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COST ASSESSMENT FOR GRID-EXPORT PV SYSTEMS USING LONG-TERM FORECASTING: A PRE-INVESTMENT STUDY FOR BESS DEPLOYMENT

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ABSTRACT

Long-term energy yield estimation plays a critical role in evaluating the financial feasibility of Photovoltaic (PV) projects, particularly for grid-export-only systems where revenue depends entirely on the amount of energy delivered to the grid. Unlike short-term forecasting used for operational control, long-horizon prediction enables investors and system planners to quantify expected annual energy generation, revenue under Power Purchase Agreement (PPA) or Time-of-Use (TOU) pricing, and project payback time. This study develops a forecast-driven economic evaluation framework to assess the baseline profitability of a grid-export-only PV plant and evaluate the pre-investment feasibility of Battery Energy Storage System (BESS) deployment. Historical PV output and meteorological variables are used to train a Gradient Boosted Trees (GBT) model, generating reliable aggregated PV predictions. These forecasts are applied to compute baseline revenue, expected curtailment, and the overall profitability of various PV-BESS capacities under PPA and TOU tariffs. Results from a 720.9 kWp/600 kW AC PV system show that combining forecasting with scenario-based assessment provides a robust estimation of economic viability. The study identifies that moderate BESS sizing (e.g., 535–750 kWh) under TOU tariffs significantly maximizes net present value (NPV) and shortens the payback period, laying a solid foundation for optimal BESS integration.

Keywords: Long-term PV forecasting, Baseline revenue, Curtailment, Investment feasibility, Gradient Boosted Trees, Techno-economic analysis.

1. INTRODUCTION

The economic feasibility of grid-export photovoltaic (PV) plants is governed primarily by long-term energy yield, which directly determines revenue under electricity pricing mechanisms such as fixed-price Power Purchase Agreements (PPA) and Time-of-Use (TOU) tariffs. Inaccurate estimation of future PV generation can therefore lead to biased revenue projections, misleading payback calculations, and elevated investment risk, particularly for export-limited systems where curtailment may occur during high-irradiance periods [1], [2].

Recent advances in machine learning have significantly improved the accuracy of PV power forecasting by capturing nonlinear relationships between historical generation patterns and meteorological conditions [3]. Models based on machine learning and deep learning have demonstrated strong generalization capability and robustness in hourly and daily PV prediction tasks [4]-[7]. However, the majority of existing studies evaluate forecasting performance primarily through statistical error metrics (RMSE, MAE, RE), without explicitly linking forecast uncertainty to economic outcomes or investment-related decision-making.

In parallel, techno-economic analyses of PV systems integrated with Battery Energy Storage Systems (BESS) have received increasing attention. Many studies directly formulate storage sizing and dispatch optimization problems based on assumed or deterministic PV generation profiles [8], [9]. While such approaches provide insight into operational benefits, they often obscure the economic baseline of the PV-only system and underestimate the influence of forecasting uncertainty and electricity tariff structures on long-term profitability.

This paper addresses these gaps by proposing a forecasting-driven economic assessment framework tailored to grid-export PV systems. Instead of treating PV generation as a known input, a data-driven GBT forecasting model is employed to establish a realistic long-term production baseline. The forecasted PV output is subsequently translated into annual revenue and investment performance indicators under both PPA and TOU tariff schemes. Furthermore, scenario-based economic robustness is evaluated by systematically perturbing electricity prices, PV generation levels, and BESS capacities, allowing assessment of financial sensitivity without modifying the forecasting model.

The objectives of this paper are as follows:

1) Develop an accurate long-term PV forecasting model using machine learning to predict energy generation trends.

2) Compute the baseline annual revenue and curtailment loss for the PV-only system.

3) Evaluate the pre-investment economic feasibility of deploying various BESS capacities under varying PPA and TOU pricing schemes.

4) Map long-term forecasting uncertainties directly onto robust investment metrics (NPV, payback period).

This framework provides the foundational macroeconomic bounds required to justify BESS investments and optimize sizing before detailed real-time execution.

