

# Toward Integrating Operation Research and Machine Learning: A Closed-Loop Predict-and-Optimize Framework and Its Application in Power Systems

Xianbang Chen, Ph.D. Candidate, Stevens Institute of Technology, USA

Lei Wu, Anson Wood Burchard Chair Professor, Stevens Institute of Technology, USA



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## I Introduction

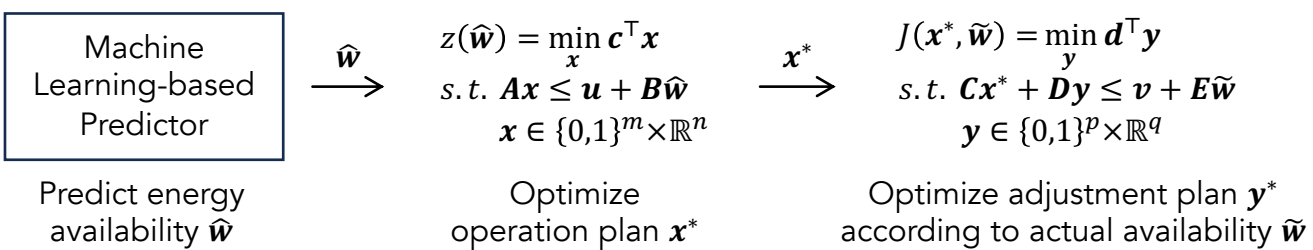
Real-world scheduling is “predict-then-optimize”:

- 1) Machine learning predicts uncertainties;
- 2) Given predictions, scheduling plans are optimized.

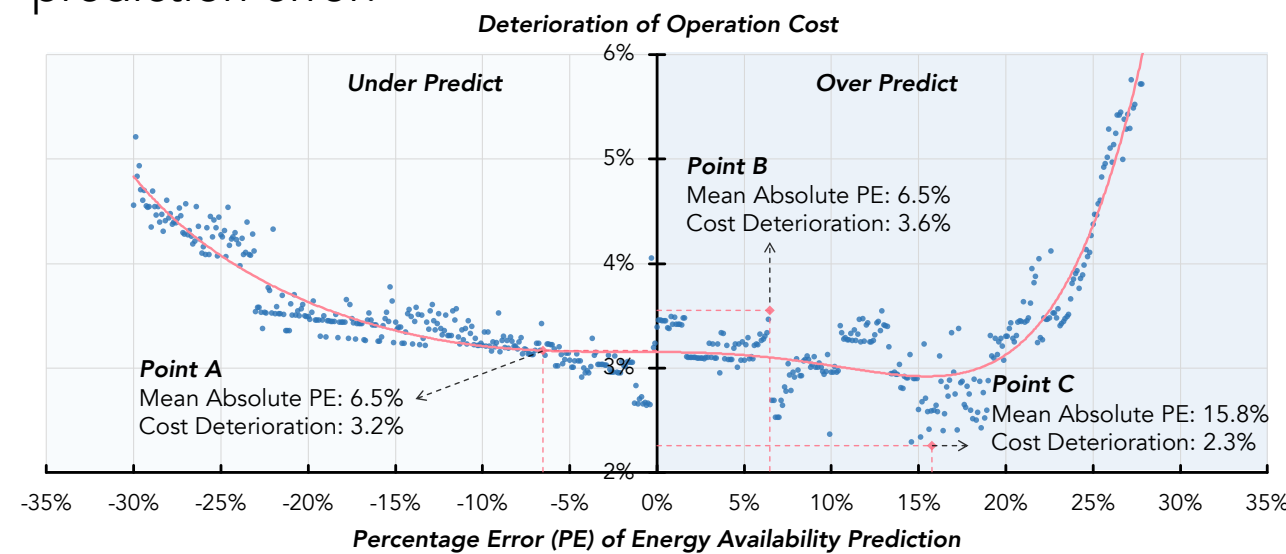
But the prediction ignores its impact on the optimization, making the process opened-loop. So, will it be beneficial to feed the optimization back to the prediction?

