Renewable Hybrid Power Plants with Power Purchase Agreements and Spot Market Participation

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***Abstract*—With the phase-out of state support for renewable energy projects in many European countries, the need for power purchase agreements (PPAs) to mitigate long-term financial risk is growing. This paper presents a stochastic optimization framework for hybrid power plants (HPPs) combining wind, solar, and battery storage, enabling joint participation in PPAs and spot markets to balance long-term revenue certainty with short-term operational flexibility. Correlated spot prices and renewable generation time series derived from multiple historical weather years (1982–2015) are used as independent scenario realizations to represent long-term uncertainty in both resource availability and market outcomes. The framework evaluates 6 shaped delivery profiles and settlement periods to determine optimal PPA commitment under uncertainty. The case study demonstrates the effectiveness of the proposed model and the role of PPAs in mitigating the long-term risk to HPP revenues.**

***Index Terms*—Hybrid power plants, power purchase agreements, spot market, stochastic optimization, long-term uncertainty.**

I. Introduction

Hybrid power plants (HPPs), combining renewable energy sources such as wind and solar with battery energy storage systems (BESS), are increasingly recognized as a key enabler of the energy transition toward a fully renewable power system. The hybridization of variable renewable energy sources (VRES) offers technical and economic advantages over stand-alone assets by mitigating intermittency, increasing grid utilization, and enabling temporal arbitrage in electricity markets [1]. The BESS in HPPs can perform energy arbitrage in spot market (SM). It provides access to short-term revenue streams, but also exposes plant owners to long-term market price risk. To ensure financial stability and bankability, particularly as feed-in tariffs and other policy supports are phased out across Europe, many renewable energy projects are increasingly relying on power purchase agreements (PPAs) as contractual hedges against long-term uncertainty [2]. For HPPs, this introduces a new research problem to balance long-term revenue stability from PPAs with short-term flexibility and arbitrage opportunities in SM.

Research on HPP participation in electricity markets has expanded rapidly in recent years. The studies mainly focus on multiple short-term market participation and different methodologies to handle uncertainties [3]. For instance, multi-stage stochastic optimization models have been developed to capture uncertainty in renewable production and market prices, enabling the coordination of bidding and storage management strategies in day-ahead and intraday markets [4]. Ref. [5] presented a two-stage stochastic framework that optimizes HPP participation across day-ahead, reserve, and balancing markets. Ref. [6] develops an energy management system using data-driven distributional robust optimization for wind-battery HPPs considering imbalance settlement. These studies demonstrate that various optimization methods effectively manage short-term market participation and generation uncertainties, thereby improving profitability. However, they generally overlook PPAs and therefore fail to address long-term uncertainty sources such as price evolution and weather variability.

PPAs have been considered in some studies as a long-term risk management strategy. On the consumer side, ref. [7] formulates a medium-term, risk-averse stochastic procurement model that lets large users combine market purchases, diverse PPA types, and solar self-generation. It shows PPAs materially hedge pool-price volatility but stop short of modeling producer-side HPP operations or the interaction with merchant arbitrage. Ref. [8] develops a hybrid procurement strategy for large customers that integrates PPAs with BESS and long-horizon price forecasting to 2050. It is also from the buyer's perspective, and without co-optimizing an HPP's simultaneous participation in PPA and spot markets. On the producer side, ref. [9] studies how PPA structures evolve from annual energy contracts toward 24/7 power delivery, quantifying the trade-space between overbuild, hybridization, and storage for firm supply design. However, it does not take into account electricity market participation. Ref. [10] studies a solar-BESS HPP under a merchant scheme, combining probabilistic forecasting with mixed integer linear programming. However, the study centers on a single-technology hybrid in a specific market and does not address multi-decadal correlated uncertainty.

According to the literature review, it can be seen that HPPs with PPAs and participation in the spot market to mitigate long-term risk and maintain short-term arbitrage flexibility have not been thoroughly studied. To address this gap, the main contributions of this paper are:

- A stochastic optimization model with conditional value-at-risk (CVaR) is proposed for HPPs consisting of wind, solar, and battery with PPAs and spot market participation
- The open-source models Balmorel [11] and CorRES [12], [13] are used to simulate 2050 spot market prices and renewable generation based on historical weather years (1982–2015), explicitly accounting for correlations between renewable output and electricity prices to ensure

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realistic long-term scenarios.
- Different PPA delivery profiles and settlement periods are evaluated to quantify their impact on the HPP's revenue distribution and risk exposure.