2. METHODOLOGY

2.1. PV Power Forecasting Model Formulation

PV power forecasting is formulated as a supervised machine learning regression problem and implemented using the RapidMiner analytical platform [10]. The forecasting task aims to generate reliable hourly PV export profiles that can be aggregated into monthly and annual energy estimates, which subsequently serve as inputs for techno-economic evaluation rather than operational control. While the ultimate objective of this study is long-term economic assessment, the forecasting model must operate at a high-resolution hourly scale. This is because battery dispatch behavior, curtailment events, and TOU arbitrage opportunities depend strictly on intra-day irradiance profiles. Therefore, continuous hourly forecasts are generated and subsequently aggregated over multi-year horizons to reliably compute long-term investment metrics such as NPV and Payback period.

The forecasting workflow begins with data normalization, where all continuous input variables are scaled using Min–Max normalization. This step maps each feature into a bounded range and prevents dominance of variables with large numerical magnitudes during model training. Normalization also improves the stability of tree-based ensemble learning when multiple heterogeneous features are involved.

Following normalization, feature extraction and selection are performed to capture the temporal and physical characteristics of PV generation. The initial feature set includes historical PV output, temporal indicators (hour of day and day of year), and meteorological variables sourced from the NASA POWER dataset [11]. While the NASA POWER dataset provides a highly accessible and sufficient basis for pre-investment macro-analysis, its spatial resolution may not entirely capture micro-climatic variations. Transitioning to the detailed engineering phase in the future would require calibrating the forecasting model with on-site ground measurements to further reduce long-term uncertainties. To enhance forecasting robustness, additional derived features are constructed, such as lagged PV values and seasonal encodings, which reinforce the model's ability to learn diurnal and annual production patterns. The complete list of input features, along with their physical meaning and units, is summarized in Table 1.

Table 1. Input features for the gradient boosted model

Feature	Unit	Description
Timestamp	–	Used to preserve the chronological structure of the dataset.
DOY (Day of Year)	–	Sequential day index from 1 to 365/366, captures seasonal effects and long-term irradiance patterns.
Lag-1h, Lag-2h, Lag-3h, …	KWh	Previous-hour values to represent short-term PV trends.
ALLSKY_SFC_SW_DWN	W/m²	Actual incoming solar radiation under all-sky conditions.
CLRSKY_SFC_SW_DWN	W/m²	Clear-sky irradiance for assessing cloud effects.
SZA	Degrees	Solar zenith angle affecting irradiance intensity.
ALLSKY_SFC_PAR_TOT	W/m²	Photosynthetically active radiation correlated with sunlight availability.
ALLSKY_SFC_UV_INDEX	–	UV index reflecting atmospheric clarity.
T2M	°C	Near-surface air temperature affecting PV module efficiency.
T2MDEW	°C	Dew point indicating air moisture influencing irradiance.
T2MWET	°C	Wet-bulb temperature combining heat and humidity effects.
QV2M	g/kg	Specific humidity affecting atmospheric absorption.
PRECTOTCORR	mm/hr	Precipitation intensity associated with cloud cover.
PS	Pa	Surface pressure related to air mass conditions.
WS10M	m/s	Wind speed influencing cloud movement and irradiance variability.

Among the available learning algorithms, Gradient Boosted Trees (GBT) is selected due to its strong predictive capability for nonlinear systems and its robustness when applied to structured energy datasets [12]. The GBT model operates by sequentially training an ensemble of decision trees, where each new tree is fitted to the residual errors of the previous ensemble. Through this iterative boosting process, the model gradually refines its predictions by focusing on difficult-to-predict regions of the data space. The final prediction is obtained as a weighted aggregation of all individual trees, allowing the model to approximate complex nonlinear relationships between PV output and its driving factors. In the RapidMiner, the key model parameters, including the number of trees, tree depth, leaf distribution, and model size, are summarized in Table 2.

Forecasting accuracy is evaluated using the Root Mean Square Error (RMSE) and the Relative Error (RE) [13], [14]. The trained GBT model achieves satisfactory hourly PV forecasting accuracy for revenue estimation, in line with reported short-term PV forecasting benchmarks (RMSE $\lesssim$ 20%) [15].

