

FORECAST BASED PREDICTIVE ENERGY MANAGEMENT OF GRID SCALE PV BESS SYSTEMS UNDER SOLAR AND LOAD UNCERTAINTY IN SENEGAL

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ABSTRACT

Nameplate capacity is a poor proxy for the quality of battery utilization. This paper develops a model predictive control (MPC) architecture for coordinating utility-scale photovoltaic generation and battery energy storage (PV-BESS) in Senegal. At each control interval, the algorithm updates charge and discharge setpoints using refreshed PV and load forecasts, enforcing constraints on state of charge, converter limits, reserves, and transmission security. We propose a unified benchmarking protocol to compare rule-based control (RBC), deterministic MPC (MPC-DET), scenario-based stochastic MPC (SMPC), and an MPC benchmark that assumes perfect forecasts (MPC-PF). The empirical context is fixed by official 2025 statistics: 7,254 GWh of national demand, a 1,261 MW system peak, 2,310.5 MW of installed capacity, and commissioning of Walo Storage, which couples 16 MWp of PV to a 10 MW/20 MWh battery. Operating records from 12–14 August 2025 provide an additional point of comparison, but they cannot reveal counterfactual MPC outcomes. Publicly available sources lack synchronized PV, demand, and battery state of charge measurements, as well as a validated AC model of the 2025 network. We therefore set out the control formulation, test cases, and validation criteria, while reserving quantitative performance claims for a follow-on study with operator telemetry and a complete network model.

KEYWORDS: Model Predictive Control; Photovoltaic Forecasting; Battery Energy Storage System; Energy Management; Uncertainty; Grid-Scale Storage; Hosting Capacity; Senegal; West Africa.

Nomenclature and Abbreviations

BESS: battery energy storage system; PV: photovoltaic; MPC: model predictive control; SMPC: stochastic or scenario-based MPC; RBC: rule-based control; SOC: state of charge; HCsecure: secure PV hosting capacity; SPS: Senegalese power system; OMVS/OMVG: regional electricity interconnections; N-1: single contingency security criterion; CVaR: conditional value at risk.

1. INTRODUCTION

The companion papers address pre-operational choices: the secure photovoltaic hosting capacity of the network and the siting and sizing of storage assets. Day-to-day operation raises a different class of decisions. Should the battery absorb energy now as solar output rises, or preserve headroom for the midday maximum? Should it discharge in response to an early demand increase, or hold energy for the evening peak? Fixed heuristics can

make the right action at the wrong time. MPC counters this by continuously re-optimizing as measurements and forecasts are updated.

The PV-battery control literature provides the methodological basis for this work. A persistent theme is that forecasts can score well on statistical error yet still induce suboptimal control actions. Other studies demonstrate how forecast uncertainty, degradation costs, and electrical constraints jointly shape operating policy. Our emphasis is at transmission level: we link real-time operation of the battery portfolio selected in Article 2 with the secure PV hosting capacity framework developed in Article 1.^[12–16]

1.1. Research question and contributions

We investigate the extent to which PV and demand forecasts can enhance BESS operation as solar

penetration rises, and whether such gains can be realized while maintaining the security margins of the Senegalese power system.

- A receding-horizon controller operating the BESS portfolio fixed in Article 2, without online reoptimization of investment.
- A harmonized benchmarking protocol spanning RBC, MPC-PF, MPC-DET, and SMPC.
- A joint evaluation of PV and load forecast accuracy and their marginal value for control.
- Explicit SOC margin, reserve, and network security constraints aligned with the HCsecure methodology.
- Senegal-specific operating scenarios, including high solar production, low demand conditions, cloud-driven ramps, reduced interconnection support, and the observed August 2025 operating window.

2. Literature review and research gap

MPC is well suited to this problem class because battery actions depend simultaneously on future trajectories and current feasibility constraints. Velarde and Gallego design a stochastic controller for PV plants. Tang and colleagues integrate voltage regulation with degradation-aware battery costs. Huang and coauthors test whether improvements in forecasts translate into superior control decisions rather than merely lower error metrics. Shabbir and collaborators couple PV forecasting and storage dispatch to relieve congestion; Nawaz and coauthors embed degradation explicitly in storage scheduling. These contributions establish the methodological toolkit and comparator set on which the present framework is constructed.^[1–5, 12–18]

Direct transfer of these results to an interconnected West African transmission context is not warranted. In

Senegal, the storage portfolio is predetermined at the time of operational control, and assistance from neighboring systems may vary with prevailing conditions. Controller performance must be judged in part by its ability to preserve the secure PV hosting envelope. Equally, any evaluation must distinguish empirically observed behavior from counterfactual performance that requires operator telemetry and a validated network model.

