

A quantitative study on AI-based PPA hedging

Reducing tail risk in co-located renewable assets

The PPA hedging challenge

Fixed-price PPA

In this study, we consider a fixed-price PPA. The buyer commits to purchasing renewable electricity at a fixed strike price for every unit delivered. The buyer profits when spot prices exceed the strike price and loses when spot prices fall below it.

Why perfect hedging is difficult

Electricity futures are the natural instrument to hedge this exposure. In practice, cannibalization, basis, and volume risk make perfect replication difficult. A co-located battery partially mitigates cannibalization but adds complexity to the hedge.

Incomplete market

Perfect replication is impossible, and hedgers require an explicit risk objective to select among available strategies. The industry-standard Value Hedge adjusts futures positions for the expected production-price correlation but does not optimize tail risk.

Sources of risk

Cannibalization: When wind or solar output is high, supply outpaces demand and whole-sale prices fall. Renewable production and prices move in opposite directions, so high volumes coincide with low prices.

Basis risk: Available futures settle against the average spot price over the delivery period. The PPA pay-off depends on the production-weighted average, which the futures cannot replicate.

Volume risk: The amount of electricity delivered depends on the weather, not on any market decision. No exchange offers a contract that compensates the buyer for low wind or solar output.

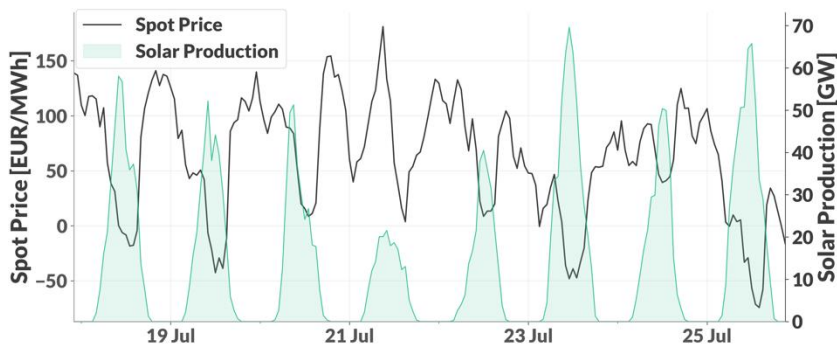


Figure 1: Cannibalization. Solar production peaks coincide with spot price troughs. Simulated data, calibrated to the German market.

Deep hedging: learning optimal positions from scenarios

The study hedges a one-year solar PPA with a co-located battery. A deep **neural network** replaces the fixed Value Hedge formula by learning the optimal hedge directly from the P&L of **thousands of simulated scenarios**. At the hedge date, the network observes forward prices, production forecasts, and capture factors, and outputs positions for the liquid futures contracts available. The training objective is Expected Shortfall at the 5% level ($ES_{5\%}$): the average loss across the worst 5% of scenarios.

Solar PPA with a co-located battery (40 MWh / 20 MW), evaluated across thousands of simulated scenarios calibrated to the German electricity market.

Strategy	ES _{5%}	Median	5 th percentile	95 th percentile
No Hedge	-565k EUR	388k EUR	-367k EUR	1,159k EUR
Value Hedge	-195k EUR	389k EUR	-52k EUR	855k EUR
Deep Hedge	-126k EUR	388k EUR	+3k EUR	819k EUR

Table 1: Comparison of hedging strategies across key P&L metrics (ES_{5%}, median, 5th and 95th percentile)

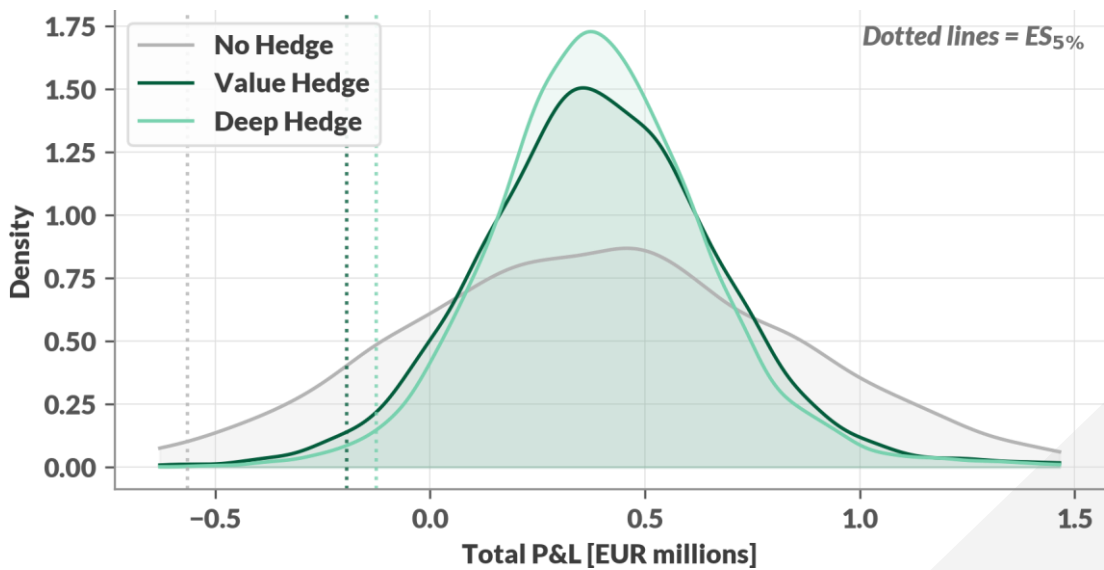


Figure 2: P&L distributions for all three hedging strategies

Key takeaways

- **The Deep Hedge outperforms other strategies.** The median P&L is preserved, while the tail risk is substantially reduced. The Deep Hedge reduces ES_{5%} by 77% vs. No Hedge.
- **Batteries raise the PPA strike by 14%.** Co-located batteries unlock additional value that can be shared between offtaker and producer.

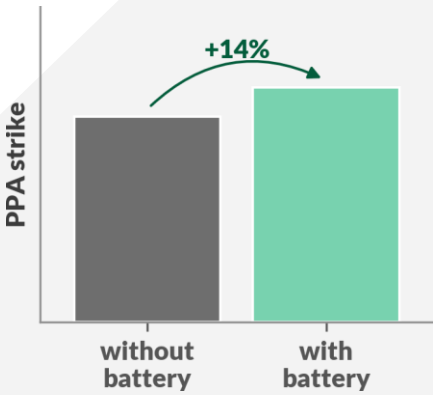


Figure 3: PPA strike with and without co-located battery

Outlook

Dynamic rebalancing. Extending the one-shot framework to frequent re-hedging, where the network updates positions as new market and weather data arrive.
Transaction costs. Including bid-ask spreads in the loss function to ensure the learned positions remain cost-efficient in practice.

May 2026. Results based on simulation calibrated to German market data.