To convert the forecasted PV generation into exportable energy, the grid connection constraint is explicitly considered to determine the actual power injected into the grid.

$$P_t^{\mathrm{exp}}=\min\left(P_t^{\mathrm{PV}},P^{\mathrm{AC,max}}\right) \tag{1}$$

Table 2. Key parameters and performance metrics of the gradient boosted trees model for PV forecasting

Category	Value
Model Type	Gradient Boosted Trees (GBT) – Regression
Number of Trees	90
Tree Depth	Min = 7, Max = 7
Leaves per Tree	8–128 (mean = 109.37)

2.2. Scenario-Based Economic Robustness Assessment

A. Revenue Calculation

The electricity revenue is calculated based on the exported PV power and the applicable electricity tariff at each simulation time step. The instantaneous revenue is given by (2):

$$R_t=P_t^{\mathrm{exp}}\cdot\pi_t\cdot\Delta t \tag{2}$$

where P_t^{exp} denotes the exported PV power, π_t is the electricity price at time step t, and Δt is the simulation time interval.

Since the simulation horizon may not cover a full calendar year, the total revenue is normalized to an annual basis to ensure economic comparability across different scenarios:

$$R_{\mathrm{annual}}=\left(\sum_{t=1}^{N}R_t\right)\cdot\frac{8760}{N} \tag{3}$$

where N is the total number of simulation time steps.

As the considered BESS configurations are sized to mitigate PV curtailment, the economic benefit introduced by battery integration is evaluated based on incremental revenue relative to the PV-only baseline. The annual revenue increase is calculated as (4):

$$\Delta R=R_{\mathrm{annual}}^{\mathrm{PV+BESS}}-R_{\mathrm{annual}}^{\mathrm{PV\text{-}only}} \tag{4}$$

The annual net economic benefit B_{net} (VND/year), representing the incremental financial gain attributable to BESS integration, is defined as (5):

$$B_{\mathrm{net}}=\Delta R-C_{\mathrm{deg}}-C_{O\&M} \tag{5}$$

where $C_{O\&M}$ is the annual operation and maintenance cost, fixed at 3% of the initial BESS CAPEX. C_{deg} denotes the battery degradation cost. To balance economic realism with computational suitability, a linear throughput-based degradation model is adopted. The battery degradation cost C_{deg} is formulated as:

$$C_{deg}=\sum_{t=1}^{N}\left(\mathrm{c}_1P_{ch,t}+\mathrm{c}_2P_{dis,t}\right) \tag{6}$$

Based on the characteristics of commercial Lithium Iron Phosphate (LFP) batteries (cycle life > 5,000 cycles at 80% EOL), we assume symmetric wear for charging $P_{ch,t}$ and discharging $P_{dis,t}$ processes at moderate 0.5C operation. Therefore, identical wear coefficients are applied: $c_1 = c_2 = 0.005$VND/kWh. This explicit formulation introduces a realistic economic penalty (0.01 VND per kWh of combined throughput) for excessive cycling over time.

This annualized revenue serves as the primary input for all subsequent economic indicators and scenario-based evaluations.

B. Net Present Value

To evaluate the long-term profitability of the PV–BESS investment, the Net Present Value (NPV) is adopted as the primary economic performance indicator, accounting for both the time value of money and the project lifetime:

$$\text{NPV} = -\ \text{CAPEX} + \sum_{y=1}^{Y} \frac{B_{\text{net}}}{(1+r)^{y}} \tag{7}$$

where CAPEX is the initial investment cost of the BESS (VND); r is the discount rate; and Y is the project lifetime in years.

In this pre-investment framework, the economic assessment utilizes a real discount rate (7%) to process real-term cash flows, effectively offsetting general inflation and O&M cost escalation. Furthermore, while typical PV panels degrade at ~0.5% annually (cumulating to ~5% over a 10-year lifetime), the economic impact of this degradation is comprehensively covered within the bounds of the scenario-based ±10% PV generation uncertainty analysis (Table 5). This approach ensures financial rigor without relying on speculative long-term inflation forecasting.

