Toward Integrating Operation Research and Machine Learning: Boosting Power System Operation Economics via Closed-Loop Predict-and-Optimize

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I. Introduction

Real-world operation is “predict-then-optimize”:

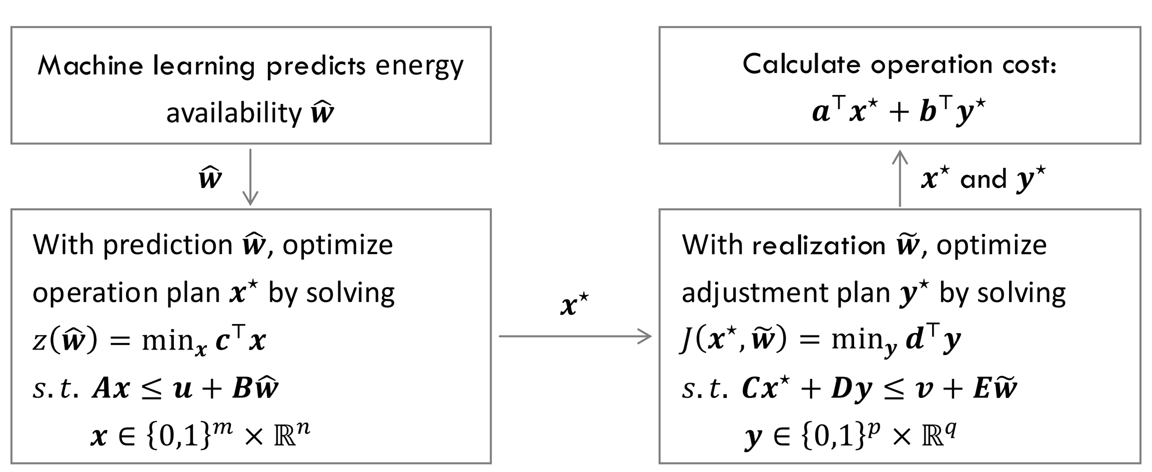
1) Machine learning predicts uncertainties;

2) Given predictions, scheduling plan is optimized.

But the prediction ignores its impact on the optimization, making the process **opened-loop**. So, **will it be beneficial to feed the optimization back to the prediction?**

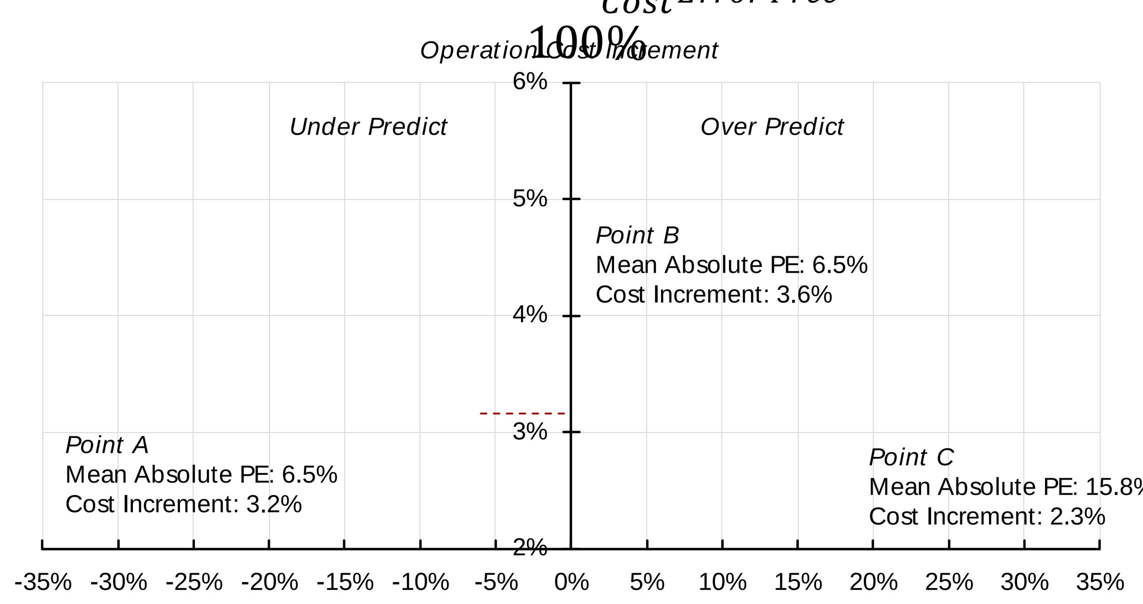
II. Motivation

Power system operations in the open-loop predict-then-optimize process:



The asymmetrical relationship between operation cost increment and prediction error:

$$Cost\ Increment = \left(\frac{Cost^{With\ Error}}{Cost^{Error\ Free}} - 1\right) \times 100\%$$