II. Overview of PPA structures for HPPs

PPAs can generally be categorized as physical or virtual. In a physical PPA, electricity is directly delivered from the producer to the offtaker, either behind the same connection point or through the public grid [9]. In contrast, a virtual PPA (vPPA) is a financial contract-for-difference without physical delivery, where the price difference between the PPA strike price and the market price is settled financially, serving primarily as a hedging instrument and a mechanism for guarantees of origin [2].

Beyond the contractual structure, PPAs also differ in delivery schemes, which define how energy is supplied. For VRES, the most common contract is pay-as-produced, where a fixed percentage of actual generation is delivered, exposing the seller to limited generation risk. Baseload contracts, instead, require constant delivery volumes over defined periods, forcing the producer to compensate shortfalls through market purchases and therefore carrying significantly higher risk under variable renewable production.

With the rapid deployment of HPPs, traditional PPA structures are becoming increasingly insufficient. HPPs enable flexible and controllable output that can be shaped to meet demand patterns, creating opportunities for shaped delivery profile (SDP) PPAs that specify target delivery profiles rather than direct production percentages. This study focuses on SDP-based PPAs for HPPs, analyzing how different settlement periods and delivery shapes influence operational flexibility and long-term financial stability.

III. Methodology

The methodology couples (i) weather-driven production time series with CorRES, (ii) market price simulations with Balmorel, and (iii) a stochastic long-term optimization of HPP operation and PPA design, as presented in Fig. 1

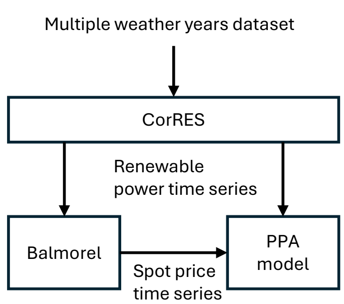

Fig. 1. Workflow of the methodology

A. Weather-driven energy system and renewable power

To represent long-term spot market prices, the Balmorel open-source energy system model is employed to simulate the future European power system. Balmorel provides a detailed representation of generation, transmission, and market dispatch, and incorporates extensive wind and solar portfolios whose production is modeled using CorRES. The CorRES model generates high-resolution wind and solar time series based on ERA5 meteorological reanalysis data [14], ensuring consistent weather-driven renewable generation across the system. To capture the long-term uncertainty, Balmorel is run for 34 historical weather years (1982–2015), producing distinct hourly price time series for the simulation year 2050. CorRES is also used to generate wind and solar power time series for the HPP in this paper, enabling the modeled spot prices and HPP production profiles to be driven by identical underlying weather conditions.

This integrated modelling approach provides a coherent set of long-term hourly scenarios for use in the HPP optimization model. It reflects realistic correlations between renewable generation patterns and market price formation, which is essential for long-term financial assessment under uncertainty.

B. PPA contract framework

The PPA design incorporates several simplifying assumptions regarding the contractual framework of the PPA. It involves:

1) Shaped delivery profile: The SDP represents a daily shaped delivery profile, specifying the relative temporal distribution of generation that HPPs must follow.

2) Settlement period: The settlement period refers to the time frame in which the agreed-upon SDP are the same in this period.

3) PPA price scheme: PPA price is an input parameter when designing PPA. It depends on negotiations between sellers and buyers. However, a widely used approach involves the capture price of each delivery profile. The capture price λ^{cp} is calculated as the volume-weighted mean spot price:

$$\lambda_h^{cp} = \frac{\sum_t \lambda_{t\in H_h}^{sp} u_t^{sdp}}{\sum_{t\in H_h} u_t^{sdp}} \tag{1}$$

where H_h is the set of hours in the pricing period h. In practice, buyers may also require a discount to account for the uncertainty of their future demand. Accordingly, a 10% discount on the capture price is applied to determine the PPA price.

4) Operational obligation: PPA obligations always have priority over SM bids in daily operations. The HPP can participate in SM with any generation not committed to PPA delivery, provided that this does not intentionally impact PPA obligations. Shortfalls in PPA deliveries are settled at the SM price at the hour of the shortfall.