C. Simple Payback Period

In addition to NPV, the simple payback period is used to provide an intuitive measure of the time required to recover the initial investment from annual net benefits:

$$Payback = \frac{\text{CAPEX}}{B_{\text{net}}} \tag{8}$$

The simple payback period is defined only when $B_{\text{net}} > 0$. If the annual net benefit is non-positive, the investment is considered economically infeasible under the corresponding scenario.

D. Scenario-Based Economic Robustness Dimensions

The above economic formulation is subsequently applied to a set of predefined scenarios that reflect uncertainties commonly encountered in real-world operation and pre-investment planning. Rather than modifying the forecasting or dispatch models, all scenarios are evaluated by perturbing economic inputs and propagating them through the same revenue and profitability equations.

1) Impact of Electricity Tariff Structure on PV Economic Planning

Two electricity pricing mechanisms are considered:

1. Fixed-price Power Purchase Agreement (PPA), representing low and constant export remuneration.

2. Time-of-Use (TOU) tariff, enabling price arbitrage between off-peak and peak periods.

The electricity price applied to exported energy at time step t is defined as (9):

$$\pi_t = \begin{cases} \pi^{\text{PPA}} \\ \pi^{\text{TOU-off}} \\ \pi^{\text{TOU-normal}} \\ \pi^{\text{TOU-peak}} \end{cases} \tag{9}$$

Under a fixed-price PPA, electricity revenue is linearly proportional to the total exported energy and is independent of the temporal distribution of PV generation. In contrast, the TOU tariff assigns different economic values to exported energy depending on the hour of delivery, thereby creating opportunities for revenue enhancement through temporal energy shifting.

2) Impact of PV Generation Uncertainty on Economic Outcomes

Uncertainty in PV generation arises from meteorological variability and forecasting limitations and primarily affects long-term energy yield estimation in pre-investment analysis. To quantify this effect, the baseline PV generation profile is uniformly perturbed by ±10%, representing realistic bounds of long-term forecasting error.

The perturbed PV profiles are directly propagated through the revenue, NPV, and payback formulations without retraining or modifying the forecasting model. By maintaining identical tariff structures and BESS operating assumptions, the resulting variations in annual revenue and payback period can be attributed solely to PV generation uncertainty.

3) Economic Robustness with Respect to BESS Capacity Selection

Finally, multiple BESS capacities are examined to assess how incremental increases in storage translate into marginal economic benefits. All configurations are sized to fully eliminate PV curtailment under the studied operating conditions, thereby excluding curtailment-related energy losses from the comparison.

Under this assumption, differences in economic performance arise exclusively from electricity price arbitrage potential and investment cost. This approach enables identification of economically stable BESS capacity ranges that maintain acceptable profitability across varying external conditions, providing practical guidance for pre-investment storage sizing decisions.

2.3. Case Study Description and Scenario Definition

The proposed framework is applied to a real-world grid-export PV plant with a rated DC capacity of 720.9 kWp and an AC export limit of 600 kW, corresponding to a DC/AC ratio of 1.2. A lithium-ion BESS is integrated to enable energy shifting and electricity price arbitrage [16]. Four BESS capacities are evaluated: 250 kWh, 535 kWh, 750 kWh, and 1000 kWh. The main technical parameters of the studied PV–BESS system are summarized in Table 3. To enhance practical applicability, these specific values were selected based on standard, commercially available off-the-shelf industrial LFP storage configurations. The 1,000 kWh capacity acts as an upper bound to fully capture peak curtailment, while the intermediate capacities test the cost-efficiency of arbitrage. This ensures the techno-economic findings directly reflect realistic procurement options for project developers.

Table 3. Technical description of the studied PV–BESS system

Item	Description
PV system type	Grid-export-only photovoltaic plant
Rated DC capacity	720.9 kWp
Maximum AC export	600 kW
DC/AC ratio	1.2
Time resolution	Hourly
Forecasting method	Gradient Boosted Trees (GBT)
Storage technology	Lithium-ion BESS
Evaluated BESS capacities	250, 535, 750, 1000 kWh

Table 4 summarizes the electricity tariff structures implemented in the economic assessment. A fixed-price PPA and a TOU tariff with three pricing periods are considered. In the sensitivity analysis, all tariff levels are uniformly scaled by ±10% to represent electricity price uncertainty, while preserving the original temporal structure of the TOU scheme.