## II Motivation from Power System

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



Asymmetrical relationship between operation cost and prediction error:



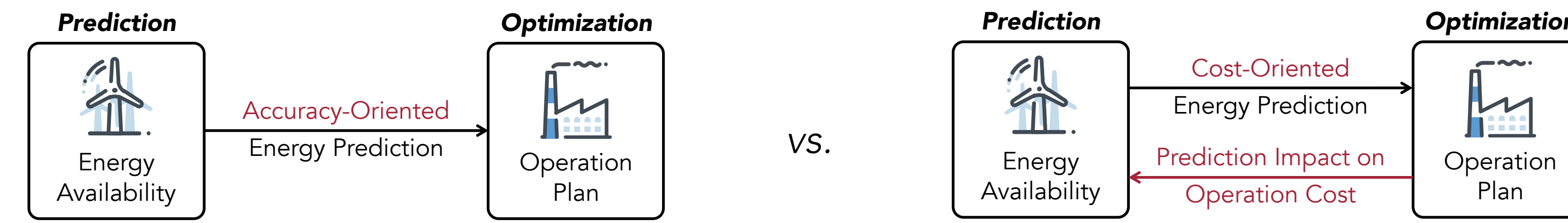
$$\text{Deterioration of Operation Cost} = \frac{\text{CostWith Error} - \text{CostError-Free}}{\text{CostError-Free}} \times 100\%$$

### Observation

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

Real-world systems are nonlinear. We should close the opened-loop between prediction and optimization.

## III What is Closed-Loop Predict-and-Optimize?



### Open-Loop Predict-then-Optimize

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

### Closed-Loop Predict-and-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?

### Data Processing

Select the most relevant feature type to form feature vectors  $f$ .

Select  $S$  representative scenarios as training scenarios.

**Goal:** Form the empirical risk minimization problem for training predictor.

### Cost-Oriented Predictor Training

Form a bilevel empirical risk minimization (ERM) problem. Then solve it via a cutting-plane method. The solution is an optimally trained predictor  $H^*(\cdot)$ .

$$\min_{H^*} \frac{1}{S} \sum_{s=1}^S b^T x_s + d^T y_s$$
$$\text{s.t. } \hat{w}_s = H(f_s); \forall s$$

$$x_s \in \argmin c^T x_s; \forall s$$
$$\text{s.t. } Ax_s \leq u + B\hat{w}_s$$
$$x_s \in \{0,1\}^m \times \mathbb{R}^n$$

$$y_s \in \argmin d^T y_s; \forall s$$
$$\text{s.t. } Cx_s + Dy_s \leq v + E\hat{w}_s$$
$$y_s \in \{0,1\}^p \times \mathbb{R}^q$$

**Goal:** Solving the ERM problem can provide a predictor  $H^*(\cdot)$  that can generate cost-oriented prediction  $\hat{w}$  (feature  $f$  as input) for the operations. The cost-oriented prediction  $\hat{w}$  is tailored to reduce the operation cost.

**Upper Level:** Given feature  $f_s$ , train predictor  $H(\cdot)$  with objective of minimum operation cost  $b^T x_s + d^T y_s$ .