C. PPA design model

To account for long-term SM price and renewable generation uncertainty, the PPA design model is formulated using stochastic optimization with CVaR. The objective function is demonstrated in (2).

$$\max\ (1-\beta)\cdot f(x) + \beta \cdot CVaR \tag{2}$$

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where $f(x)$ is the mean revenue of HPP with PPA and SM participation defined in (3). The CVaR is defined in (4).

$$f(x) = \frac{1}{N} \sum_s \sum_t (\lambda_t^{ppa} p_t^{sdp} - \lambda_{t,s}^{p} |p_{t,s}^{ppa} - p_t^{sdp}| + \lambda_{t,s}^{sp} p_{t,s}^{sm}) \tag{3}$$

$$CVaR = \zeta - \frac{1}{1-\alpha} \cdot \frac{1}{N} \sum_s \gamma_s \tag{4}$$

λ_t^{ppa} represents the PPA price. p_t^{sdp} and $p_{t,s}^{ppa}$ are the SDP and delivered PPA power of the HPP, respectively. $\lambda_{t,s}^{p}$ is the penalty for not achieving the SDP. Although the penalty in the operational obligation is the same as spot prices, the model uses ten times the spot prices to achieve a conservative PPA design without overpromising. $\lambda_{t,s}^{sp}$ and $p_{t,s}^{sm}$ are the spot market price and power, respectively. It is noted that this paper focuses only on long-term uncertainty of renewable power and SM price time series, meaning under each scenario s, renewable power and spot price are perfectly known at the operational stage. The constraints of the PPA design model are given as below:

$$p_{t,s}^{total} = p_{t,s}^{sm} + p_{t,s}^{ppa} \tag{5}$$
$$p_{t,s}^{ppa} = p_{t,s}^{ppa,w} + p_{t,s}^{ppa,s} + p_{t,s}^{ppa,dis} \tag{6}$$
$$p_{t,s}^{sm} = p_{t,s}^{sm,w} + p_{t,s}^{sm,s} + p_{t,s}^{sm,dis} \tag{7}$$
$$p_{t,s}^{sm,w} + p_{t,s}^{sm,s} + p_{t,s}^{ppa,w} + p_{t,s}^{ppa,s} + p_{t,s}^{cha} \leq p_{t,s}^{ava,w} + p_{t,s}^{ava,s} \tag{8}$$
$$p_{t,s}^{ppa,dis} + p_{t,s}^{sm,dis} \leq p^{b,max} \cdot z_{t,s} \tag{9}$$
$$p_{t,s}^{cha} \leq p^{b,max} \cdot (1 - z_{t,s}) \tag{10}$$
$$e_{t+1,s}^{b} = e_{t,s}^{b} - \frac{p_{t,s}^{ppa,dis} + p_{t,s}^{sm,dis}}{\eta^{dis}} \cdot \Delta t + p_{t,s}^{cha} \cdot \eta^{cha} \cdot \Delta t \tag{11}$$
$$e^{min} \leq e_{t+1}^{b} \leq e^{max} \tag{12}$$
$$p_{t,s}^{total} \leq p^{grid} \tag{13}$$
$$e_0^b = 0.5 \cdot e^{b,max} \tag{14}$$
$$p_t^{sdp} = u_i^{sdp} \cdot S_h^{ppa}, \forall h \in H \tag{15}$$
$$\sum_t (\lambda_t^{ppa} p_t^{sdp} - \lambda_{t,s}^{p} |p_{t,s}^{ppa} - p_t^{sdp}| + \lambda_{t,s}^{sp} p_{t,s}^{sm}) \geq \zeta - \gamma_s \tag{16}$$

