Real-time dispatch of hybrid renewable energy systems and batteries

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Problem and Context

A **Battery Energy Storage System (BESS)** dynamically adjusts its charge/discharge power to follow a dispatch target, **minimizing output deviations** under battery constraints and renewable energy generation uncertainty.

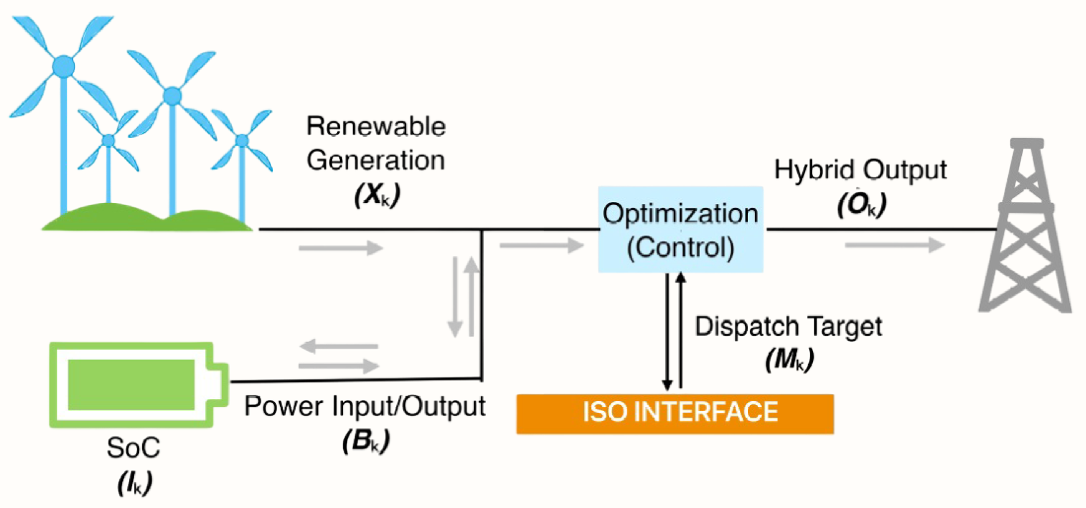

Figure 1: A schematic description.

System Model

Finite-horizon stochastic optimal control problem.

State

- Wind power generation(MW) $\mathbf{X_k}$
- State of charge (SOC) of BESS(MWh) $\mathbf{I_k}$

Action

- Battery charge/discharge power(MW) $\mathbf{B_k}$

Dynamics

- Stochastic wind power generation:

$$X_{k+1} = X_k + \alpha(m_k - X_k)\,\Delta t + \sigma \cdot Z_k$$

- Battery SoC evolution:

$$I_{k+1} = I_k + \left(\eta B_k \mathbb{I}_{\{B_k \geq 0\}} + \frac{1}{\eta} B_k \mathbb{I}_{\{B_k < 0\}}\right)\Delta t$$

Cost

- Minimize deviation from the dispatch target:

$$\min_{\{B_t\}} \mathbb{E}\left[\sum_{t=0}^{T-1} \ell(P_t^{\text{out}} - P_t^{\text{target}}) + \phi(I_T)\right]$$

Constraints

- Battery power and energy transfer limits:

$$\mathrm{SoC}_{\min} I_{\mathrm{cap}} \leq I_k \leq \mathrm{SoC}_{\max} I_{\mathrm{cap}}$$
$$B_{\min} \leq B_k \leq B_{\max}$$

Control Method

- The problem is formulated as a **finite-horizon stochastic optimal control problem** and solved using **Dynamic Programming**.
- The Bellman equation is approximated via a **Regression Monte Carlo (RMC)** scheme.
- **Gaussian Process regression** is used to approximate the continuation (Q-) value and the optimal feedback policy.
- This yields a **closed-loop** control policy for continuous state and action spaces under battery power and energy constraints.

Experiments and Results

A. Stationary Simulation-based Experiments

A stationary model with time-invariant parameters (m_k and M_k). The controller is trained using Monte Carlo samples and evaluated via closed-loop rollouts from fixed initial conditions.

