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Enhancing the viability and bankability of hybrid RES-BESS systems with corporate power purchase agreements and electricity market participation ☆

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ABSTRACT

Renewable Energy Sources (RES) play a significant role in the green energy transition. Recently, state support for RES has been declining or even abandoned. In this context, corporate Power Purchase Agreements (PPAs) represent an alternative financial instrument for new RES installations. PPAs can mitigate investment risks and the active participation in different market segments, which is achievable considering the co-location of Battery Energy Storage Systems (BESS). A hybrid scheme of a corporate PPA for a co-located Photovoltaic (PV) and BESS asset is examined in this paper under a semi-contracted and semi-merchant scheme aiming at ensuring bankability for the asset and profit maximization through market participation. A probabilistic neural network is developed to determine a secure Pay as Delivered PPA delivery profile, and a Mixed Integer Linear Programming model is developed for the optimal sizing, scheduling, and dispatch of stored energy to different electricity market segments. The Greek electricity market is selected for the investigation of the proposed methodology, being a market with a high share of PV. The findings suggest that higher capital expenditures reduce optimal BESS capacity, while lower offer greater flexibility in BESS size. As the amount of delivered power under the PPA increases, the RES investor, as active market participant, must schedule the asset up to several days if grid charging is not possible.

1. Introduction

Renewable Energy Sources (RES) play a crucial role in energy transition, offering solutions to meet the growing electricity demand and mitigate the environmental impacts from fossil fuels [1]. Indicatively, for the year 2024, RES accounted for 92.5% of global net power capacity additions, with Photovoltaics (PV) alone contributing more than three-quarters of this growth [2]. To further support RES integration, governments incentivize private investment through various support mechanisms including Feed-in Tariffs (FiT), Feed-in Premiums (FiP), Contracts for Difference (CfD) and Tradable Green Certificates (TGC) [3,4], which are typically Pay as Produced (PaP) contracts with corporations or governments as prominent buyers [5]. However, since such supporting schemes result to discriminatory market rules for renewable energy injection, grid stability is significantly challenged. This often leads to RES curtailments that may reduce project profitability by lowering the optimal RES size, decreasing the Net Present Value (NPV) and increasing the Levelized Cost of Electricity (LCOE) [6,7].

As technology costs decrease, governmental support is reduced [8] and RESs are forced to seek new financial and technological solutions to remain viable following the common market rules. As a result, corporate Power Purchase Agreements (PPAs) have emerged as one of the most effective financial risk mitigation instruments for RES investments for RES without any other financial support [9]. With a fixed or indexed price for a predefined electricity volume over a multiyear horizon, PPAs reduce exposure to spot price fluctuations (i.e., market clearing price of Day-Ahead Market (DAM) and Intra-Day Market), providing revenue certainty that can attract investments [5], and improve the bankability of RES [10]. Under conventional PPAs, producers commit to selling the entire volume of electricity generated [11]. Among PPAs, Pay as Delivered (PaD) PPAs create a prevalent unsubsidized business model, shifting from pure generation-based approaches toward consumption-oriented contracts that emphasize real-time, on-demand renewable power delivery without putting stress on the operational limits of the electricity system.

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Nomenclature

Symbol	Definition
P^t_{PV}	PV power output at time t (MW)
P^t_{PPA}	Contracted power under PPA at time t (MW)
$P_{PPA,max}$	Maximum Power contracted under the PPA (MW)
P^t_{BESS}	Power output of Battery Energy Storage System (MW)
$P_{\mathrm{PV,\ y\text{-}1}}$	The PV power output of time-step t for the previous year $y-1$ (MW)
$P^t_{\mathrm{BESS,max}}$	Maximum Power output of Battery Energy Storage System (MW)
P^t_{B2PPA}	Power delivered from BESS to fulfill PPA (MW)
$P^t_{\mathrm{C,PV}}$	Power Surplus of PV production and contracted Power under the PPA (MW)
P^t_C	BESS charging power at time t (MW)
P^t_D	BESS discharging power at time t (MW)
P^t_{rej}	Rejected (curtailed) power at time t (MW)
$P^t_{PPA,del}$	Power delivered to PPA contract (MW)
P^t_{ISPup}	Power sold in ISPup (MW)
P^t_{mFRRup}	Power sold in mFRRup (manual Frequency Restoration Reserve up) (MW)
P^t_{DAM}	Power sold in day ahead market (MW)
P^t_{G2B}	Power imported from the grid to BESS
$P_{DIF,cl}$	The Diference $P^t_{PV} - P^t_{PPA}$
η_C	BESS charging efficiency
η_D	BESS discharging efficiency
$c_{BESS,losses}$	coefficient of losses for self-discharge
SoC^t	State of Charge of BESS at time t (MWh)
SoC^t_{max}	Maximum State of Charge of BESS (MWh)
c^t_{DAM}	Day-ahead market clearing price at time t (€/MWh)
c^t_{ISPup}	Integrated Scheduling Process up (ISPup) price (€/MWh)
c^t_{mFRRup}	mFRRup price (€/MW)
c_{PPA}	Strike price of PPA (€/MWh)
c^t_{rej}	Penalty price for rejected PV power (€/MWh)
c_{pen}	Penalty amount per MW not delivered to PPA (€/MWh)
$pen^{t,y}$	Amount of penalty for power not delivered €
$N(m,h)$	The number of time-steps referring to the hour h of the day of the month m
$CAPEX_{PV}$	Capital expenditure for PV system (€/kW)
$CAPEX_{BESS}$	Capital expenditure for BESS (€/kWh)
$CAPEX_0$	Capital expenditure for the PV-BESS asset at year 0(€)
$CAPEX^0_{PPA}$	Capital expenditure of the asset contracted under the PPA (€)
$qCAPEX$	The quota of CAPEX that REP covers through the PPA revenue
$OPEX_{PV}$	Operational expenditure for PV (€/kW)
$OPEX_{BESS}$	Operational expenditure for BESS (€/kWh)
$OPEX_y$	Operational expenditure for PV-BESS asset (€)
$OPEX^t_{PPA}$	Operational expenditure of the asset contracted under the PPA (€)
y	Year of the PPA
y_{PPA}	Duration of PPA in years
r	Discount rate
ru	Discount rate for Utility functions
bh	BESS capacity in hours (h)
cl	Certainty level (%)
lb	Lower bound $lb = 1 - cl$
U_{REP1}	Utility of REP in Scenario 1 in Nash Bargaining
U_{REP2}	Utility of REP in Scenario 2 in Nash Bargaining
$U_{\text{off-taker}}$	Utility of off-taker in Nash Bargaining
NU	Nash Utility function
RMSE	Root mean square error
$E_{PPA,cl}$	Energy traded under the PPA for certain cl

A technological option for RES to improve competitiveness and remain financially viable is the hybridization with Battery Energy Storage Systems (BESS), which reduces RES stochasticity and optimizes direct market participation strategies [12]. Optimal market participation can be further enhanced with accurate power output forecasting. Therefore, new RES probabilistic forecasting methodologies have emerged, which enable the quantification of forecast uncertainty and its integration into market bidding, and BESS scheduling [13], thereby hedging against imbalance costs and price volatility [14]. Quantile regression provides a simple and computationally efficient way to estimate conditional quantiles, though its performance is limited. Machine learning and deep learning methods, such as quantile forests, or neural networks, offer more accurate and distributional forecasts, but at the cost of higher computational requirements. This is particularly relevant in electricity markets with high PV penetration, such as Greek, where prices are strongly influenced by weather-driven variability and follow the so-called “duck curve” effect [15].

The motivation of this work is to explore how PV-BESS assets can achieve both financial viability and operational flexibility in modern electricity markets. With the integration of storage and accurate forecasting, PV-BESS systems evolve from variable generators into dispatchable assets, capable of participating providing firm and controllable output. However, despite this enhanced capability, financing such projects remains challenging due to high capital costs and uncertain merchant revenues. In this context, we examine a semi-contracted, semi-merchant PV-BESS asset, an area that remains unexplored. The contracted share under a PaD PPA secures long-term revenues and enhances bankability, while the merchant share allows the producer to benefit from high market prices. In this work, the BESS is employed not only to balance deviations from the contracted PPA profile, but also to participate in electricity markets and capture additional value. A Probabilistic Neural Network is used to generate a secure PPA delivery profile. Specifically, a Bayesian Long Short-Term Memory (B-LSTM) network is applied to capture temporal dependencies in PV generation, quantifying uncertainties, thereby providing a probabilistic forecast that supports risk-aware contract scheduling. Mixed-Integer Linear Programming (MILP) are widely used in energy system optimization, particularly for unit commitment, investment planning, and storage scheduling, as they can capture operational decisions and continuous power flows alongside binary choices [16]. However, its combination with deep learning probabilistic forecasting has not yet been extensively explored. This combination is well-suited for addressing the challenge of uncertainty management and revenue maximization in dual corporate PPA and the direct electricity market exposure framework.