where equation (5) defines the total HPP power outputs, $p_{t,s}^{total}$, delivered for PPA, $p_{t,s}^{ppa}$, and spot market, $p_{t,s}^{sm}$, respectively. Constraint (6) and (7) calculate the delivered HPP power from wind, solar, and battery discharging for PPA and spot market, respectively. Constraint (8) restricts the dispatched wind and solar power for PPA and spot markets, as well as the battery charging power, to be less than the available wind and solar power. Constraint (9) and (10) limit the charging and discharging of the battery by the rated power $p^{b,max}$ and ensure they can not happen simultaneously. The energy evolution of the battery is presented in (11), where $e_{t,s}^{b}$ is the energy stored in the battery. Constraint (12) sets the limits of the battery energy, where e^{min} and e^{max} signify the battery's minimum and maximum stored energy. Constraint (13) ensures the HPP output meets the grid connection limit. The initial energy capacity of batteries is defined by (14). Constraint (15) defines the SDP of HPP, where u_i^{sdp} is the normalized SDP at hour i, which is the hour of the day, calculated as $t\%24$. S_h^{ppa} is the peak power of the designed SDP with a specific settlement period h. Constraint (16) is the CVaR constraint, reflecting the risk aversion related to uncertain revenue streams.

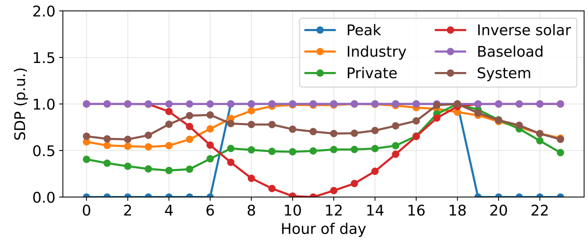

Fig. 2. Six shaped delivery profiles

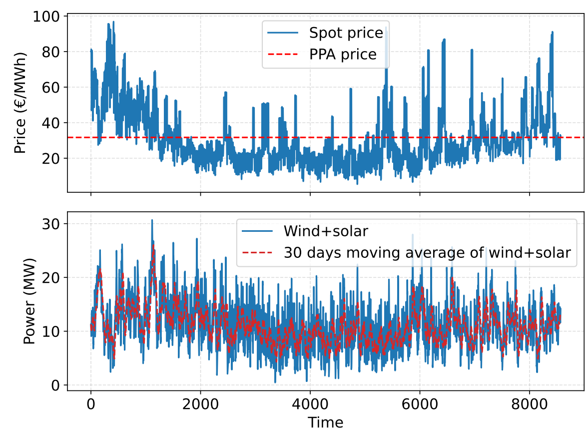

Fig. 3. Mean spot price, and mean renewable power from 7 representative weather years as well as yearly fixed PPA price

IV. Case Study

A real HPP with 37.8 MW wind and 15 MW solar plant with 52 MW grid connection capacity located in Western Denmark is used to perform the case study. A battery with 20 MW power capacity and 120 MWh energy capacity is assumed to be co-located with wind and solar. This paper studies six SDPs as presented in Fig. 2 in per-unit form. Monthly, seasonal, and yearly settlement periods, along with the yearly fixed PPA price, are also included to perform the case analysis. The confidence level α is assumed to be 20%.

A. PPA design

To conduct the study, the first year out of every five weather years is selected as input to the proposed model, resulting in a total of 7 representative weather years. The remaining 27 weather years were reserved for out-of-sample performance evaluation. Fig. 3 presents the mean spot price of the 7 representative weather years and the PPA price, as well as the mean renewable power. It can be observed that spot prices