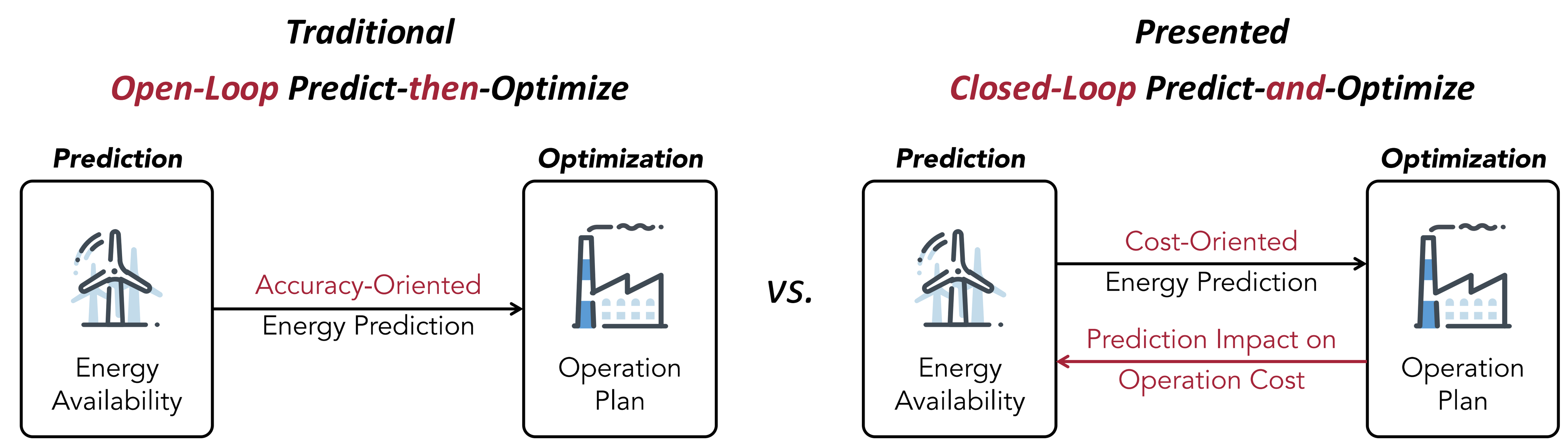


Interesting Observations

- **Point A vs. Point B:** Same error but different costs.
- Point B vs. Point C: Worse error but lower cost.

Power systems are nonlinear. We should **close the open-loop between prediction and optimization.**

III. What is Closed-Loop Predict-and-Optimize? It is an idea.



- Measure prediction quality with prediction accuracy. (Open-loop and accuracy-oriented)
- Sequentially predict energy and optimize operation. (Predict-then-Optimize)

- Measure prediction quality with operation cost. (Closed-loop and cost-oriented)
- Simultaneously predict energy and optimize operation. (Predict-and-Optimize)

IV. How to Closed-Loop Predict-and-Optimize? Two steps to go.

Step 1: Cost-Oriented Predictor Training

Based on S scenarios, form and solve the following bilevel empirical risk minimization problem. The solution is a trained predictor $\boldsymbol{H}^\star(\cdot)$ taking feature $\boldsymbol{f}$ as input. $\boldsymbol{H}^\star(\cdot)$ can generate cost-oriented predictions that are tailored to reduce the operation cost.

$$\min_H \tfrac{1}{S}\textstyle\sum_{s=1}^{S} \boldsymbol{a}^\top \boldsymbol{x}_s + \boldsymbol{b}^\top \boldsymbol{y}_s$$
$$s.t.\ \widehat{\boldsymbol{w}}_s = \boldsymbol{H}(\boldsymbol{f}_s);\ \forall s$$

Upper Level: Given feature $\boldsymbol{f}_s$, train predictor $\boldsymbol{H}(\cdot)$ with objective of minimum operation cost $\boldsymbol{b}^\top \boldsymbol{x}_s + \boldsymbol{d}^\top \boldsymbol{y}_s$.

$\widehat{\boldsymbol{w}}_s$

$$\boldsymbol{x}_s \in \operatorname{argmin} \boldsymbol{c}^\top \boldsymbol{x}_s\,;\ \forall s$$
$$s.t.\ \boldsymbol{Ax}_s \le \boldsymbol{u} + \boldsymbol{B}\widehat{\boldsymbol{w}}_s$$
$$\boldsymbol{x}_s \in \{0,1\}^m \times \mathbb{R}^n$$

Lower Level: Given prediction $\widehat{\boldsymbol{w}}_s$, optimize operation plan $\boldsymbol{x}_s$.

$\boldsymbol{x}_s^\star$

$$\boldsymbol{y}_s \in \operatorname{argmin} \boldsymbol{d}^\top \boldsymbol{y}_s\,;\ \forall s$$
$$s.t.\ \boldsymbol{Cx}_s + \boldsymbol{Dy}_s \le \boldsymbol{v} + \boldsymbol{E}\widetilde{\boldsymbol{w}}_s$$
$$\boldsymbol{y}_s \in \{0,1\}^p \times \mathbb{R}^q$$

Lower Level: Given plan $\boldsymbol{x}_s$ and actual realization $\widetilde{\boldsymbol{w}}_s$, optimize adjustment plan $\boldsymbol{y}_s$.