2. Literature review

2.1. The role of PPAs in RES financing and risk management

Bilateral contracts like PPAs help reduce exposure to uncertainties as discussed. PPAs, typically spanning 5 to 20 years, use transmission or distribution networks to deliver electricity and establish a direct agreement between a producer and a corporate off-taker. RES PPAs are becoming more mature and cost-competitive, attracting businesses and investors seeking sustainability and clean power procurement, while helping corporations reduce their environmental footprint [17]. An extended review that dives into the identity, the description, and finally classifies renewable PPA structures and the relevant contracted parameters is presented in [18]. PPAs can be classified into PaP and PaD contracts. PaP PPAs typically have lower electricity prices, and PaD contracts, studied in this work, command higher prices due to the stochasticity of RES, which generates additional costs for the producer, while also facilitating demand matching.

Research in [11,13,19,20], examines reliant PPA structures based on the PaD concept, combining energy storage technologies like BESS for ensuring the delivery of production when required. Optimal mixes when moving from annual obligation to time-matched PPAs, and the effect of geographical pooling of different RES technologies in the PPA parameters is examined, concluding that solar and wind projects have limited locations suitable for installation, which limits the options of geographical distribution in providing firm power supply [19]. The procurement of large consumers through PaD PPAs is considered showing that off-site renewable low priced PPAs are preferred over conventional PPAs despite variability [20]. A PV-BESS asset to sell electricity to host buildings under a PaD or Time-of-Use PPA showing that, under the proposed procurement model, community-owned solar projects can regain economic viability by combining PaD PPA with Demand-Side Management (DSM) services [21]. A credit risk model for renewable energy PPAs that jointly values the PPA from the offtaker's and producer's perspective, that takes into account the implicit value of reducing price fluctuations and quantifies the expected benefit and loss is suggested in [22].

While research examines PaD RES PPAs, often incorporating BESS to firm delivery, no research has examined a PV-BESS asset partially contracted under a PaD PPA structure, where part of the generation is sold under a contract and the rest is exposed to market conditions.

2.2. Power forecasting for PaD RES PPAs

Predictive and probabilistic modeling, which can quantify uncertainties, is used in [11,13] to mitigate risks of PaD RES PPAs. Since the accuracy of power production is of outmost importance the Long-term PV power output predictions are crucial for identifying trends and seasonal variations in generation [23], necessitating effective balancing strategies for generation under PaD PPAs and contributing to optimal BESS sizing. A variety of machine learning techniques, including hybrid machine learning architectures [24], B-LSTM models, which we use in this work, have been applied for PV forecasting, offering improved capability to capture temporal dependencies and quantify uncertainty in generation profiles [25,26]. Short-term PV power output predictions can contribute to optimal scheduling and provide advantages such as micro-grid balancing [27] and appropriate short-term energy delivery [28] and reducing balancing costs [11].

Nevertheless, the literature on methodologies to construct and determine a secure delivery profile for multi-year horizon PaD PPAs is scarce. In our work, we employ a long-term, year-ahead B-LSTM model to generate a monthly delivery profile, quantifying the uncertainty of falling short of the contracted volume.

2.3. RES-storage systems as active market participants and dispatchable entities

Accurate forecasting combined with storage transforms a REP into an active market participant like a dispatchable entity and a Balancing Service Provider (BSP) to the system. This perspective is examined in the literature. Some research focuses on long-term analysis for energy trading in different market segments [29] and long-term planning of co-located RES storage assets [30] and others on short-term analysis [31,32]. The optimal siting of BESS in Distribution Networks (DN) under high PV [33] and wind [34] is examined, concluding that significant improvement in energy losses, voltage, and line profile is achieved by the introduction of BESS units in a DN with high PV and wind penetration energy market. Another aspect of research aims at the optimal sizing of RES-BESS installation under market participation or self-consumption [35–37]. In [35] authors explore BESS in hybrid PV-BESS setups, emphasizing their role in energy self-consumption, frequency and congestion management, and DSM. They analyze BESS research into four key areas: (a) Techno-economic Analysis, (b) Operational Control, (c)System Sizing, and (d) Demand Response (DR), highlighting a research gap in DR integration. The optimal residential PV-BESS sizing and power-to-energy ratio values based on electricity price, consumption class, and supporting schemes (self-consumption vs. net-billing) across five Mediterranean countries is examined in [36]. Hybrid RES-BESS systems, primarily addressing BESS sizing, operation economic performance and viability through participation in short-term wholesale electricity markets is optimized in [12]. In [38] a hybrid RES-BESS setting employs a stochastic optimization approach to optimize the operation of a price-taker PV-BESS hybrid station in both DAM and balancing markets (BM).

A comprehensive review of the literature on the combined operation of variable RES and different storage assets in short-term markets is provided in [39]. The study investigates how joint ownership of renewable and storage assets can create economies of scope in competitive electricity markets. It evaluates the economic viability of adding BESS to existing PV systems under different market types and ownership models, finding that user-owned BESS yields greater individual savings, while developer-owned shared BESS delivers broader community benefits. It underscores the need to promote and incentivize BESS for efficient trading and shared infrastructure. Policymakers should encourage diverse electricity trading mechanisms like peer-to-peer to optimize BESS capacity and economic returns [40]. Some researchers are engaged in optimal sizing and market participation of wind-BESS stations [41,42] examining their engagement in different energy markets, including the energy reserve market and providing short-term frequency control. A novel algorithm is developed to optimize the sizing and long-term operation of a hybrid station, comprising RES units such as a PV plant, a wind plant, or a combination with a behind-the-meter BESS. The primary objective is to determine the optimal BESS configuration that maximizes the net operating revenues of the hybrid energy system through its participation in various wholesale market segments over the long term. Authors investigate the operation of a hybrid pumped storage wind-solar system under different seasonal conditions, assessing the cost advantages and disadvantages before and after adding a hydro-pump station. It focuses on the dispatching of the asset to enhance overall system efficiency [43]. Evaluation of the economic feasibility of hybridizing an existing grid-connected wind farm with co-located PV, with or without embedded BESS, from an investor's perspective is examined in [44]. The study compares the LCOE of the co-located and purely PV asset and models hybrid plant operations over its lifetime. The findings indicate that co-location improves export capacity utilization, reduces curtailments, especially with longer duration BESS, and enhances grid access opportunities while making hybridization a financially viable option for RES investors.

It is evident that the sizing, operational and economic performance, and viability of RES-BESS assets in different electricity market models and segments is extensively analyzed. However, while all these studies expose stochastic assets to market uncertainties non of the above is examining the aspect of bankability of a co-located RES-BESS asset. In the present work we examine a PV-BESS asset which has a firm income under a PaD PPA while it can participate in different market segments.

2.4. Contribution of this paper

In this work, a PaD PPA for a PV-BESS asset, with a single connection to the grid point, which can absorb or which cannot absorb energy from the grid is studied. A portion of the generated power from the PV is contracted in order to ensure the project's bankability. Only a part of the PV-generated power is contractually committed under the PPA, while the BESS plays a supporting balancing, role in meeting the contractual obligations. The main purpose of the BESS is to enable market exposure for the excess of generated power and taking advantage of potential high market prices becoming more profitable.

This work aims to contribute to the corporate PPA sector with the following points:

1. Unlike previous studies focused mainly on contracting the full PV production using BESS to balance the miss-matches, or the assets are fully exposed to market uncertainties, this paper suggests a semi-merchant, semi-contracted financial framework in which a portion of the PV generation is contracted a PaD PPA. In this way, the investment risks are reduced, while the bankability of the PV with BESS is improved. This partial contract simultaneously retains flexibility for additional market participation to exploit market opportunities, taking advantage of potentially high market prices improving profitability.
2. We construct a monthly dependent hourly firm delivery profile for the PaD PPA. This is achieved using a B-LSTM. B-LSTMs have been used to forecast PV output quantifying uncertainties in the short and medium term but not in the long term (year-ahead) and not to construct PaD PPA delivery profiles according to the REP risk profile. Within this framework, the BESS plays a primarily supportive role for low-risk REPs profiles by firming the contract, while its main function is to capture market opportunities.
3. We formulate a MILP optimization model that simulates the semi-merchant, semi-contracted condition and jointly determines the optimal sizing of the BESS and its hourly dispatch strategy to satisfy PPA delivery obligations while maximizing revenues from participation in multiple electricity market segments. The proposed framework integrates probabilistic forecasting outputs into the MILP model, enabling risk-adjusted operational scheduling that accounts for forecast uncertainty and minimizes PPA's imbalance costs.
4. We evaluate the operational and economic impacts of varying PPA contracted proportions, BESS capacities, and certainty levels, thereby providing an analytical foundation for assessing the trade-off between project bankability and exposure to high market prices.