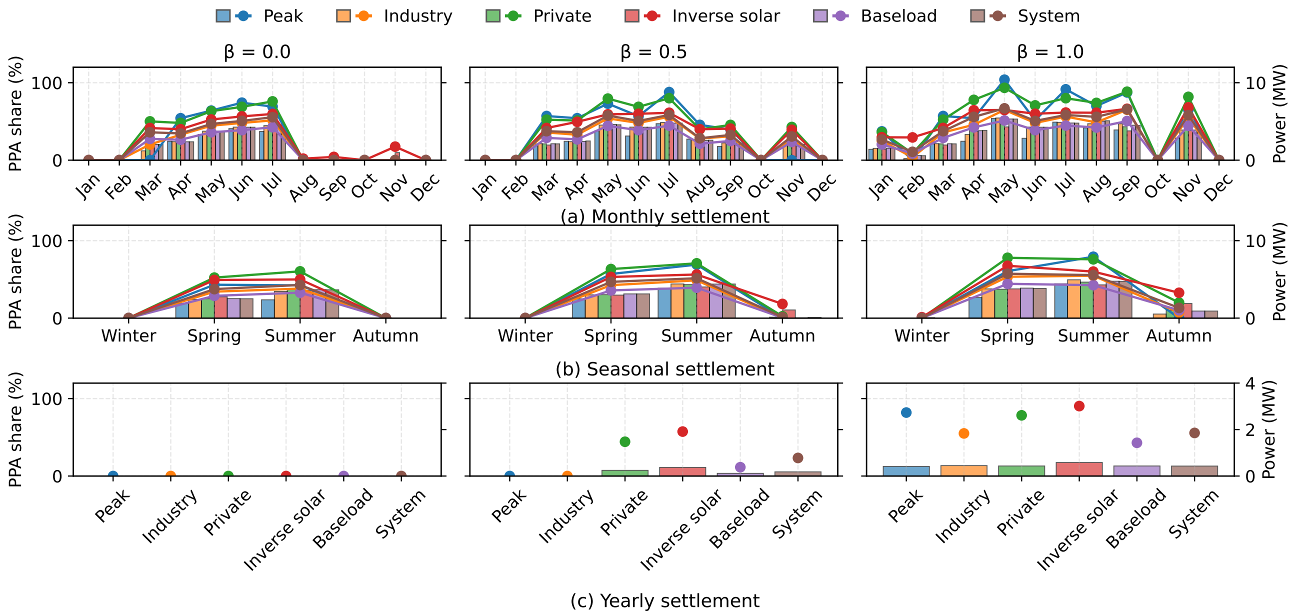

Fig. 4. Share of energy committed in PPA (bar plot) and peak power of SDPs (dot-line): (a) monthly settlement periods (b) seasonal settlement periods; (c) Yearly settlement periods

are higher than the PPA price during most hours in winter, whereas they are lower during most hours in summer. Fig. 4 demonstrates the PPA designs under different risk preference parameters, settlement periods, and SDPs

Across all settlement periods, an increase in risk preference parameter β leads to higher PPA commitments. In Fig. 4 (a), several months exhibit zero PPA share at $\beta = 0$, but become partially contracted when $\beta = 1$, indicating that higher risk aversion makes it attractive to lock in revenue even in periods where purely spot-based operation was preferred under risk-neutral conditions. Similarly, in the seasonal case in Fig. 4 (b), where Autumn has no PPA commitment at $\beta = 0$ but becomes contracted at $\beta = 1$, reflecting that this season is particularly exposed to lower spot prices and is therefore only included when hedging motives are strong. In Fig. 4 (c) it can be observed that all SDPs have zero PPA share at $\beta = 0$ and positive shares at $\beta = 1$, showing that yearly settlement is only accepted when risk aversion is high enough to justify sacrificing operational flexibility. In total, these patterns demonstrate a consistent shift from pure SM participation at low risk preference to increasing PPA-based operation as risk aversion increases.

Fig. 4 clearly indicates that shorter settlement periods support higher PPA commitments, while longer ones restrict them. Under the monthly settlement, the PPA commitment has the highest share, with the maximum commitment occurring in July, reaching approximately 50% of the available energy. In contrast, no PPA commitment occurs in January, February, October, and December, primarily due to higher SM prices during these months, as seen in Fig. 3. This reflects that the shorter settlement period allows the contract to adapt more closely to intra-annual price variability. In the seasonal case, the highest commitment happens in summer, remaining above 40 %, consistent with higher solar availability and steady wind output as well as the relatively lower spot prices. Conversely, the winter season shows negligible PPA commitments, again reflecting the influence of high SM prices on contract allocation. When the settlement horizon extends to a full year, commitments fall below 20 % across all SDPs, illustrating that the longer settlement period forces a more conservative PPA design to minimize delivery risk.

Comparing the different SDPs, both the PPA shares and the resulting peak power levels are relatively similar across profiles, which reflects the flexibility provided by battery storage in reshaping the delivery profile and smoothing operational differences. The battery enables temporal shifting of energy, reducing the influence of SDP shape on both contracted volume and required peak power.