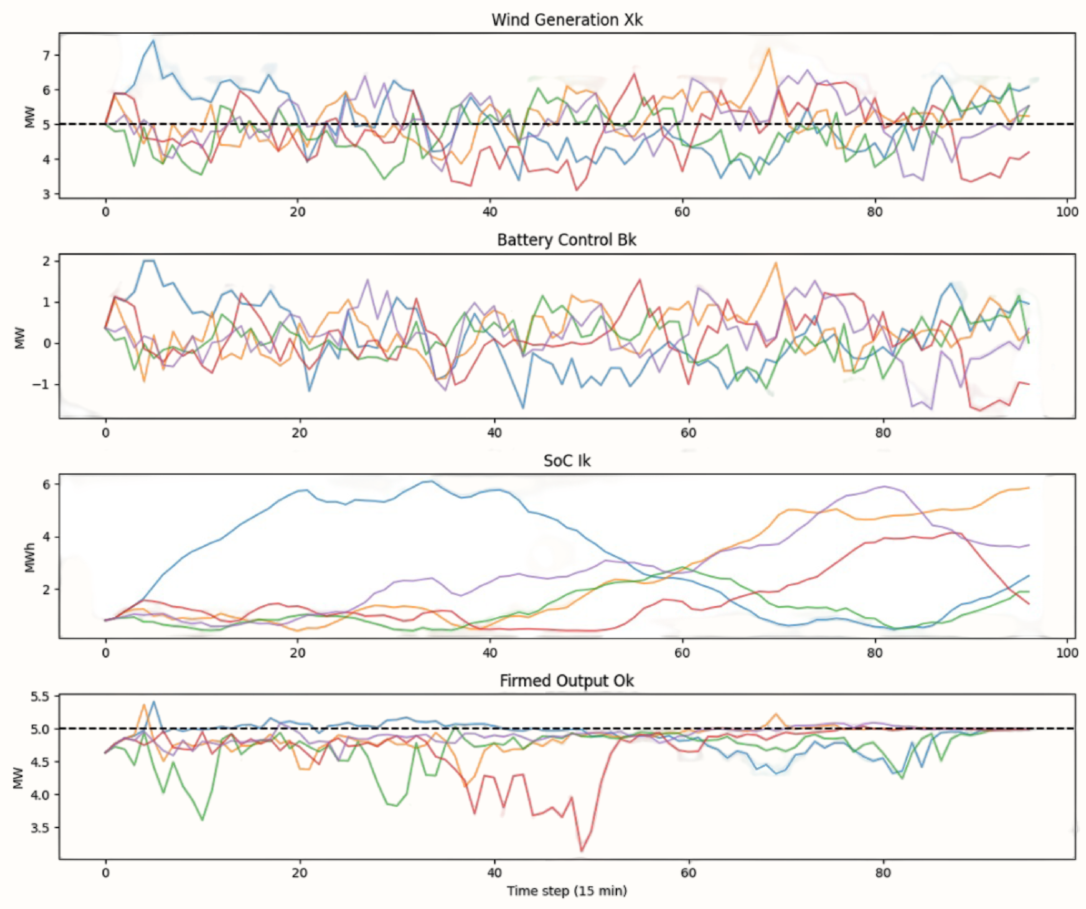

Figure 2: Closed-loop rollouts of the learned feedback policy for five stochastic trajectories. Each trajectory corresponds to an independent stochastic realization starting from the same initial condition.

The learned controller significantly reduces output variability compared to raw renewable generation X_k, while maintaining the battery state of charge within physical limits.

B. Non-Stationary Data-Calibrated Experiments

In contrast to the simulation-based setting in Section A, this experiment uses real wind forecast data to construct time-dependent targets and uncertainty profiles.

- Time-varying dispatch target M_k
- Non-stationary wind generation dynamics
- Adaptive simulation domains D_k