3. Methodology

3.1. Problem description

In this paper, a REP with a utility scale PV and co-located BESS is examined, while the BESS can absorb or cannot absorb energy from the grid. REP's primary objective is to contract a long-term PaD PPA for a portion of the power produced, with an electricity consumer at a fixed price, avoiding market price fluctuations and, to partially secure the investment. The following assumptions have been considered in this paper: (a) the REP's top priority is to ensure the delivery of the contracted power by appropriately scheduling the usage of BESS in the event of a PV power deficit between the contracted power and the actual PV generation, (b) the off-taker's electricity consumption exceeds the contracted power under the PPA scheme, eliminating the need for DSM, (c) the REP operates in an electricity market with high PV penetration, leading to market congestion and PV curtailments, and thus the sale of excess energy generated beyond the contracted PV power output is prevented in the case that the BESS cannot absorb energy from the grid. On the other hand, in case that the BESS can absorb energy from the grid, the REP may store low-market electricity during off-peak periods to enhance revenue opportunities and support PPA delivery. The BESS cannot charge from the grid during periods of PV generation. This restriction arises from the single point of grid connection, which prioritizes PV output. When PV production exceeds the contracted PPA power, the surplus must be directed either to the BESS because the market is congested. Conversely, if PV production falls short of the contracted power, the BESS must discharge to cover the deficit, thereby precluding simultaneous grid charging. (d) Since the PPA contracted power is matched with the demand of the off-taker, we assume that the energy traded under the corporate PPA contract cannot be curtailed. In this context, the surplus energy can be stored for later delivery or sold in the market, while in the grid-charging scenario, additional stored energy may come from DAM purchases.

The second objective concerns the maximization of the income with the optimal allocation of the stored energy in the appropriate electricity market segments considering the dispatchable PV-BESS asset. The REP stores energy that is the result of excess power not contracted under the PPA or, in the case of grid-charging capability, from off-peak DAM purchases and uses BESS to engage in electricity markets. Depending on the scenario, the BESS is either charged exclusively from PV or both from PV and the grid. In both cases, the stored energy can be sold in DAM and BM in the upward direction, i.e. through the Integrated Scheduling Process up (ISPup) or the manual Frequency Restoration Reserve up (mFRRup). The market selection criterion therefore, the profit maximization, with the additional opportunity in the grid-charging scenario to perform price arbitrage between low-price and high-price periods.

The proposed dual approach guarantees that the REP:

- Achieves the financial stability necessary to make the PV-BESS asset bankable through the PaD PPA.
- Maximizes revenue through a BESS discharging strategy for market participation, capitalizing on periods of high market prices and, in the grid-charging scenario, on price arbitrage opportunities, enhancing viability.

3.2. PV-BESS characteristics and PaD PPA profiles, terms, and conditions

Initially, the REP implements a long-term forecast for the PV generation. Accurate forecasts contribute to cost reduction by enabling more competitive bidding strategies. Probabilistic forecasting is particularly valuable as it accounts for uncertainties, quantifies them and mitigates errors associated with point forecasting. LSTM neural networks, when combined with numerical weather data, have demonstrated strong performance across various time series forecasting tasks, offering reliable predictions for different input types and forecasting horizons. A detailed review of deep learning applications in PV forecasting is presented in [45]. The PV generation is normalized using a min–max scaler to a range of 0 to 1 to facilitate modeling based on a beta distribution. In this paper, a year-ahead forecast is performed, utilizing a beta-distributed variable to predict PV generation over 8,760 h. As input data, we use historical PV generation values and relevant weather data. The output of B-LSTM is a beta distribution function calculation for each time step of the year $t \in [1, 8760]$. To evaluate the long-term forecasting model, we export the expected PV power output $P(t, cl = 50\%)$ and we select the certainty level cl and the relevant lower bound with $lb = 1 - cl$ to construct three different PPA power delivery profiles, for the scenario where the BESS cannot absorb energy from the grid (Scenario 1), and another for the scenario in which the BESS can absorb energy (Scenario 2), relevant to the risk profile of the REP as follows:

For each month of the year m, we calculate the average of each hour of the day $(h_1 - h_{24})$ using the scaled values.

$$P(m, h, lb) = \frac{1}{N(m, h)} \sum_{t \in T(m,h)} P(t, cl) \tag{1}$$

The PV power contracted under the PPA for the selected cl scheme is:

$$P^t_{PPA} = P(m_t, h_t, lb) \tag{2}$$

where: P^t_{PPA} is the reconstructed time series value at timestep t, m_t is the month corresponding to timestep t, h_t is the hour of the day corresponding to timestep t and $P(m_t, h_t, lb)$ is the precomputed average production for that specific month and hour.

Using this approach, REP designs a daily delivery profile for the PPA that adjusts on monthly basis to account for seasonal variations in weather conditions. This ensures that the contracted PPA power accurately takes into account the seasonal fluctuations in PV power generation. As a result, power delivery during winter is lower and available for fewer hours, whereas in summer, the PPA power is higher and extends over more hours of the day. The contracted power in the PPA remains aligned with realistic production capabilities while factoring in a lb deal with the uncertainties of PV generation. This enables the REP to make well-informed decisions that balance risk and reliability, ultimately optimizing the performance of the PPA without relying much on the BESS or any absorbing grid power to fulfill the PPA Scenario 1 or if REP wises more market exposure for the PV produced energy in Scenario 2. The PV system has an installed capacity of $P_{PV,max}$, while the BESS is designed to handle the maximum difference between the generated PV power of the previous year and the contracted power in the PPA, or the maximum contracted power, whichever is greater. Specifically, the BESS must be capable of absorbing the peak difference while preventing over-sizing and simultaneously be able to cover the maximum demand of the PPA. The terms and conditions of the PPA are the following (a) the duration of the PPA concerns y_{PPA} years, (b) the producer is obliged to always deliver the contracted power. Considering that demand consistently exceeds the contracted power, the off-taker intends to get green energy for a portion of the consumed energy. The main incentives for the off-taker are avoiding electricity market price uncertainty, attracting investments through a greener profile, and potential benefits from Guarantees of Origin (GOs), although GOs are not quantified in this problem. The producer aims to cover part of the investment cost through a fixed price contract to ensure the asset is bankable, while also maintaining flexibility to participate in electricity market segments for the remaining part of the produced energy improving viability.

3.3. Simulation of market participation and BESS dimensioning

The scheduling and sizing of the BESS are determined by a MILP model that maximizes the NPV of the PV-BESS asset over the PPA duration y_{PPA}. Two operating scenarios are considered as discussed:

- **Scenario 1:** BESS can only be charged from surplus PV generation (no grid charging).
- **Scenario 2:** BESS can be charged from surplus PV generation or from the grid (price-arbitrage enabled).

3.3.1. Mathematical formulation

Mathematical formulation scenario 1.

