Paper No: 23PESGM0568

Boosting Power System Operation Economics via Closed-Loop Predict-and-Optimize

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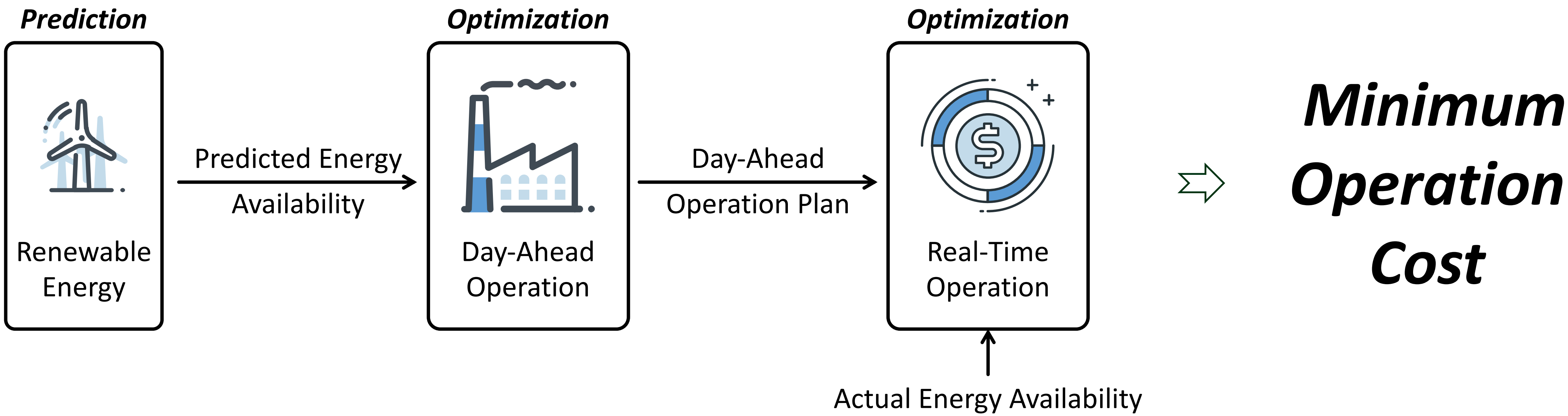
Background: Power System Operations