Table 4. Electricity tariff structures

Tariff Scheme	Time Period	Hour Range	Electricity Price (VND/kWh)
PPA	All hours	00:00–24:00	1400
TOU – Off-peak	Off-peak	22:00–06:00	900
TOU – Normal	Normal	06:00–17:00, 22:00–24:00	1800
TOU – Peak	Peak	17:00–22:00	3600

3. RESULTS

3.1. Hourly and Aggregated Forecast Performance

The predictive performance of the proposed GBT model is evaluated using multiple error metrics to verify its suitability for long-horizon PV energy forecasting. The model achieves an average RMSE of 0.152 kW with a standard deviation of 0.034 kW, indicating consistent accuracy across validation folds. The mean absolute error is limited to 0.066 kW, while the average relative error (RE) remains at 6.65%, which is acceptable for long-term energy estimation used in economic assessment.

In addition, the low squared error (0.024) and the stable prediction average (130.46 kW) indicate the absence of systematic bias and cumulative drift, implying that forecasting deviations are predominantly random. This property is particularly important for monthly and annual energy aggregation, where random errors tend to offset each other and have limited impact on revenue estimation.

As illustrated in Fig. 1, there is a close agreement between the predicted and measured PV power profiles, demonstrating that the proposed model accurately captures the temporal variation and peak generation behavior.

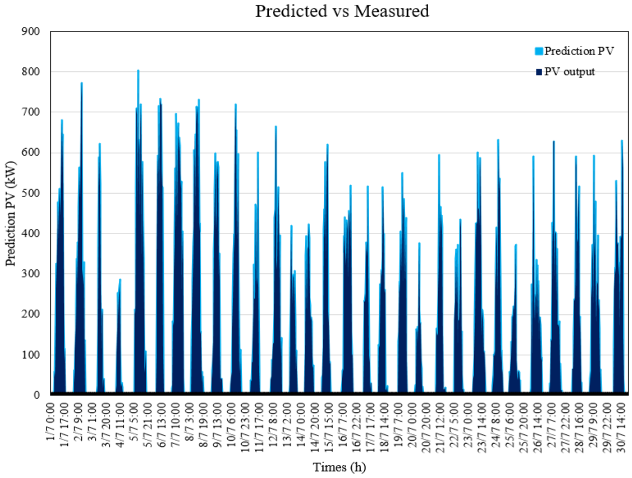

Fig. 1. Hourly PV power forecasting performance on the validation dataset (GBT model)

Overall, the obtained results confirm that the GBT-based forecasting model provides sufficient accuracy and robustness to serve as a reliable input for subsequent scenario-based economic evaluation of the PV–BESS system.

3.2. Scenario-Based Economic Robustness Assessment

The economic assessment shows that electricity tariff structure has a stronger influence on profitability than moderate PV generation uncertainty (±10%). Under the TOU tariff, all BESS capacities up to 750 kWh maintain positive NPV and short payback periods across all scenarios.

Specifically, the TOU–535 kWh configuration achieves a payback period of approximately 1.5–1.8 years, with NPV values exceeding 21 billion VND under base conditions. In comparison, PPA-based configurations exhibit longer payback periods and higher sensitivity to price reductions. For instance, the PPA–1000 kWh case results in negative NPV (down to –5.36 billion VND) and payback periods exceeding 10 years, indicating economic infeasibility.

As illustrated in Fig. 2a, the economic sensitivity of the PV-BESS system is highly dependent on electricity price structures. Under both tariff schemes, the NPV increases with BESS capacity up to an intermediate range, beyond which diminishing returns are observed.