**Lower Level:** Given prediction  $\hat{w}_s$ , optimize operation plan  $x_s$ .

**Lower Level:** Given plan  $x_s$  and actual realization  $\tilde{w}_s$ , optimize adjustment plan  $y_s$ .

Feedback the prediction impact on the operation optimization

### Predict and Optimize

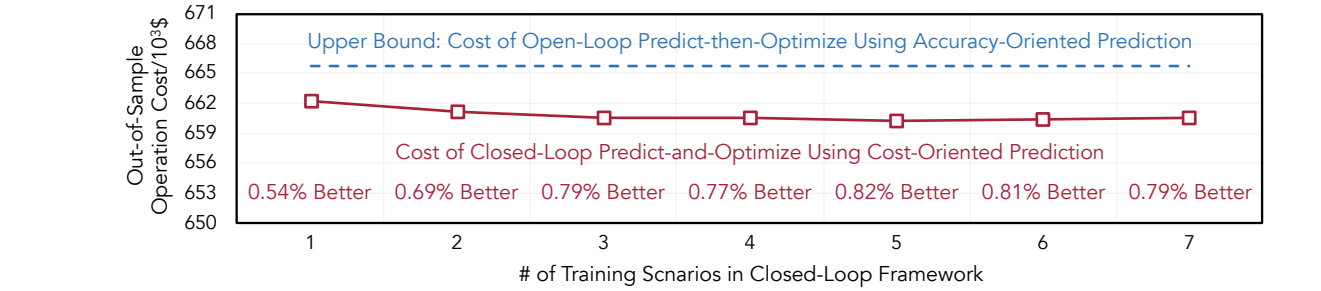
Embed the trained predictor  $H^*(\cdot)$  into the original operation model to form a prescriptive model:

$$z(f) = \min_{x, \hat{w}} c^T x$$
$$\text{s.t. } Ax \leq u + BH^*(f)$$
$$x \in \{0,1\}^m \times \mathbb{R}^n.$$

Now, the operation plan  $x$  is driven by feature  $f$ .

**Goal:** Use the prescriptive model to predict and optimize simultaneously.

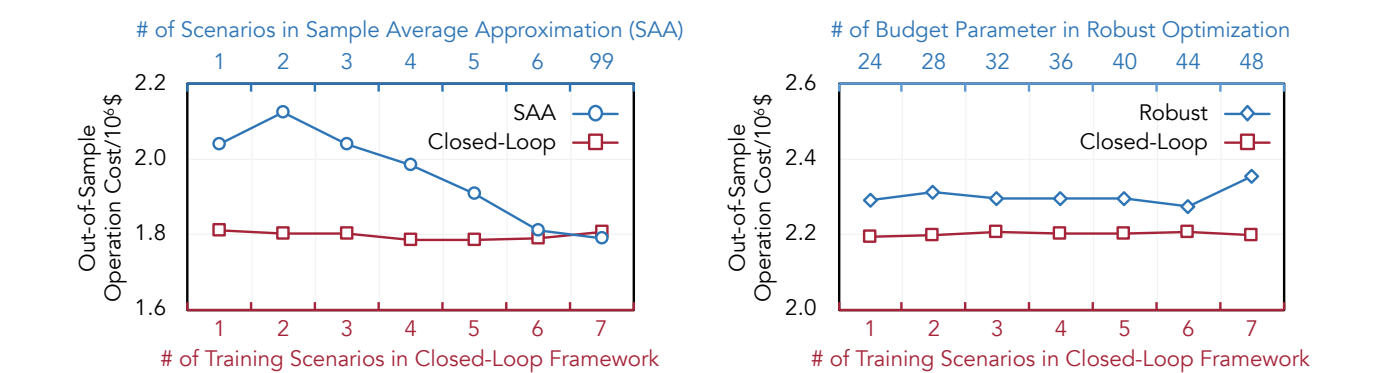
## V Major Results



Type of Prediction $\hat{w}$	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
Accuracy-Oriented	15.0MW	21.0MW
Cost-Oriented	16.5MW	23.2MW

### Closed-Loop vs. Open-Loop

- Closed-loop reduces operation cost by 0.54%-0.82%. **Implication:** Closed-loop is economically effective.
- Cost-oriented  $\hat{w}$  is worse in MAE and RMSE. **Implication:** A more accurate prediction may not result in a better optimization.



### Closed-Loop vs. SAA

- Closed-loop outperforms SAA when scenarios are limited.

### Closed-Loop vs. Robust

- Closed-loop achieves 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.