3. Senegalese power system context and data provenance

Senelec's 2025 report records 7,964 GWh of total generation, 7,254 GWh of national demand, and 2,310.5 MW of installed capacity. The system peak was 1,261 MW at 23:30 on 4 November 2025. Walo Storage entered service on 14 July 2025, integrating 16 MWp of PV with a 10 MW/20 MWh battery; Senelec indicates that it supports the evening peak. These figures define the scale of the proposed case study. The commissioning of Walo alone does not determine the optimal storage configuration for the broader system.^[6]

Evidence is organized by provenance. Class A comprises official operating measurements and reports. Class B includes historical technical studies, such as PATRP. Class C covers peer-reviewed publications and verifiable manufacturer specifications. Class D consists of assumptions reserved for sensitivity analysis. PATRP informs dynamic and security requirements and the regional interconnection context, but its historical parameters are not treated as measurements of the 2025 Senegalese system, which is characterized here using Senelec's operating report.^[6–9, 11]

Table 1: Senegalese operational reference points used in the Article 3 framework.

Indicator	Value/status	Role in Article 3
National demand	7,254 GWh (2025)	Energy scale and time series
System peak	1,261 MW (4 Nov. 2025, 23:30)	High load scenario
Installed capacity	2,310.5 MW (2025)	System scale
Walo Storage	16 MWp PV + 10 MW/20 MWh BESS	Observed PV-BESS reference
Walo availability	100% reported for 2025	Operational availability reference
SEN-AUG2025	12–14 August 2025	Empirical renewable/frequency window

Closed loop PV-BESS predictive control architecture

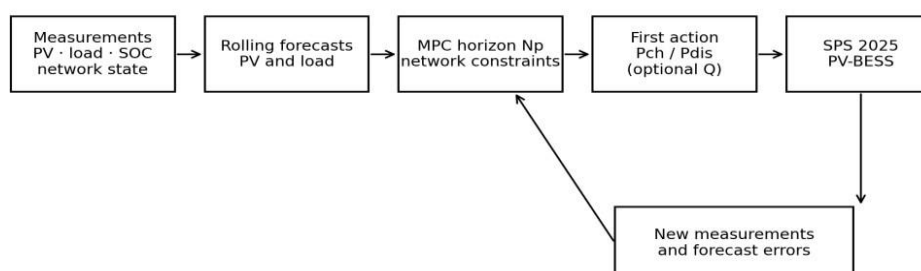


Figure 1: Closed loop architecture of forecast driven MPC for grid scale PV-BESS operation.

4. Forecasting framework

4.1. Target variables, temporal resolution, and horizons

The controller relies on short-term predictions of PV generation and demand over its optimization window. A 15-minute cadence is preferred when the operator's telemetry supports it; otherwise, results will be reported at an hourly interval. Forecast horizons of 6, 12, and 24 hours will be examined for sensitivity analysis and should not be interpreted as reflecting current operational practice. Model evaluation requires strict temporal separation between training and testing periods, implemented through a rolling-origin scheme to avoid leakage.^[14, 16]

4.2. Forecasting models and uncertainty

Persistence provides the baseline to surpass. More sophisticated statistical and machine learning approaches, including XGBoost and LSTM, warrant consideration only where historical series are sufficiently long and of high quality. Scenarios for stochastic MPC may be constructed from empirical forecast residuals or from calibrated probabilistic forecasts. When data permit, the scenario generation process should preserve spatial and temporal dependence across sites and time steps. Non-anticipativity must be respected: the controller cannot exploit measurements that would not yet be available at the decision time.^[3, 12–14, 18]

4.3. Forecast metrics and control-oriented metrics

$$\text{MAE} = (1/N) \sum |y_t - \hat{y}_t|$$

$$\text{RMSE} = \sqrt{(1/N) \sum (y_t - \hat{y}_t)^2}$$

$$\text{nMAE} = \text{MAE}/P_{\text{rated}} \text{ for PV, or } \text{MAE}/P_{\text{peak}} \text{ for load}$$