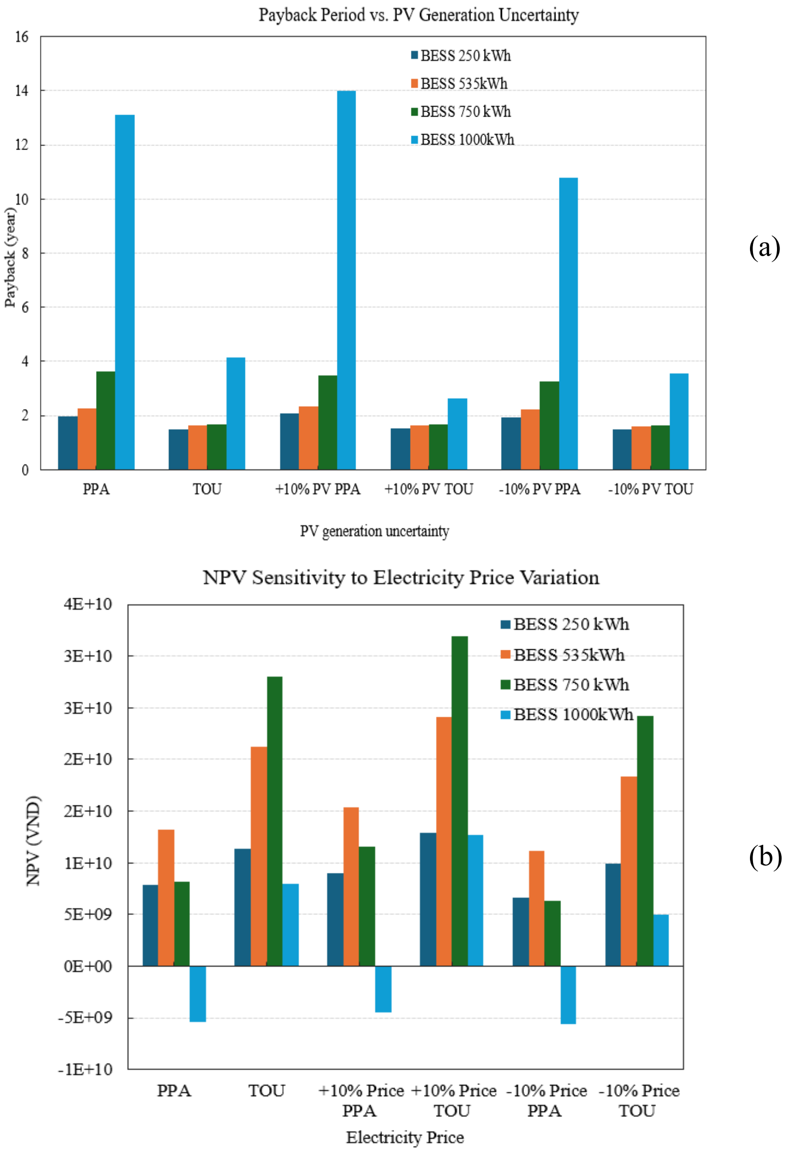

Fig. 2. Impact of parameter variations on system profitability for various BESS capacities: (a) NPV sensitivity to electricity price variation, (b) Payback period vs. PV generation uncertainty.

Under the TOU tariff, BESS capacities of 535–750 kWh consistently yield the highest economic performance. In contrast, the 1000 kWh configuration exhibits negative NPV under the PPA scheme and only marginal profitability under TOU, indicating clear over-sizing relative to the available PV generation.

Electricity price variation has a pronounced impact on economic outcomes. A ±10% change in electricity price leads to an NPV variation of approximately 20–30%, whereas the impact of ±10% PV generation uncertainty remains within a narrower range. This trend is further confirmed by the payback period results (Fig. 2b), where TOU-based configurations with BESS capacities between 250 and 750 kWh maintain payback periods below 2 years across all PV uncertainty scenarios.

In contrast, systems operating under a fixed PPA exhibit longer and more volatile payback periods, particularly for larger BESS sizes. The 1000 kWh configuration under PPA shows payback periods exceeding 10 years in most cases, reflecting poor capital utilization and heightened investment risk.

A comprehensive summary of the economic outcomes across all tariff and PV uncertainty scenarios, including NPV and payback period for each BESS configuration, is provided in Table 5.