- ***Operations in Open-Loop Predict-then-Optimize (O-PO)***

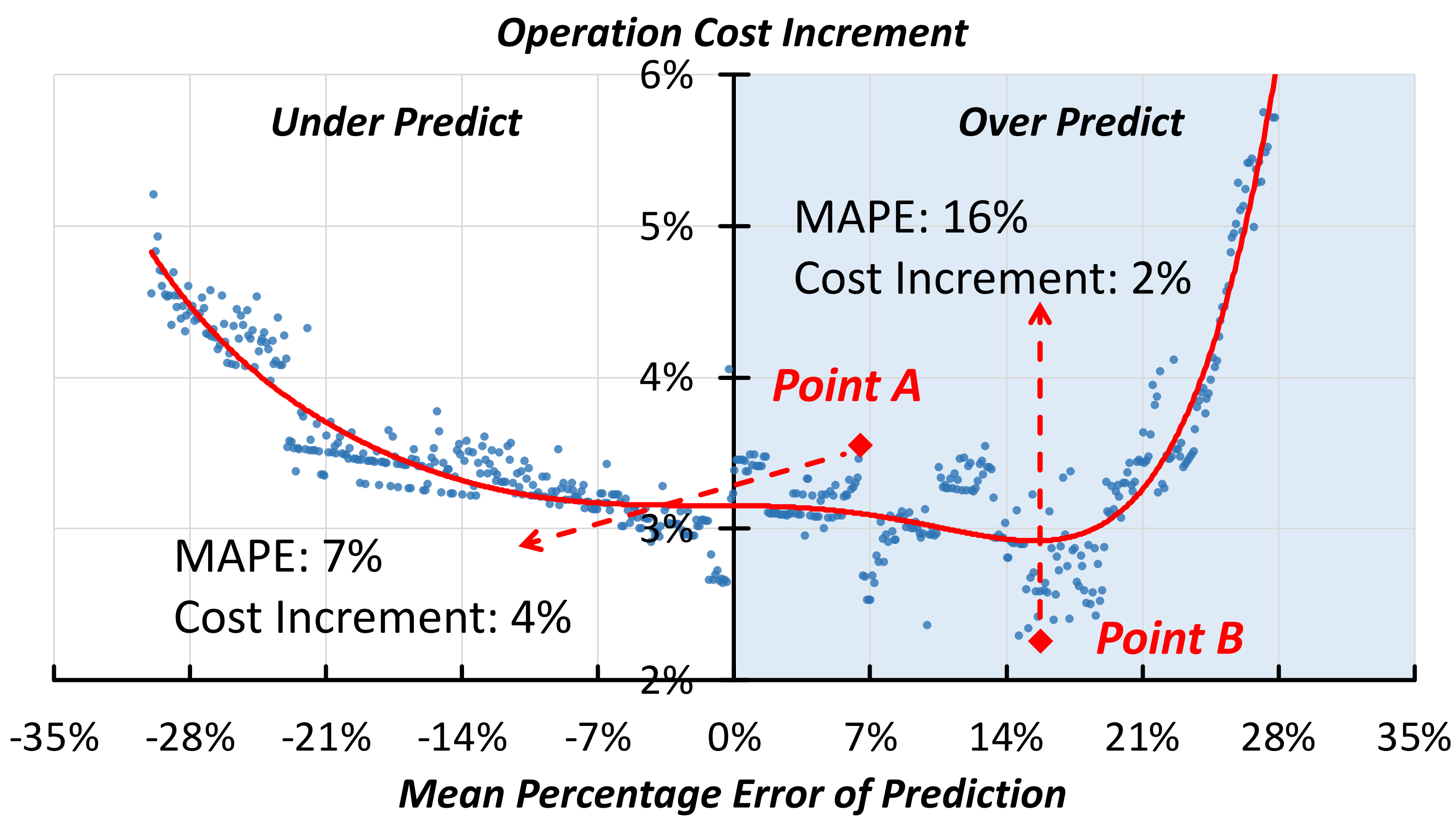


- ***Lower Operation Cost ⇔ Better Operation Economics***

Motivation: Flaw in Open-Loop Process

- ***More Accurate Prediction ⇏ Lower Operation Cost***

MAPE: Mean absolute percentage error



Point A vs Point B

Worse error enables better operation economics.

Why?

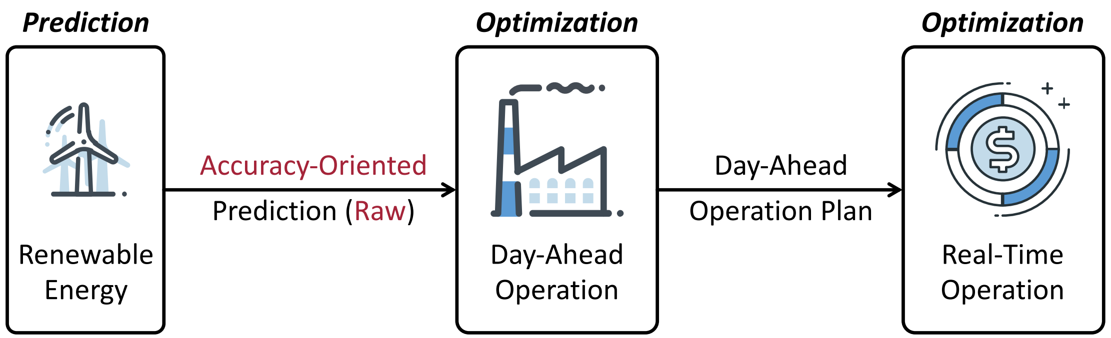
Systems are complex.

The accuracy-economics relationship is nonlinear.

O-PO ignores this.

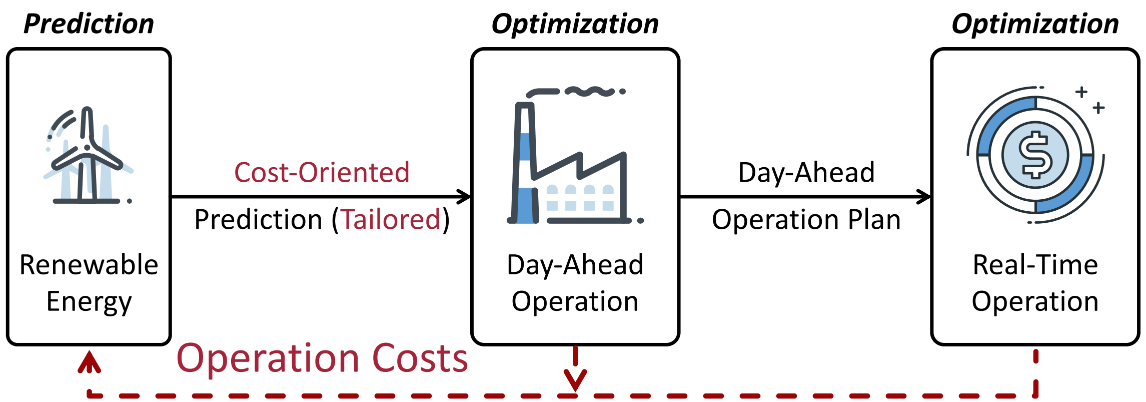
Our Idea: Closed-Loop Predict-and-Optimize

Open-Loop
Predict-then-Optimize (O-PO)



- Train predictor with accuracy criterion
- Open-loop and accuracy-oriented

Closed-Loop
Predict-and-Optimize (C-PO)



- Train predictor with cost criterion
- Closed-loop and cost-oriented

C-PO.v1: Train Cost-Oriented Predictor *H*

$$\min_{\boldsymbol{H}} \frac{1}{k} \sum_{k=1}^{K} SPO\ \ell oss_k$$

- $SPO\ \ell oss = \left| Operation\ Cost(\boldsymbol{H}) - Operation\ Cost^{\mathrm{Perfect}} \right|$
  $Operation\ Cost^{\mathrm{Perfect}}$ is resulted by error-free prediction
- Measure operation cost increment caused by predictor $\boldsymbol{H}$.
- Predictor $\boldsymbol{H}$ learns to generate cost-oriented predictions that can make the operation cost closer to its perfection.