Objective Function 1

$$\max\ NPV = \sum_{y=1}^{y_{PPA}} \frac{1}{(1+r)^y}\Bigg[\sum_{t=1}^{8760}\big(P^{t,y}_{\text{PPA,del}}c_{\text{PPA}} + P^{t,y}_{\text{DAM}}c^t_{\text{DAM}} + P^{t,y}_{\text{ISPup}}c^t_{\text{ISPup}} + P^{t,y}_{\text{mFRRup}}c^t_{\text{mFRRup}} - \text{pen}^{t,y} - c^{t,y}_{\text{rej}}P^{t,y}_{\text{rej}}\big) - \text{OPEX}_y\Bigg] - \text{CAPEX}_0 \tag{3}$$

Constraints Scenario 1

$$P^t_{\text{PPA,del}} = P^t_{\text{PPA}} - \max\left\{0,\ P^t_{\text{PPA}} - P^t_{\text{PV}} - P^t_{\text{B2PPA}}\right\} \tag{4}$$

$$\text{pen}^t = max[0, \left(P^t_{\text{PPA}} - P^t_{\text{PPA,del}}\right) c_{\text{pen}}] \tag{5}$$

$$\text{SoC}^t = \text{SoC}^{t-1} + \eta_C P^t_C - \frac{P^t_D}{\eta_D} - c_{\text{BESS,losses}}\,\text{SoC}^{t-1} \tag{6}$$

$$0 \le \text{SoC}^t \le bh \cdot P_{\text{BESS,max}} \tag{7}$$

$$0 \le P^t_D = P^t_{\text{B2PPA}} + P^t_{\text{DAM}} + P^t_{\text{ISPup}} + P^t_{\text{mFRRup}} \tag{8}$$

$$P_{\text{BESS,max}} = \max\left\{ P_{\text{PPA,max}},\ \max_t\left(P^t_{\text{PV}} - P^t_{\text{PPA}}\right)\right\} \tag{9}$$

$$0 \le P^t_{C,PV} = \max\left(P^t_{\text{PV}} - P^t_{\text{PPA}}, 0\right) \tag{10}$$

$$0 \le P^t_C \le P^t_{C,PV} \tag{11}$$

$$P^t_C \cdot P^t_D = 0 \tag{12}$$

$$P^t_{\text{PV}} \cdot P^t_D = 0 \tag{13}$$

$$P^t_{\text{rej}} = P^t_{\text{PV}} - P^t_{\text{PPA}} - P^t_C \tag{14}$$

$$\text{CAPEX}_0 = CAPEX_{PV}\ P_{\text{PV,max}} + CAPEX_{BESS}\ P_{\text{BESS,max}}\ bh \tag{15}$$

$$\text{OPEX}_y = OPEX_{PV}\ P_{\text{PV,max}} + OPEX_{BESS}\ P_{\text{BESS,max}}\ bh \tag{16}$$

Mathematical formulation scenario 2.

Objective Function 2

$$\max\ NPV^{(2)} = \sum_{y=1}^{y_{PPA}} \frac{1}{(1+r)^y}\Bigg[\sum_{t=1}^{8760}\big(P^{t,y}_{\text{PPA,del}}c_{\text{PPA}} + P^{t,y}_{\text{DAM}}c^t_{\text{DAM}} + P^{t,y}_{\text{ISPup}} c^t_{\text{ISPup}} + P^{t,y}_{\text{mFRRup}}c^t_{\text{mFRRup}} - \text{pen}^{t,y} - c^{t,y}_{\text{DAM}}P^{t,y}_{G2B} - P^{t,y}_{\text{rej}}c_{\text{rej}}\big) - \text{OPEX}_y\Bigg] - \text{CAPEX}_0 \tag{17}$$

Constraints Scenario 2 Eqs. (4)–(13), (15), (16) are applied.

$$0 \le P^t_C \le \begin{cases} P^t_{C,\text{PV}}, & \text{if } P^t_{C,\text{PV}} > 0, \\ P^t_{\text{G2B}}, & \text{otherwise,} \end{cases} \tag{18}$$

$$0 \le P^t_C \le P_{\text{BESS,max}} \tag{19}$$

3.3.2. MILP model interpretation

The first step for the REP is to select the contracted lower bound (cl) for the delivery of the PV power output according to its risk profile, thereby securing the PPA. Subsequently, the REP commits to an hourly contractual electricity delivery obligation, P^t_{PPA}, for each time step t of the year. Since the terms of the PPA include the obligation to deliver the contracted power, BESS dimensioning plays a critical role in fulfilling the agreement. Specifically, the BESS is activated in situations where PV generation alone is insufficient to meet the PPA obligation. Furthermore, BESS sizing is crucial for optimal market participation. In our formulation, the PPA power delivery profile is provided as an input to the optimization, while the BESS capacity and market participant scheduling is co-optimized over the contracted duration y_{PPA} of the PPA. The parameter battery hours (bh) refers to continuous discharging at maximum power. We implement a day-ahead forecasting model using a LSTM neural network to predict PV output. This forecast serves as the final piece of information the REP relies on to make well-informed scheduling decisions for market participation. For the day-ahead PV power forecast, the LSTM takes as input historical PV generation data, relevant numerical weather data, and forecasted weather conditions for time step t. The literature suggests that day-ahead PV power forecasting is highly accurate [45,46]. Therefore, for this analysis, we assume the forecast to be 100% accurate for day-ahead or several days ahead, with $\hat{P}^t_{\text{PV}} = P^t_{\text{PV}}$, and use it to determine power surplus and deficit in fulfilling the electric power delivery obligations under the PPA. There is extensive research in the field of electricity market prices prediction [47], and the relevant evaluation metrics have decreased, leading to more accurate electricity market price predictions. As a result, we assume that REP knows the electricity market prices $c^t_{\text{DAM}}, c^t_{\text{ISPup}}, c^t_{\text{mFRRup}}$, in different segments of the electricity market. The mean hourly values are used if the resolution in time is different for the market parameters. Therefore, P^t_{PPA} for different cl, P^t_{PV} and market prices, are fed into the model. The objective functions (3) for Scenario 1 and (17) for Scenario 2 both maximize the NPV from PPA revenues and market participation in the DAM, ISPup, and mFRRup segments, while subtracting penalties, OPEX, and CAPEX. In Scenario 2, an additional cost term is included for purchasing energy from the grid to charge the BESS.

In both scenarios:

- Constraint (4) determines the contracted PPA power delivered, with any deficit supplied by BESS discharging.
- Constraint (5) applies a high penalty for non-delivery.
- The SoC dynamics in (6) include charging and discharging efficiencies as well as self-discharge losses, while (7) enforces the BESS energy capacity limit.
- Discharging allocation is defined in (8), with simultaneous charging and discharging prevented by (12).

The key difference lies in the charging constraints:

- **Scenario 1:** Constraint (11) limits charging strictly to PV surplus after PPA fulfillment, as determined by (10).
- **Scenario 2:** Constraints (18)–(19) allow charging either from PV surplus or from grid imports, enabling price-arbitrage opportunities.

In both cases, the BESS power rating is determined by (9), ensuring sufficient capacity to meet either peak PPA shortfalls or the largest PV surplus. Rejected renewable power by the PV is calculated via (14), and CAPEX and OPEX are computed using (15) and (16), respectively. To calculate the total investment cost of the asset, the capital expenditures for the PV and BESS components were considered separately. The literature regarding cost estimation for co-located assets is limited, especially for hybrid PV-BESS systems that do not absorb energy from the grid. Such configurations, can effectively reduce connection costs due to simplified grid integration requirements [48].

$$Cost_{PV} = (CAPEX_{PV} + OPEX_{PV})P_{PV,max} \tag{20}$$

$$Cost_{BESS} = (CAPEX_{BESS} + OPEX_{BESS})P_{BESS,max}bh \tag{21}$$

3.3.3. PPA fair price calculation

The optimization of the capacity of BESS in battery hours bh and the optimal scheduling of market participation is a result of the PPA fair price. After the co-optimization described in Section 3.3.2 is implemented, the next step is to find a fair price for the PPA. Nash Bargaining Theory provides an effective framework for determining the strike price in a PPA negotiation between a REP and an off-taker. The objective of this negotiation is to establish a mutually beneficial agreement that optimizes the gains for both parties. The Nash Bargaining Solution (NBS) offers a structured resolution to this problem by identifying an optimal strategy pair. Let U_{REP} and $U_{off-taker}$ denote the utility functions of the two negotiating parties, and let S_1 and S_2 represent their respective strategy sets. A strategy pair (s_1^*, s_2^*), where $s_1^* \in S_1$ and $s_2^* \in S_2$, is considered a Nash Bargaining Solution if it satisfies the following condition for each party i [11]:

$$U_i(s_i^*, s_{(-i)}^*) \geq U_i(s_i, s_{(-i)}^*), \quad \forall s_i \in S_i \tag{22}$$

where s_i represents the strategy of one party, and $s_{(-i)}^*$ denotes the strategy of the other party.

In the context of PPA strike price negotiations, the strategy choices correspond to different possible strike prices, while the utility functions represent the net benefits each party derives from the PPA at those prices.