Table 5. Economic robustness results

ID	Scenario	Payback (years)	NPV (VND)	ID	Scenario	Payback (years)	NPV (VND)
1	PPA BESS 250.0 kWh	2.0	7828727220	13	+10% PV Base Price PPA BESS 750.0 kWh	3.5	8887212307
2	TOU BESS 250.0 kWh	1.5	11397512991	14	+10% PV Base Price TOU BESS 750.0 kWh	1.7	27833278871
3	PPA BESS 535.0 kWh	2.3	13238332494	15	+10% PV Base Price PPA BESS 1000.0 kWh	14.0	-5763511184
4	TOU BESS 535.0 kWh	1.6	21263570405	16	+10% PV Base Price TOU BESS 1000.0 kWh	2.6	19292766871
5	PPA BESS 750.0 kWh	3.6	8156073775	17	-10% PV Base Price PPA BESS 250.0 kWh	1.9	8025181590
6	TOU BESS 750.0 kWh	1.7	28055871533	18	-10% PV Base Price TOU BESS 250.0 kWh	1.5	11546898556
7	PPA BESS 1000.0 kWh	13.1	-5361454635	19	-10% PV Base Price PPA BESS 535.0 kWh	2.2	13611878560
8	TOU BESS 1000.0 kWh	4.2	7988393656	20	-10% PV Base Price TOU BESS 535.0 kWh	1.6	21707024121
9	+10% PV Base Price PPA BESS 250.0 kWh	2.1	7396199794	21	-10% PV Base Price PPA BESS 750.0 kWh	3.2	10261832026
10	+10% PV Base Price TOU BESS 250.0 kWh	1.5	11050131903	22	-10% PV Base Price TOU BESS 750.0 kWh	1.6	28769312723
11	+10% PV Base Price PPA BESS 535.0 kWh	2.3	12851049814	23	-10% PV Base Price PPA BESS 1000.0 kWh	10.8	-4025921949
12	+10% PV Base Price TOU BESS 535.0 kWh	1.6	21065758327	24	-10% PV Base Price TOU BESS 1000.0 kWh	3.5	11367656248

Note: For brevity, only the baseline, +10% PV, and -10% PV scenarios under constant pricing are presented. Full permutations including price uncertainties exhibit consistent trends as illustrated in Fig. 2.

4. DISCUSSION

The results demonstrate that the economic value of PV–BESS systems is governed more by tariff structure and storage sizing than by moderate uncertainty in PV generation. Although forecasting errors inevitably exist, the observed ±10% variation in PV output leads only to limited changes in Net Benefit and payback period, particularly for BESS capacities below 750 kWh. This confirms that long-term PV forecasting accuracy at the level achieved by the proposed GBT model is sufficient for pre-investment economic planning. By bridging the gap between machine-learning forecast uncertainty and long-term financial metrics (NPV, Payback), this study extends beyond conventional statistical evaluations of forecasting models [3], [4].

A key finding is that TOU pricing consistently enhances the economic resilience of PV–BESS systems. Under TOU, storage is not only utilized to mitigate curtailment but also to perform effective price arbitrage, resulting in higher and more stable cash flows. In contrast, under fixed-price PPA schemes, the economic contribution of BESS relies almost exclusively on curtailment reduction. Once curtailment is fully eliminated, additional storage capacity yields rapidly diminishing returns, explaining the negative NPV observed for oversized BESS configurations.

The analysis further highlights the importance of proper BESS sizing relative to PV surplus energy. For the studied system (720.9 kWp DC, 600 kW AC export limit), BESS capacities in the range of 250–535 kWh strike a favorable balance between utilization rate, investment cost, and economic benefit. Beyond this range, particularly at 1000 kWh, storage utilization decreases while capital expenditure increases, leading to inferior financial performance despite technical feasibility. These findings align with recent techno-economic assessments [8], [9], which indicate that while moderate storage effectively resolves curtailment, oversizing yields rapidly diminishing marginal economic returns, particularly in grid-export scenarios where local load matching is absent.

Overall, these findings underline that storage oversizing poses a greater economic risk than PV forecast uncertainty in export-oriented PV plants. Consequently, establishing a forecast-based baseline and evaluating economic robustness across tariff scenarios are essential steps before committing to large-scale BESS investments. This insight directly motivates the conclusions and practical recommendations presented in the next section.

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