While MAE, RMSE, and nMAE quantify point forecast accuracy, they do not capture the operational impact of errors. We will therefore relate these metrics to control outcomes, including PV curtailment, security constraint breaches, realized operating objective values, and residual SOC headroom. This linkage is essential because the forecast with the smallest RMSE may still induce an inferior battery dispatch.^[3, 14]

5. MPC formulation

5.1. Receding horizon principle and variables

At decision time k , the controller observes the current system state $x(k)$, exogenous inputs $d(k)$, and forecasts through $k + N_p$. It solves an optimization problem over the prediction horizon and implements only the first control input $u^*(k)$. At the next sampling instant, the procedure is repeated with updated measurements and forecasts. The state vector $x(k)$ includes the battery state of charge (SOC) and relevant network states. The control vector $u(k)$ comprises charge and discharge power and, where modeled, BESS reactive power and PV curtailment. Exogenous variables $d(k)$ encode PV generation, load, and interconnection status,^[15, 16]

5.2. Battery dynamics and terminal condition

$$\text{SOC}(k+1) = \text{SOC}(k) + \eta_{\text{ch}} P_{\text{ch}}(k) \Delta t / EB - P_{\text{dis}}(k) \Delta t / (\eta_{\text{dis}} EB) \quad \text{SOC}_{\text{min}} \leq \text{SOC}(k) \leq \text{SOC}_{\text{max}} ; 0 \leq P_{\text{ch}}(k) \leq P_B ; 0 \leq P_{\text{dis}}(k) \leq P_B.$$

Simultaneous charging and discharging are disallowed, enforced through a binary constraint or an equivalent complementarity condition. A terminal SOC target or band is imposed to avoid myopic depletion of the battery that would otherwise improve the short-horizon objective at the expense of future feasibility.^[15, 16]

5.3. Objective function

The deterministic objective is

$$J = \sum_k [w_1 P_{\text{curt}} \Delta t + w_2 P_{\text{loss}} \Delta t + w_3 C_{\text{ramp}} + w_4 C_{\text{security}} + w_5 C_{\text{throughput}} + w_6 C_{\text{SOC}}] + J_{\text{terminal}}.$$

The terms penalize renewable curtailment (P_{curt}), network losses (P_{loss}), rapid variations in net load or interconnection exchange (C_{ramp}), and security violations under soft constraints, including voltage, thermal, and reserve margins (C_{security}). $C_{\text{throughput}}$ curbs excessive cycling, while C_{SOC} preserves operational headroom. The weights are design parameters. They will be explicitly reported and varied in sensitivity studies rather than inferred from public Senegalese datasets.^[5, 17, 20]

5.4. Network, reserve, and security constraints

Any feasible control must satisfy voltage limits, line flow limits, reactive power limits, and BESS power and SOC bounds, while maintaining the prescribed reserve margin. Contingencies identified in Article 1 are tested against the same security envelope. A reduced-order or linearized network model may be required for real-time tractability; if so, its fidelity will be evaluated independently with AC power flow and $N-1$ security checks.^[4, 19]

5.5. Stochastic and scenario-based MPC

For a set of scenarios s with probabilities p_s , the problem is $\min \sum_s p_s J_s + \lambda_{\text{risk}} \text{Risk}(\{J_s, \text{violation}_s\})$, with the non-anticipativity requirement that the first control action be identical across scenarios since the realized future is unknown at decision time. CVaR and chance constraints are suitable for selected security criteria only when the forecast error distributions have been robustly calibrated. In the absence of such calibration, we will assess performance directly over the specified scenarios.^[1, 12, 13, 15, 18]

5.6. Reproducibility and real-time feasibility

Reproducibility extends beyond the objective specification. We will disclose the solver and version, sampling interval, horizon N_p , initial and reduced scenario counts, chronological train-test split, random seeds, objective weights, battery parameters, and network approximation. We will also report AC validation tolerances, mean and 95th percentile solution times, and the proportion of decisions completed before the subsequent sampling deadline.^[15, 16]

6. Benchmark controllers and validation workflow

Table 2: Benchmark controllers used in the comparative evaluation.