C-PO.v2: Bilevel Training for Predictor $\boldsymbol{H}$

Upper Level (Predictor Training)

Total Operation Cost

$$\min_{\boldsymbol{H}} \frac{1}{K}\sum_{k=1}^{K}(\boldsymbol{a}^{\top}\boldsymbol{x}_k + \boldsymbol{b}^{\top}\boldsymbol{y}_k)$$

$$\widehat{\boldsymbol{w}}_k = \boldsymbol{H}\boldsymbol{f}_k;\ \forall k$$

Prediction $\widehat{\boldsymbol{w}}_k$

Lower Level 1 (Day-Ahead Operation)

$$\boldsymbol{x}_k \in \operatorname*{argmin}_{\boldsymbol{x}_k \in \mathcal{X}(\widehat{\boldsymbol{w}}_k)} \boldsymbol{c}^{\top}\boldsymbol{x}_k;\ \forall k$$

Day-Ahead Operation Cost $\boldsymbol{a}^{\top}\boldsymbol{x}_k$

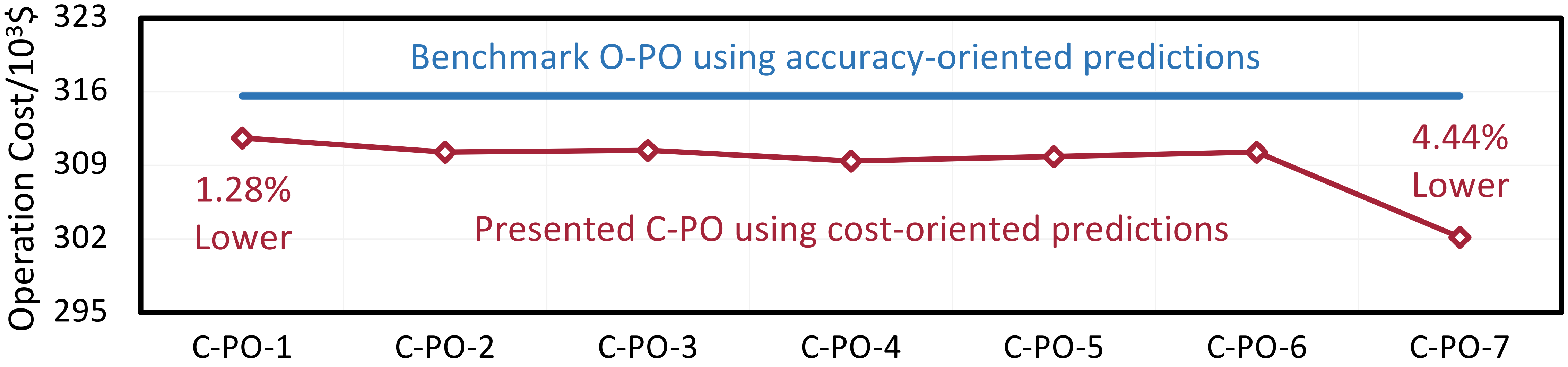
Day-Ahead Operation Plan $\boldsymbol{x}_k$

Lower Level 2 (Real-Time Operation)

$$\boldsymbol{y}_k \in \operatorname*{argmin}_{\boldsymbol{y}_k \in \mathcal{Y}(\boldsymbol{x}_k, \widetilde{\boldsymbol{w}}_k)} \boldsymbol{d}^{\top}\boldsymbol{y}_k;\ \forall k$$

Real-Time Operation Cost $\boldsymbol{b}^{\top}\boldsymbol{y}_k$

C-PO vs O-PO on Real-World Dataset



Type of Prediction	Mean Absolute Percentage Error (MAPE)	Root Mean Square Error (RMSE)	Mean Over-Predicting Percentage Error (MOPE)	Mean Under-Predicting Percentage Error (MUPE)
Accuracy-Oriented	39%	130MW	34%	6%
Cost-Oriented	34% (Better)	149MW (Worse)	21% (Lower)	12% (Higher)

Summary and Thinking

- ***Conclusions***
  - **Closed-Loop predict-and-optimize (C-PO)** shows potential to lower down the operation cost by generating **cost-oriented predictions**.
- ***Thinking***
  - Could we use **reinforcement (or deep) learning** to do it?
- ***References and Codes***

"Feature-Driven Economic Improvement for Network-Constrained Unit Commitment: A Closed-Loop Predict-and-Optimize Framework," *IEEE Transactions on Power Systems*, 2022.

"Towards Improving Operation Economics: A Bilevel MIP-Based Closed-Loop Predict-and-Optimize Framework for Prescribing Unit Commitment," *arXiv:2208.13065*, 2023.