REP wants to invest in an asset PV-BESS, but the usage of BESS is limited in the framework of the PPA according to the certainty level of the contracted power, and a part of the nominal capacity of the PV is used to deliver the PPA contracted power.

$$U_{\text{off-taker}} = \sum_{y=1}^{y_{PPA}} \frac{\sum_{t=1}^{8760} P_{\text{PPA}}^{t,y}\left(c_{\text{DAM}}^{t,y} - c_{\text{PPA}}^{t,y}\right)}{(1+ru)^y} \tag{23}$$

Table 1
Cost specifications for PV and BESS.

Cost items	Cost specifications
$CAPEX_{BESS}$	120–180 €/kWh [40]
$CAPEX_{PV}$	450–500 €/kW [55]
$OPEX_{BESS}$	4% of $CAPEX_{BESS}$ [40]
$OPEX_{PV}$	7.5 €/kW [55]
Discount rate	4%, 8% 12% [56,57]
PPA duration y_{PPA}	10, 12, 14 years

$$U_{\text{REP1}} = \sum_{y=1}^{y_{PPA}} \frac{\sum_{t=1}^{8760}\left(P_{\text{PPA,del}}^{t,y} c_{\text{PPA}}^{t,y}\right) - \text{OPEX}_{\text{PPA}}^{y}}{(1+ru)^y} - \text{CAPEX}_{\text{PPA}}^{0} \tag{24}$$

$$U_{\text{REP2}} = \sum_{y=1}^{y_{PPA}} \frac{\sum_{t=1}^{8760}\left(P_{\text{PPA,del}}^{t,y} c_{\text{PPA}}^{t,y} - \bar{c}_{DAM} P_{B2PPA}^{t,y}\right)}{(1+ru)^y} - \frac{\text{OPEX}_{\text{PPA}}^{y}}{(1+ru)^y} - \text{CAPEX}_{\text{PPA}}^{0} \tag{25}$$

$U_{\text{off-taker}}$ quantifies the off-taker's discounted savings by contracting power below the market price. U_{REP1} represents the REP's total discounted revenue from the PPA minus associated operational and investment costs related to the PPA for scenario 1. For Scenario 2 REPs utility function U_{REP2}, the term involving $\bar{c}_{\text{DAM}} P_{\text{B2PPA}}^{t,y}$ accounts for cost of stored energy to fulfill the PPA obligations. Since the origin of the stored energy cannot be explicitly tracked we conservatively assume that discharging from the BESS to fulfill the PPA incurs an average cost equal to the mean day-ahead market price of previous years, $\bar{c}_{\text{DAM}}$. This approach represents a simplified but cautious estimation.

Both scenarios are formulated with MILP in GAMS, using hourly resolution over one year. Parameters are common across scenarios. The solver co-optimizes optimal BESS power and energy ratings ($P_{\text{BESS,max}}, bh$), hourly dispatch schedules, PPA compliance metrics, market revenues, penalties, and curtailed energy while the PPA strike price is determined through an iterative procedure. From modeling and equations the conclusion that the optimal sizing of BESS and optimal BESS scheduling are independent of the fair price calculation can be obtained.

4. Case study and simulation

4.1. Data and parameters setup

For the evaluation of the results, a case study is conducted on the participation of the REP in the Greek electricity market. The Greek electricity market is structured in accordance with the European Target Model, which establishes harmonized regulatory and operational rules and implementation frameworks across all segments of the electricity market [49]. Also, it exhibits a high share of renewable energy, with PV capacity accounting for 28.6% of the total installed capacity, comparable to Italy (24.3%) and Bulgaria (20.1%), with a direct connection with them, Spain (25%), and Germany (31.5%) during the year of the case study [50]. Such high renewable PV penetration affects significantly DAM price patterns, leading to the emergence of the duck curve phenomenon [15] and curtailments due to market congestion. The data of the market refer to 2023 [51,52] and a comprehensive review about the functionality of the Greek electricity market is reviewed in [53], and especially electricity balancing market in [54]. The PV generation data are coming from an existing PV in Northern Greece in the city of Kozani.

The parameters used in the numerical analysis are summarized in Table 1. In addition to the values shown in the table, different values of cl are examined for both PV and BESS. For the analysis, we use a discount rate of $r = ru = 8\%$ as the central value for the calculation of the NPV and the U_{REP1} and U_{REP2}, since this is a common internal rate of return for RES projects in the EU, and especially in

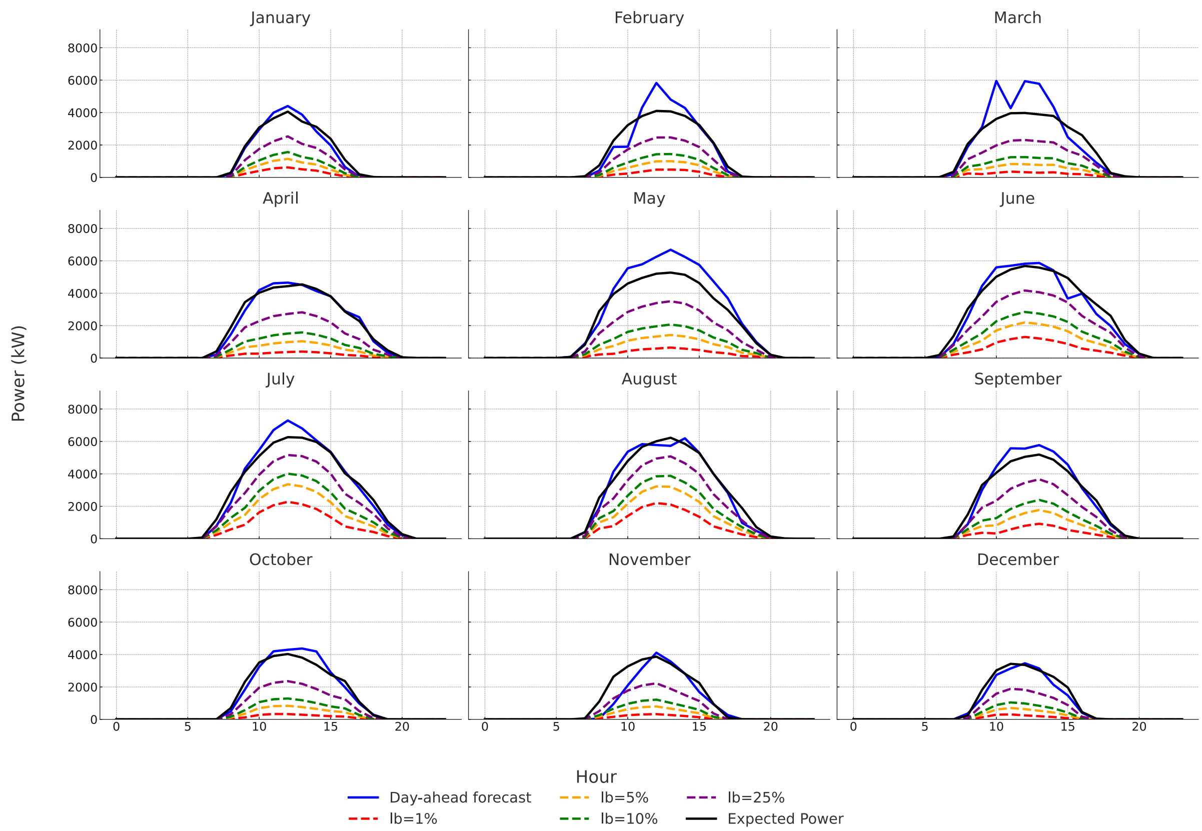

Fig. 1. Monthly PPA profiles, Expected power output and typical day for each month.

Greece [56,57]. Moreover, the PPA duration is set to $y_{\mathrm{PPA}} = 12$ years in the main case, and these values for r and y_{PPA} should be assumed unless stated otherwise. We allocate the installation and grid connection costs e.g. inverters, cables, and mounting systems, SCADA, between the PV and BESS components to avoid double counting one time for PV and one for BESS. These costs form part of the Balance of System (BOS), which typically account for around 65% of the total installed cost of utility-scale PV systems, according to [58]. The same report indicates a total installation cost of approximately 590 €/kW, with a projected reduction to 513€/kW by 2025. BESS costs declined by 93% from 2010 to 2024, falling from 2230 €/kWh to 172€/kWh. In co-located PV-BESS projects, a portion of the BOS specifically the grid connection, cables, transformer, switchgear, and SCADA systems, excluding inverters, is shared between the two components resulting in a lower per-unit CAPEX compared to standalone PV and BESS installations. The upper values of Table 2 are consistent with the report, but since we examine a co-located project with cost sharing, we conduct a sensitivity analysis with lower cost assumptions to account for the cost-sharing and the ongoing decline in infrastructure prices.