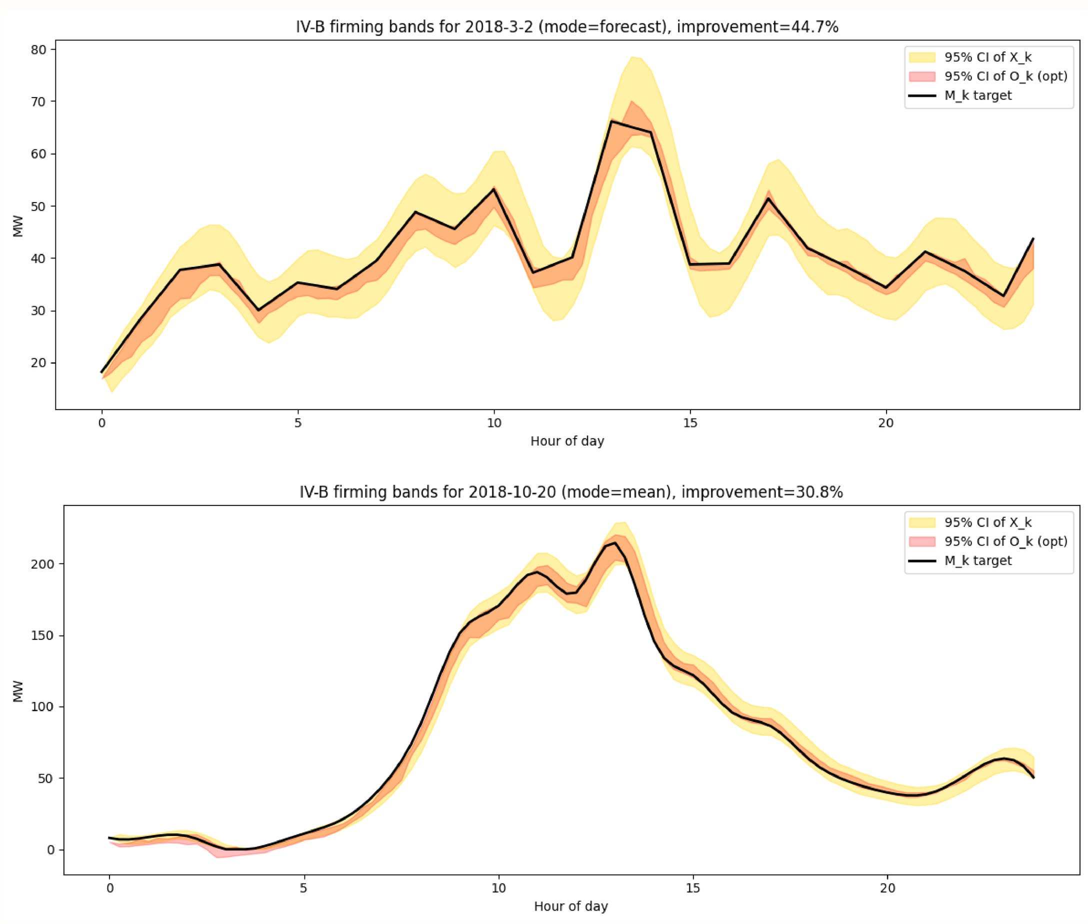

Figure 3: Firming performance under non-stationary renewable generation. *Upper panel:* $M_k = \mathbb{E}[X_k]$. *Lower panel:* piecewise linear M_k based on original DA forecast.

The BESS provides significant firming, with the variance of O_k being an order of magnitude smaller than that of the uncontrolled X_k.

C. Baseline comparison and sensitivity

Table 1: Sensitivity analysis of firming performance to BESS power rating $B_{\max}$ and energy capacity I_{cap}.

$B_{\max}$	I_{cap}	Opt L^2 Cost	Greedy L^2 Cost	% Impr
Impact of battery power rating $B_{\max}$				
2.5	30	4777.49	4931.95	3.2%
5	30	3638.18	3823.06	4.8%
10	30	2395.13	3014.79	20.6%
15	30	2062.30	2780.78	25.8%
Impact of battery capacity I_{cap}				
10	20	2970.96	3327.70	10.7%
10	30	2395.13	3014.79	20.6%
10	40	2255.75	2901.53	22.3%
10	50	2192.48	2857.17	23.3%

Key Observations from Sensitivity Analysis:

- Increasing battery power rating $B_{\max}$ consistently improves firming performance.
- Larger energy capacity I_{cap} yields diminishing but stable performance gains.
- The optimized policy consistently outperforms the greedy baseline.

Note: An alternative experiment replaces LHS sampling with two years of historical wind data and yields comparable firming performance, suggesting robustness of the control policy and limited sensitivity to the data source.

Limitations and Future Work

Model assumptions: Wind power generation is modeled using a simplified stochastic process; this could be extended to richer data-driven models.

Data usage: Real wind data are used for calibration of targets and uncertainty only; it can also be used for direct policy training.

Scalability: The current approach considers a single renewable–battery system; extension to multi-asset or networked settings remains for future work.

Computation: Regression Monte Carlo with Gaussian Processes can be computationally expensive; scalable approximations or alternative function approximators could be explored.

Cost modeling: The current objective focuses on firming performance; incorporating energy prices to enable joint firming and energy arbitrage.

Conclusion

We studied optimal firming of wind power generation using a Battery Energy Storage System formulated as a finite-horizon stochastic control problem. A regression Monte Carlo approach with Gaussian Process approximation yields an effective closed-loop policy that significantly reduces output variability under both stationary and non-stationary, data-calibrated settings. Sensitivity and robustness studies demonstrate consistent performance across battery configurations and data sources.

The framework is agnostic to the specific type of renewable generation and can be applied to other clean energy sources, such as solar power, by adopting appropriate state representations and dynamics. More generally, the approach can be extended by augmenting the state variables to form mixture or multi-regime models that capture multiple energy resources.

References

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[2] National Renewable Energy Laboratory, "Solar PV, Wind Generation, and Load Forecasting Dataset for ERCOT 2018," NREL/DA-5C00-79498, 2023. [Online]. Available: https://docs.nrel.gov/docs/fy23osti/79498.pdf.

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