Controller	Forecast information	Optimization	Scientific role
RBC	None / thresholds	No	Transparent conventional benchmark
MPC-PF	Perfect knowledge of the future	Yes	Theoretical upper benchmark for information value
MPC-DET	Point forecasts	Yes	Practical deterministic predictive controller
SMPC	Scenarios/distributions	Yes	Uncertainty aware predictive controller

Validation workflow and benchmark controllers

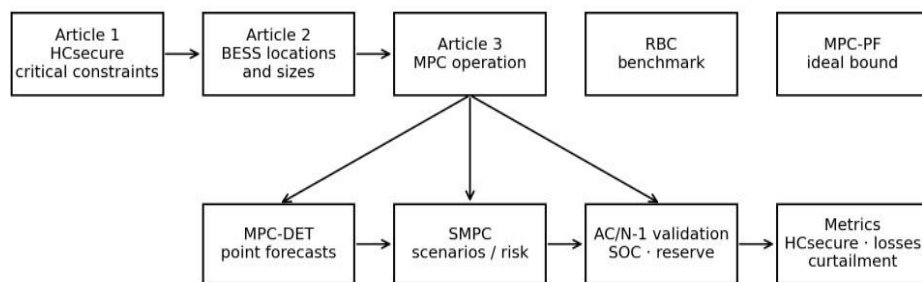


Figure 2: Validation workflow linking HCsecure, BESS planning, and the four operating controllers.

7. Simulation scenarios and empirical validation in Senegal

Table 3: Consolidated operating scenarios for Article 3.

Case	Operating condition	Forecast/interconnection challenge	Objective
M1	Typical high PV generation day	Normal	Baseline predictive operation
M2	Low load / high PV	Normal	Stress curtailment and SOC headroom
M3	Evening peak	Load forecast error	Peak support
M4	Cloud induced ramp	PV forecast error	Rapid forecast correction
M5	Weak interconnection	PV and load uncertainty	Sensitivity to regional support
M6	Critical HCsecure condition	Combined uncertainty	Preserve the secure envelope
SEN-AUG2025	114 August 2025	Observed renewable variability	Empirical validation window

7.1. SEN-AUG2025 empirical window

Senelec's 2025 report designates 12 to 14 August as an empirical window suitable for benchmarking model outputs. It notes the absence of significant congestion attributable to renewable generation during this interval. For each day, the system frequency remained within the 49.7–50.3 Hz corridor for more than 95% of the time. The corresponding daily means were 49.995, 50.019, and 50.004 Hz, and the observed minima and maxima were 49.277 and 50.565 Hz, 49.297 and 50.602 Hz, and 49.331 and 50.775 Hz, respectively. These figures are intended for subsequent replay-based validation and do not constitute evidence of MPC efficacy.^[6]

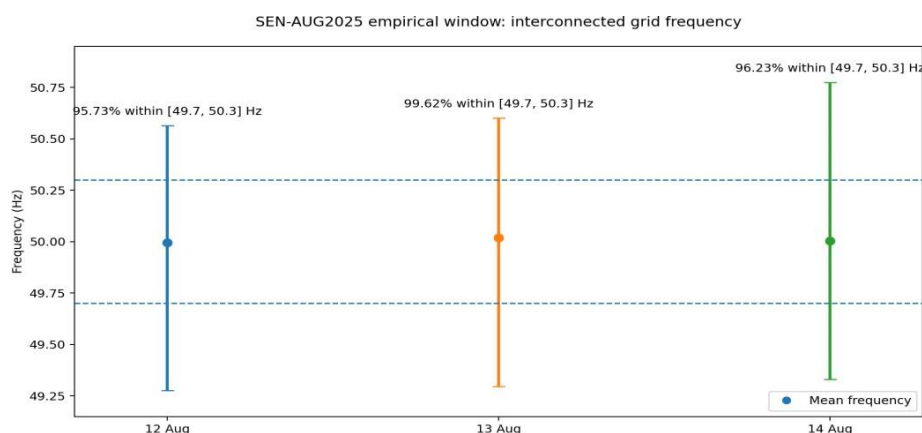


Figure 3: Observed frequency envelope during the SEN-AUG2025 validation window. Source: Senelec 2025 operations report.

The report further identifies Walo Storage as a 16 MWp photovoltaic facility paired with a 10 MW/20 MWh battery system that entered commercial operation on 14 July 2025. Reported availability for 2025 was 100%.

Walo therefore serves as an empirical reference for operational performance, although its two-hour storage duration should not be interpreted as the optimal configuration at the national level.^[6]

8. Performance metrics and hypothesis tests

Table 4: Hypotheses, comparisons, and acceptance criteria.