OPEX includes annual operation and maintenance costs as well as degradation costs, which are often included in OPEX [40] or modeled as extra costs directly in the objective function [59], assuming a PPA with duration y_{PPA} years.

4.2. PPA power profiles and long-term forecasting evaluation

Initially, the REP models PV power output with a year-ahead hourly forecast. After that, REP calculates the mean hourly values for each month to create a monthly dependent corporate PPA. Fig. 1 illustrates the mean non-scaled hourly power output for each month and the PPA obligation delivery. The year-ahead forecast's is $RMSE = 681$ kW. For our calculations, the min–max scaled values 0–1 for the power production of the PV in the MILP simulation, are used so we assume a $P_{PV,max} = 1$ MWp and the PPA power profiles are scaled appropriately.

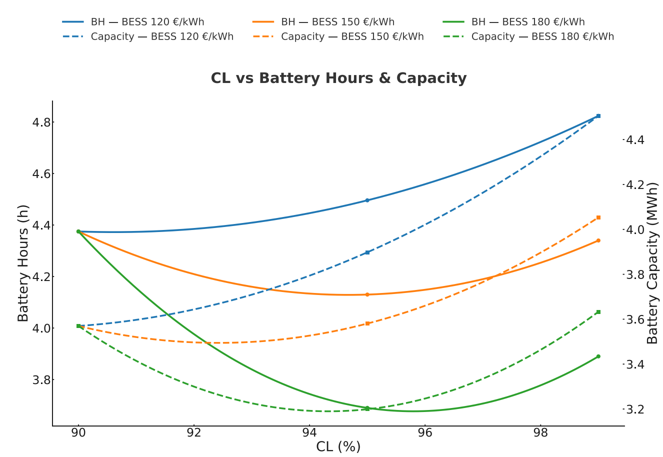

Fig. 2. Certainty level vs optimal BESS size.

4.3. Sensitivity analysis economic evaluation

We assume that the fully renewable PaD PPA, which is the most likely to be incentivized, serves as the main scenario on which we conduct a more detailed analysis. We implement a sensitivity analysis for different cost cases, as they appear in Table 1 and different value cl, for PV and BESS. In Scenario 1, we simulate the case for $cl = 99\%, 95\%$ and 90%. In Scenario 2 the BESS can use grid-imported energy to cover the PPA obligations. So in Scenario 2 we simulate the case for lower values [11] of $cl = 75\%$ and 50% which correspond to the expected average value.

Fig. 2 analyzes the relationship between certainty levels and required BESS hours at varying CAPEX values (120, 150, and 180

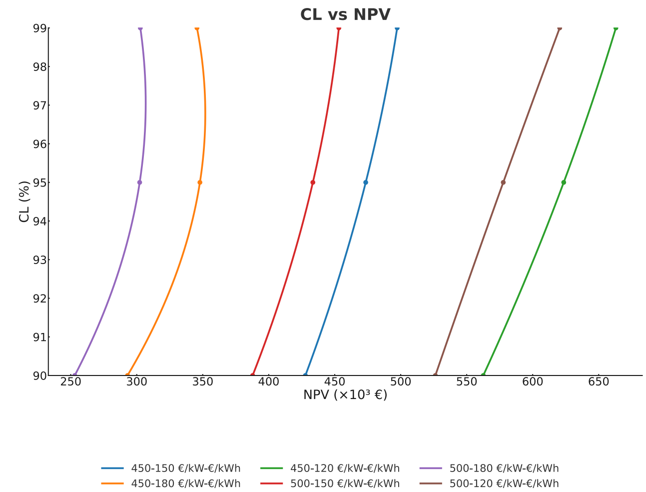

Fig. 3. Certainty level vs Net Present Value.

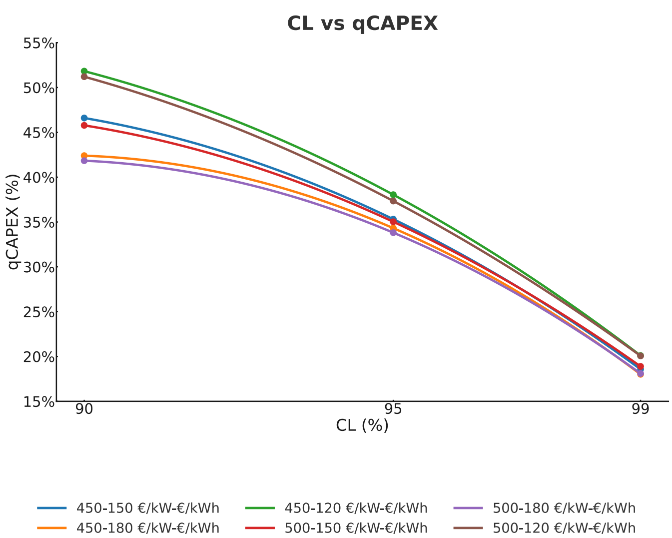

Fig. 4. Certainty level vs PPA revenue quota over annualized CAPEX.

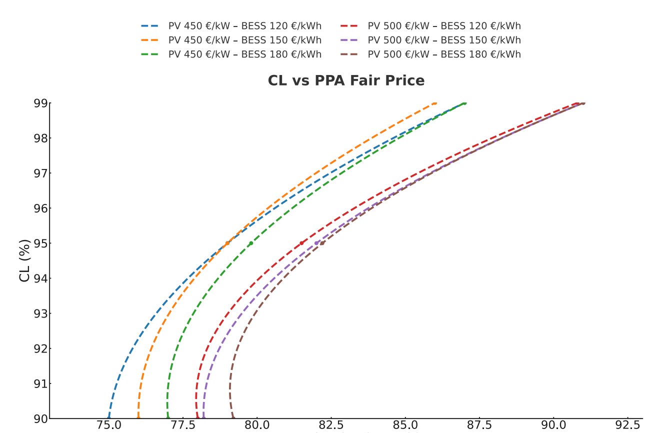

Fig. 5. Certainty level vs PPA fair price (c_{PPA})

€/kWh). The continuous curves refer to capacity in hours and the intermittent to capacity in MWh. The findings suggest that higher CAPEX reduces optimal BESS capacity and storage hours, while lower CAPEX offers greater flexibility in storage system sizing. We observe

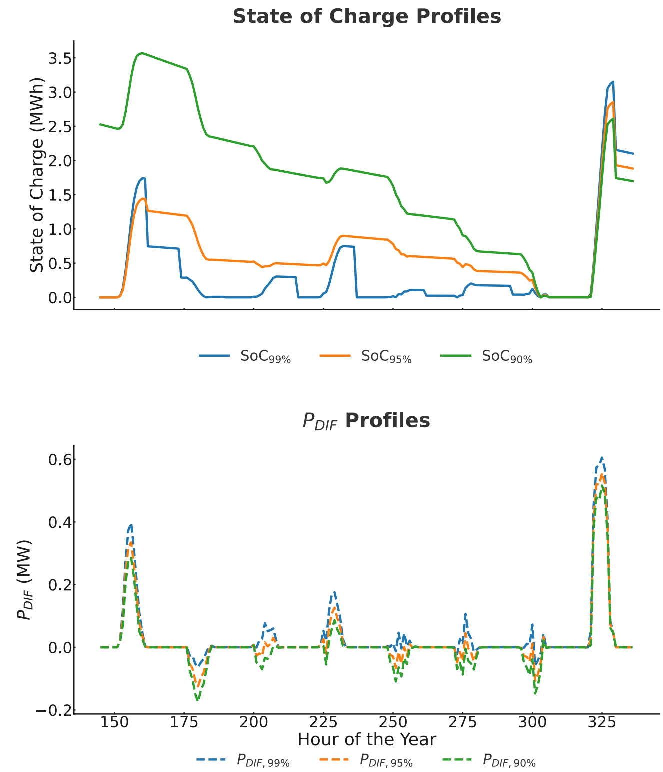

Fig. 6. BESS scheduling over the worst case period of PV production.

that the optimal capacity for $cl = 90\%$ is independent of the considered $CAPEX_{BESS}$. This suggests that securing the PPA at a relatively low cl requires a large BESS capacity, indicating that the REP is willing to invest in a more expensive BESS to make the agreement viable. After dimensioning BESS we calculate the fair PPA price c_{PPA}. Fig. 5 illustrates the impact of cl and CAPEX conditions on the c_{PPA}. Increased cl leads to higher fair prices. This happens because as cl gets lower, more energy is traded during market periods when electricity prices are low due to high PV penetration and the disagreement price of the off-taker is decreased. Also, the REP can offer a lower disagreement price due to the increased PPA traded energy. Conversely, lower CAPEX values reduce fair PPA prices, enhancing competitiveness.