$\boldsymbol{x}_s^\star$ $\boldsymbol{y}_s^\star$

Feedback the prediction impact on the operation optimization

Step 2: Predict and Optimize

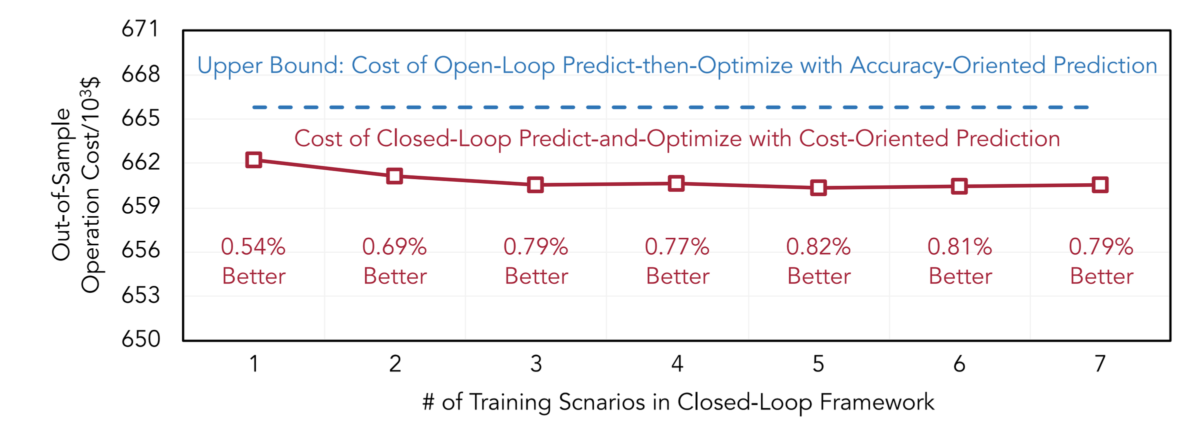
Embed the predictor $\boldsymbol{H}^\star(\cdot)$ into the operation model to form a feature-driven model:

$$z(\boldsymbol{f}) = \min_{x,\widehat{w}} \boldsymbol{c}^\top \boldsymbol{x}$$
$$s.t.\ \boldsymbol{Ax} \le \boldsymbol{u} + \boldsymbol{B}\boldsymbol{H}^\star(\boldsymbol{f})$$
$$\boldsymbol{x} \in \{0,1\}^m \times \mathbb{R}^n$$

This feature-driven model can do the prediction and optimization simultaneously.

V. Major Results

Closed-Loop vs. Open-Loop

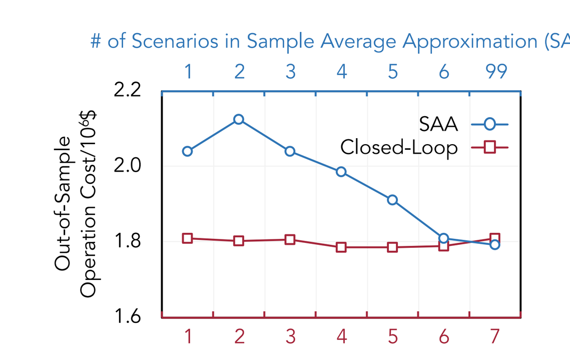


- Economics: Closed-loop reduces 0.5%-0.8% cost. Implication: Closed-loop is effective.

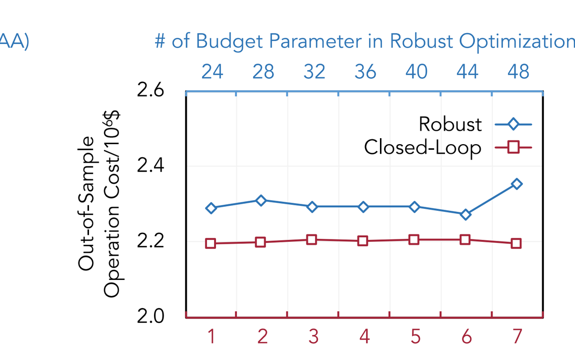
Type of Prediction $\widehat{\boldsymbol{w}}$	Mean Absolute Percentage Error (MAPE)	Root Mean Square Error (RMSE)
Accuracy-Oriented	39%	**21.0MW**
Cost-Oriented	**34%**	23.2MW

- **Accuracy:** Cost-oriented $\widehat{\boldsymbol{w}}$ has a better MAPE (34%) but a worse RMSE (23.2MW).
  Implication: A more accurate prediction may NOT result in a better operation economics.

Closed-Loop vs. SAA



Closed-Loop vs. Robust



- Closed-loop is effective even if scenarios are few.
- Closed-loop has a better operation cost.

VI. References

[1] X. Chen, Y. Yang, Y. Liu and L. Wu, “Feature-Driven Economic Improvement for Network-Constrained Unit Commitment: A Closed-Loop Predict-and-Optimize Framework,” *IEEE Transactions on Power Systems*, 2022.

[2] X. Chen, Y. Liu and L. Wu, “Towards Improving Operation Economics: A Bilevel MIP-Based Closed-Loop Predict-and-Optimize Framework for Prescribing Unit Commitment,” *arXiv:2208.13065*, 2023.