neither party is obligated to follow a predefined supply or purchase profile: the buyer acquires energy only when needed, avoiding re-selling risks, while the seller provides production only when available, without delivery constraints. Similarly, volume risk is balanced between the two parties. The introduction of an hourly demand structure allows for a more diversified portfolio, reducing volume risk without forcing the seller to always meet a fixed demand level. As a result, the PPA structure developed in this study places all major risks in an intermediate position between buyers and sellers, ensuring a more balanced contract framework.

To conclude, it can be observed that the contractual solution differs significantly depending on whether the NPV is maximized or the risk is minimized. Each approach has its own advantages and drawbacks. Ultimately, the choice between the two portfolios rests with the buyer, according to their preferred level of risk exposure.

Future works could focus on implementing a variable energy demand, rather than a base load, to account for collective self-consumption effects within energy communities. Additionally, further research should explore the integration of physical storage solutions with PPAs and compare them with the already implemented virtual one. Finally, future research could also involve shifting PPA risks more towards sellers, for instance by exploring solution without curtailment penalties, with specific delivery profiles or with constraints on hourly demand to be met. These efforts would move research in this field towards pay-as-consumed logics within PPAs, making these contracts more accessible to non-corporate users and ultimately supporting full decarbonisation of urban contexts.

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