Fig. 3 shows the relation of NPV and cl for different CAPEX. NPV increases with higher cl, because of the high market prices relative to the PPA fair price. Lower CAPEX leads to higher NPV due to less initial investment needed. While $cl = 99\%$ seems to be the most profitable choice, it changes for high $CAPEX_{BESS}$ and the optimal choice is $cl = 95\%$. Fig. 4 examines the relationship between cl and the recovery of CAPEX PPA revenues. It finds that increased certainty leads to a smaller percentage of annual CAPEX recovery, where annual CAPEX is the total CAPEX of the PV-BESS divided by y_{PPA}. The formula that describes the procedure is:

$$qCAPEX = \frac{\dfrac{\sum_{t=1}^{8760} \left(P^t_{\mathrm{PPA}} c_{PPA} - OPEX_{\mathrm{PPA}}\right)}{(1-r)}}{\dfrac{\mathrm{CAPEX}^0}{y_{\mathrm{PPA}}}} \tag{26}$$

A higher value for this fraction means a more secure and bankable investment.

4.4. Optimal market participation and BESS scheduling

To study the behavior of REP in the electricity market, the most critical factor is the scheduling of BESS. REP has four choices for BESS,

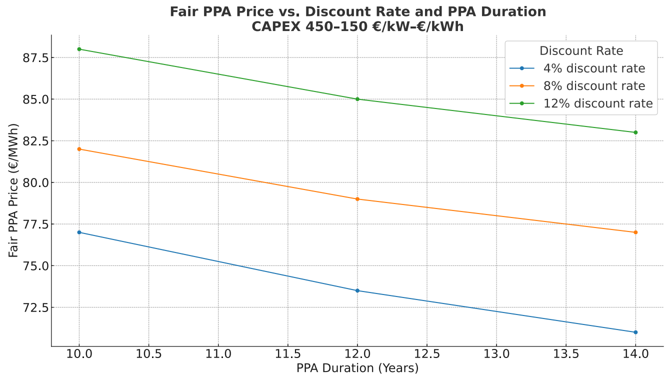

Fig. 7. PPA fair price for different discount rates and duration of the contract.

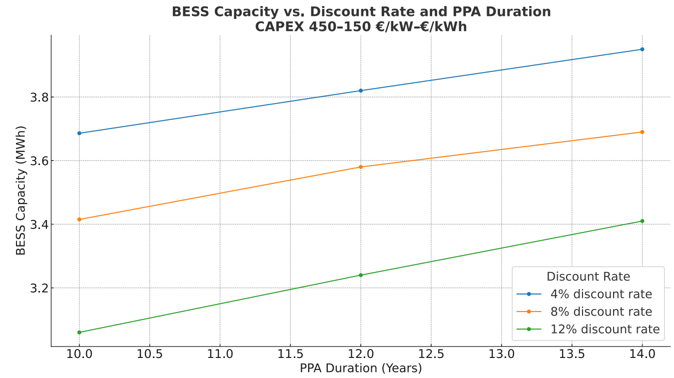

Fig. 9. BESS capacity for different discount rates and duration of the contract.

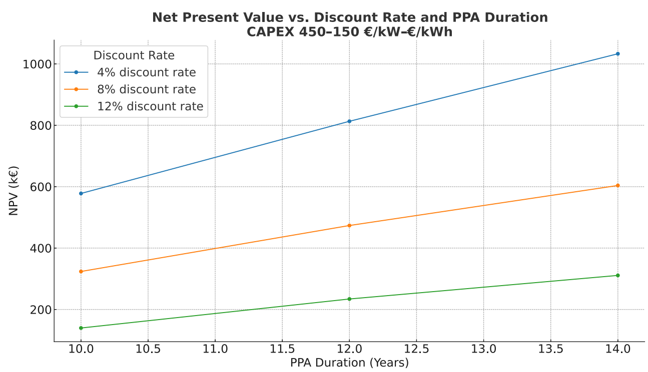

Fig. 8. NPV for different discount rates and duration of the contract.

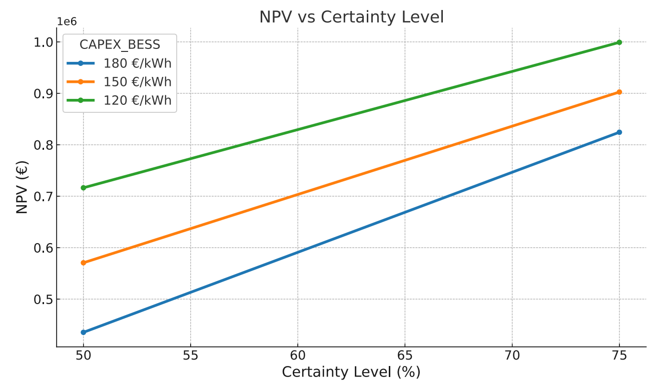

Fig. 10. NPV for different cl in Scenario 2.

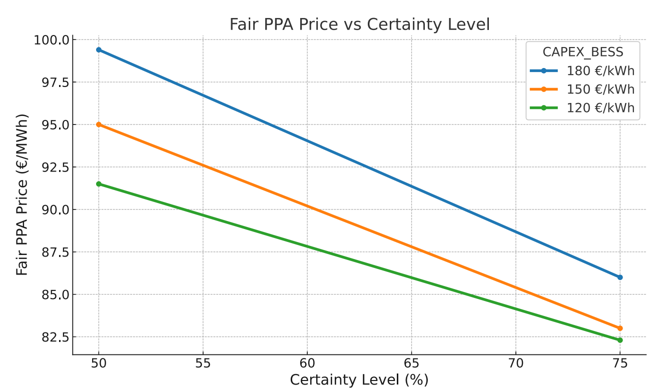

Fig. 11. PPA fair price for different cl in Scenario 2.

i.e. to cover PPA mismatches in case of PV production lack as a top priority, or sell the stored energy to DAM, ISPup, mFRRup. Fig. 6 shows the behavior of REP for different cl in the worst-case scenario of continuous low PV power production. In case of $cl = 99\%$ and $cl = 95\%$, REP initially has fully discharged BESS. Throughout this period, the REP is more active in the markets and fully discharges the battery in case $cl = 99\%$. In the case of $cl = 95\%$, the REP participates in the markets but does not fully discharge the battery to cover the production shortfall on the following day. For $cl = 95\%$, market participation decreases, and there is no full battery discharge for the next six days. When $cl = 90\%$, the REP's battery state remains sufficiently charged to handle the large contracted power amounts that must be delivered under the PPA. Its market participation is almost zero since it does not discharge during hours when the PV system is not generating. The peak of the SoC curve for $cl = 90\%$ coincides with the battery's maximum capacity Fig. 2. In conclusion, as cl decreases, the REP must schedule his operational strategy several days in advance.

4.5. Sensitivity analysis for discount rate and y_{PPA} of the contract

To examine how the discount rate and the duration of the PPA affect the key techno-economic parameters of the project, we conduct a sensitivity analysis for the case with CAPEX values of 450€/kW for PV and 150€/kWh for BESS and $cl = 95\%$. The results focus on three critical outputs: the fair PPA price, NPV, and the optimal BESS capacity.

As shown in the figures, the fair PPA price decreases with longer PPA durations Fig. 7. Conversely, it increases with higher discount rates, reflecting the need for greater revenue to meet investor return expectations under more stringent financing conditions. For instance, at a 10-year duration, the fair price rises from 77€/MWh at a 4% discount rate to 88€/MWh at 12% discount rate. The NPV shows a strong positive correlation with the PPA duration across all discount rate cases, as presented at Fig. 8. At a 4% discount rate, extending the contract from 10 to 14 years increases the NPV from approximately €578 thousands to over €1 million, which is normal for 4 years greater duration. On the other hand, higher discount rates significantly reduce the NPV. Finally, the impact of different BESS capacity is illustrated at Fig. 9. Lower discount rates and longer PPAs enable higher economically optimal storage capacities. This reflects the improved revenue certainty and cost recovery potential, which justifies greater investment in flexibility infrastructure like storage. Overall, the sensitivity analysis underscores the importance of favorable financing terms and long-term contracting in enhancing both the profitability and the storage integration of hybrid RES systems under corporate PPAs.