Hypothesis	Comparison	Main metrics	Acceptance criterion
H1	MPC-DET/SMPC vs RBC	Curtailment, violations, losses	Support only if gains are robust at identical installed BESS capacity
H2	Forecasting models	RMSE vs closed loop objective	Support if ranking by accuracy differs from ranking by control value
H3	SMPC vs MPC-DET	Violations, CVaR/risk, feasibility	Support if robustness improves as forecast errors increase
H4	SOC margin policies	Reserve availability, curtailment, cycles	Support if ramp/peak response improves with a measurable tradeoff
H5	Weak vs strong interconnection	Dispatch, reserve, local violations	Support if regional support changes dispatch without eliminating local value

We will additionally report renewable energy delivered, the maximum net-load ramp, BESS energy throughput with the corresponding number of equivalent full cycles, the shortfall relative to perfect-forecast control, changes in HCsecure, and the computation time per MPC step. Stochastic evaluations will be summarized by the median and dispersion across multiple random seeds or scenario samples; a single favorable trajectory will not suffice.

9. Results Supported By Available Data

9.1. Empirical operating evidence

The motivation for analyzing storage dispatch is rooted in observed practice in Senegal. Walo Storage was commissioned in July 2025 with 16 MWp of PV paired with a 10 MW/20 MWh battery, and Senelec associates the facility with evening peak support. Records from August indicate that frequency and voltage remained within acceptable bounds despite variable renewable output, with coordinated dispatch and regional assistance in evidence. These observations render predictive control a pertinent research question, although they do not demonstrate that such a controller would have achieved superior performance.^[6, 10]

9.2. Outcomes that are not yet numerical MPC results

The publicly available sources do not provide a synchronized dataset that aligns PV output, demand, Walo battery power and SOC, nodal network states, and the forecasts that informed each operating decision. A fully specified AC network model for 2025 is also absent from the materials used in Articles 1 and 2. As a result, we cannot substantiate any specific percentage reduction in curtailment or quantifiable increase in hosting capacity attributable to MPC, and we report neither as an empirical result.

9.3. Protocol for producing numerical results for publication

Once the required telemetry and a validated network model are available, results will be presented in a predetermined order: forecast accuracy and calibration; observed and predicted trajectories; power and SOC profiles for each controller; curtailment, losses, ramps, and security metrics; the value lost to imperfect forecasts; a replay of the August 2025 operating window; sensitivity to horizon length, terminal SOC, and interconnection support; and solver times. Committing to this ordering before running comparisons limits the

scope for selective presentation.

10. DISCUSSION

A forecast has value only insofar as the controller can exploit it while preserving system security. MPC-PF provides an idealized benchmark. Holding the BESS portfolio fixed, its advantage over alternative controllers identifies the cost of forecast error. Comparing that performance gap with forecast RMSE then tests whether improved predictive accuracy translates into superior closed-loop decisions.^[3, 14]

SOC embodies an intertemporal option value that short-horizon energy balance can obscure. Withholding discharge ahead of anticipated cloud cover or an evening peak may reduce immediate gains but preserve responsiveness when it is most valuable. Regional interconnections add flexibility, provided their availability and limits are modeled realistically. Even robust regional support cannot override local voltage constraints or thermal line limits.^[12, 13, 15, 18]

Battery aging is represented through a penalty on energy throughput and cycling. Detailed electrochemical degradation mechanisms and grid-forming control operate on different data and time scales, and they fall outside the operational model developed here.^[5, 17, 20]

10.1. Limitations and scope of validity

Any quantitative conclusions will depend on forecast calibration, temporal resolution, network model fidelity, battery efficiency and SOC constraints, interconnection status, and the set of contingencies evaluated. PATRP offers historical security practices and validation concepts, but it cannot replace 2025 operating telemetry. The August observations do not establish that an MPC controller was actually deployed. A subsequent operator-led data study should document the observation window, treatment of missing data, forecast training and test partitions, and the specific network model version used.^[6-9]

11. CONCLUSION

This paper delineates how forecast-based MPC could operate PV-BESS assets on the Senegalese grid under uncertain solar generation and demand. It builds on earlier analyses of secure PV hosting capacity and BESS investment planning, while treating those investment choices as fixed during operations. RBC, MPC-PF, MPC-DET, and SMPC are defined under a common set of constraints and performance metrics. Official 2025 statistics provide a credible operating backdrop, including the 1,261 MW system peak, 2,310.5 MW of installed capacity, the Walo Storage facility, and records from 12-14 August. These data do not establish numerical gains from MPC. Quantifying such gains requires synchronized operator telemetry and a validated AC network model.

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