B. Comparison between PPA+SM and SM only

Fig. 5 presents the out-of-sample revenue distributions of the six SDPs across 27 historical weather years, comparing the combined PPA + SM participation strategy with the SM-only benchmark. Across most profiles and settlement schemes, the mean revenues obtained under the combined strategy are consistently higher, highlighting the effectiveness of PPAs in hedging against unfavorable market and weather conditions. In contrast, revenues from the spot market alone exhibit wider dispersion, reflecting higher exposure to stochastic renewable generation and price volatility. For instance, as shown in Fig. 5(c), the System and Private SDPs exhibit notably broader revenue distributions in the SM-only case, despite having mean values similar to those in the PPA + SM case. These results confirm that well-designed PPAs significantly enhance the financial robustness and revenue stability of HPPs, ensuring more predictable cash flows over extended operational horizons.

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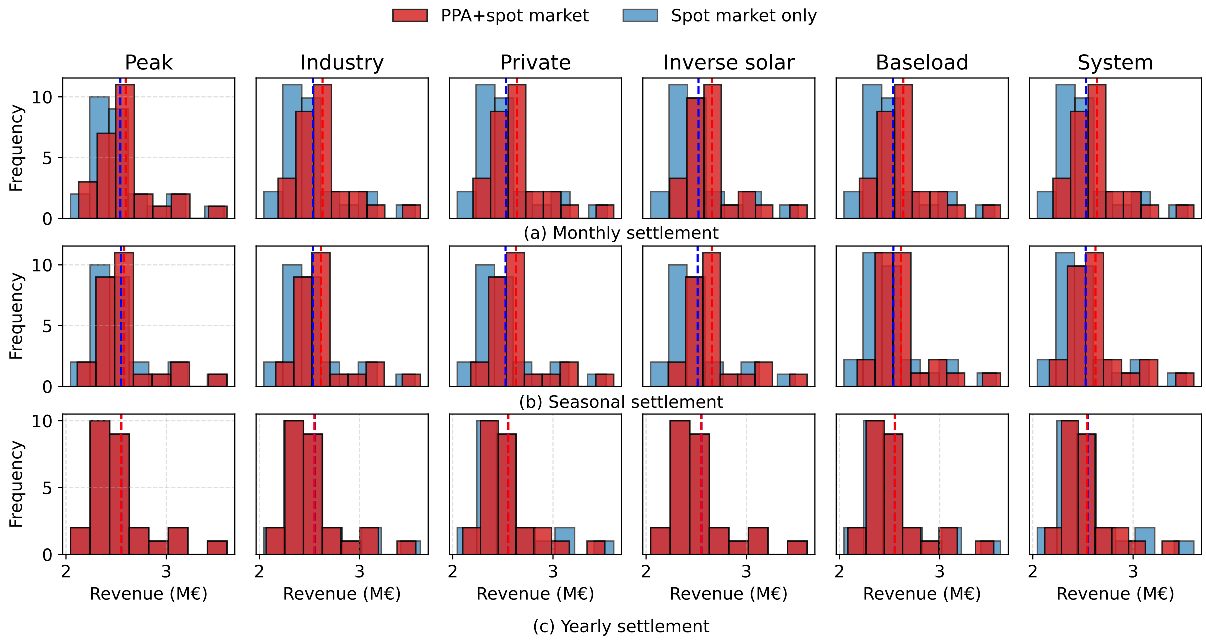

Fig. 5. Probability distribution of revenues over 27 out-of-sample weather years for the six SDPs with (a) monthly settlement periods; (b) seasonal settlement periods; (c) Yearly settlement periods

V. Conclusion

This paper presents a stochastic optimization framework for hybrid power plants (HPPs) combining wind, solar, and battery storage in joint power purchase agreements (PPAs) and spot market participation, using correlated multi-year weather scenarios to capture long-term variability. The results show that low risk preference leads to zero or limited PPA commitments in several periods, while higher risk aversion increases PPA shares as a hedging strategy. Settlement length significantly affects commitment levels, with monthly and seasonal contracts enabling maximum shares of approximately 50% and 40%, respectively, whereas yearly settlement limits commitments to below 20%. Furthermore, the shape of different SDPs does not show significant impacts on PPA share and peak power. Besides, out-of-sample evaluations confirm that PPAs effectively reduce revenue volatility and enhance financial stability relative to spot-only operation. Future work will incorporate short-term forecasting uncertainty.

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