Table 2
BESS capacity in hours penalizing green energy rejection.

Certainty Level and BESS capacity (hours)	
$bh_{cl=99\%}$	7.896
$bh_{cl=95\%}$	7.719
$bh_{cl=90\%}$	7.551

4.6. Energy imported from the grid (scenario 2)

This scenario, being the most common in the literature [11,60], considers that BESS can also charge from the grid. A comparison with Scenario 1 takes place by examining certainty levels (75% and 50%), $CAPEX_{PV}$ = 500 €/kWh and different $CAPEX_{BESS}$ values. The results indicate that enabling import energy from the grid improves significantly the economic performance, especially at higher certainty levels cl = 75%, where market exposure is greater. This is reflected at Fig. 10, where the NPV vs. Certainly level are presented for different CAPEX of BESS. In Scenario 2, the total energy traded by the REP is much greater due to charging of BESS from the grid. The fair prices of PPAs for this scenario are illustrated in Fig. 11 and are higher than in Scenario 1, due to the higher impact of $CAPEX_{BESS}$ in U_{REP2}. The flexibility to charge from the grid enhances arbitrage opportunities and enables more effective participation in the electricity market, making the investment more profitable, however the total amount of energy used for BESS charging is not from renewable sources anymore. As a result, the PaD PPA cannot be considered as green one. This fact makes the investment less likely to be incentivized.

The optimal BESS capacity remains unchanged at cl = 50% across all CAPEX levels, with bh = 6.543 hours. This indicates that under market exposure conditions, the BESS sizing is primarily driven by price arbitrage opportunities rather than PPA firming needs, resulting in a longer duration compared to Scenario 1. Even at cl = 75%, the variation in optimal capacity is relatively small, from bh = 4.247 for $CAPEX_{BESS}$ = 180 and 150 to bh = 4.255 for $CAPEX_{BESS}$ = 120. Overall, allowing grid import provides additional economic value and requiring requires larger storage investments.

4.7. Allocation of energy

REP has different obligations to deliver energy for different cl and the $CAPEX_{BESS}$ affects the size of the BESS and therefore the optimal energy allocation in the market segments. As cl decreases, the energy that REP has the obligation to trade via the PPA increases. The majority of the sold energy from BESS goes to ISP. The rejected energy increases for more expensive BESS installations. The energy allocation is constant for the selected scenarios for $CAPEX_{BESS}$ because the MILP algorithm converges to the same optimal size for BESS.

Fig. 12 illustrates the optimal energy allocation in the market and energy losses in percentage of the total produced energy by the PV which is approximately 1670 MWh for the scaled PV, $P_{PV,max}$ = 1 MWp nominal power. While $\frac{E_{PPA,cl=99\%}}{E_{PPA,cl=95\%}}$ = 0.51 the fraction $\frac{P_{PPA,max,cl=99\%}}{P_{PPA,max,cl=95\%}}$ = 0.68. This is the reason why the REP can offer more competitive prices in the PPA as the cl decreases as described in Section 4.3.

In case we penalize the rejection of green PV energy, the REP must dimension the BESS with bigger capacity independent from the $CAPEX_{BESS}$. Fig. 13 illustrates the energy allocation in this case. Energy losses increase in this scenario because of the charging and discharging coefficients and the self-discharge of the BESS. BESS capacity in hours bh in this scenario for different cl is shown in Table 2. The NPV decreases significantly and even becomes negative for $CAPEX_{BESS}$ = 180 €/kWh.

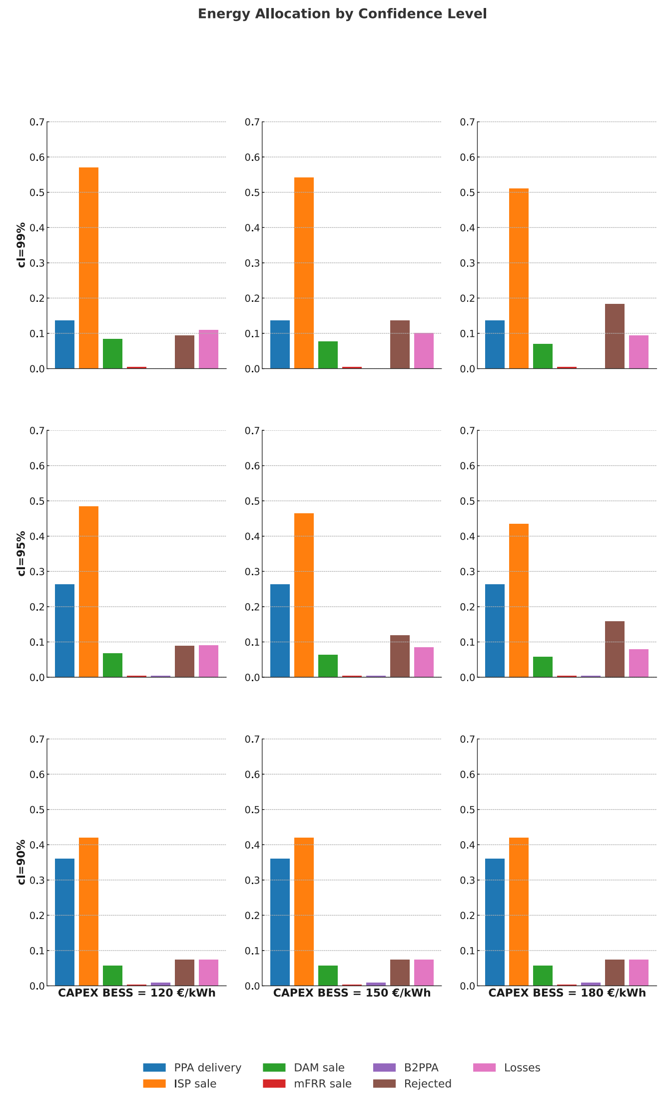

Fig. 12. Energy allocation in PPA and market segments.

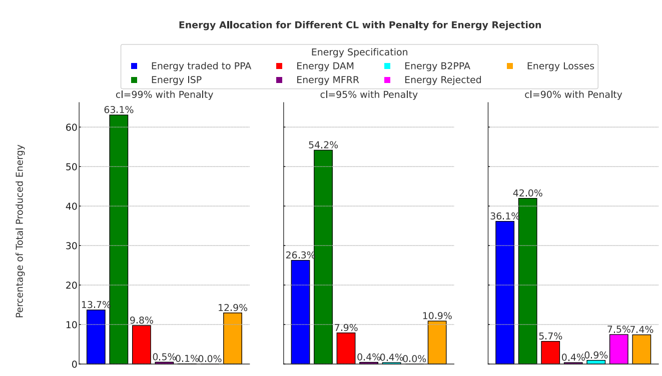

Fig. 13. Energy allocation penalizing rejection.

5. Conclusions and discussion

The study explores a corporate PaD PPA model, with partial contracting of generated power under the PPA, incorporating a PV-BESS under market conditions with high PV penetration. A probabilistic B-LSTM for long-term PV power forecasting is used to ensure the contracted power profile aligns with realistic production expectations.

A MILP optimization model determines the optimal BESS sizing and scheduling. The results highlight a fundamental trade-off between cl and BESS capacity. Lower cl increase the BESS requirement but allow less market exposure, while higher cl values reduce PPA obligations, enabling more active market engagement sacrificing the bankability aspect. Lower $CAPEX_{BESS}$ enhances the financial viability of the project by allowing flexible storage sizing. Sensitivity analysis on PPA duration and discount rate demonstrates that longer contract lengths significantly increase NPV, justify larger BESS capacities, and reduce the required PPA price, thereby improving bankability. In contrast, short-term contracts and higher discount rates constrain profitability and limit optimal BESS investment. Allowing the BESS to import energy from the grid (Scenario 2) improves economic performance, particularly at higher cl values where the producer benefits from price arbitrage. However, this option may undermine the project's renewable integrity and reduce eligibility for CAPEX-related incentives tied to 100% renewable energy usage, which remains a key consideration for regulators and investors. Finally, penalizing the rejection of renewable energy enforces larger BESS sizing and results in higher energy losses due to storage inefficiencies, reducing economic performance.

CRediT authorship contribution statement

Georgios Gousis: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Nikolaos Koltsaklis:** Supervision, Software, Methodology. **Konstantinos Oureilidis:** Writing – review & editing, Visualization. **Georgios Christoforidis:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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