Integrating Machine Learning and Operation Research for Improving Unit Commitment: A Closed-Loop Predict-and-Optimize Framework

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For OR Talk

Content

Integrating Machine Learning (ML) and Operation Research(OR) for Unit Commitment (UC)

Ⅰ *Preliminaries and Motivations*

Ⅱ *Presented Closed-Loop Predict-and-Optimize Framework*

Ⅲ *References and Q&A*

Preliminaries and Motivations

- ***Preliminaries: UC Based on Mixed-Integer Linear Programming***

  - ***Objective***
    Minimizing operation costs including start-up and shut-down costs ($\boldsymbol{c}^\top \boldsymbol{x}$), and generation cost ($\boldsymbol{d}^\top \boldsymbol{y}$).

  - ***Unit constraints***
    Ramping limits;
    Generation limits;
    …

  - ***System constraints***
    Power balance;
    Network constraints;
    …

Binary decision

$$
\begin{aligned}
z(\widehat{\boldsymbol{w}}) = \min_{\boldsymbol{x},\boldsymbol{y}} & [\boldsymbol{c}^\top \boxed{\boldsymbol{x}} + \boldsymbol{d}^\top \boxed{\boldsymbol{y}}] \\
s.t.\ & \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y} \le \boldsymbol{g} \\
& \boldsymbol{F}\boldsymbol{y} \le \boxed{\widehat{\boldsymbol{w}}} \\
& \boldsymbol{x} \in \{0,1\}^M
\end{aligned}
$$

Continue decision

Prediction vector of uncertainty
Such as renewable energy source (RES)

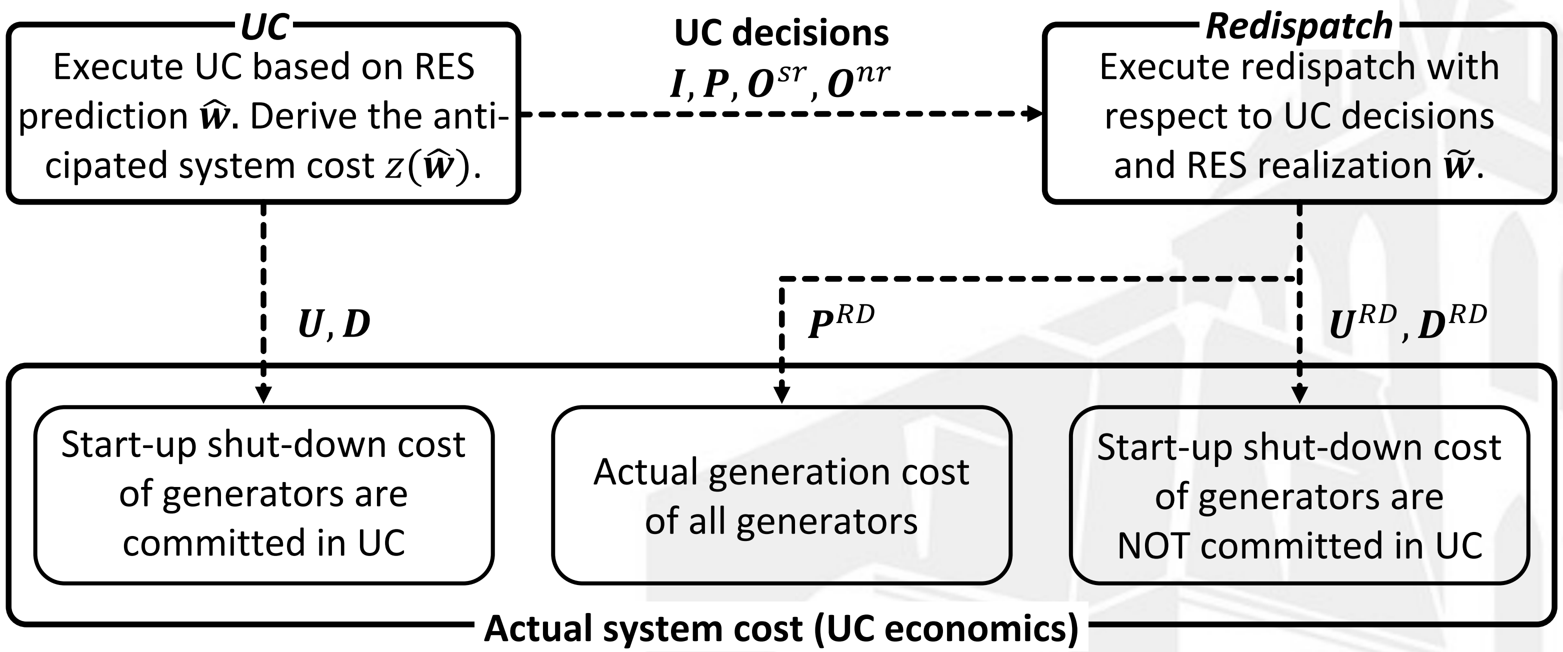
Preliminaries and Motivations

- **Preliminaries: Some Basic ML**
  - ***Unsupervised learning***
    K-means
  - ***Supervised learning***
    KNN
    Linear regression
    Neural networks
    Decision trees
    Support vector machines
  - ***Reinforcement learning***
    Q-learning
    Deep Q network

- **Preliminaries: Goals for ML-based UC**[1]
  - ***Improving UC economics***
  - ***Improving UC reliability***
  - ***Accelerating UC computation***
  - ***Enhancing UC models***
  - ***Predicting uncertainty (RES and load)***

Preliminaries and Motivations

- ***Preliminaries: Evaluation of UC Economics (Actual System Cost)***

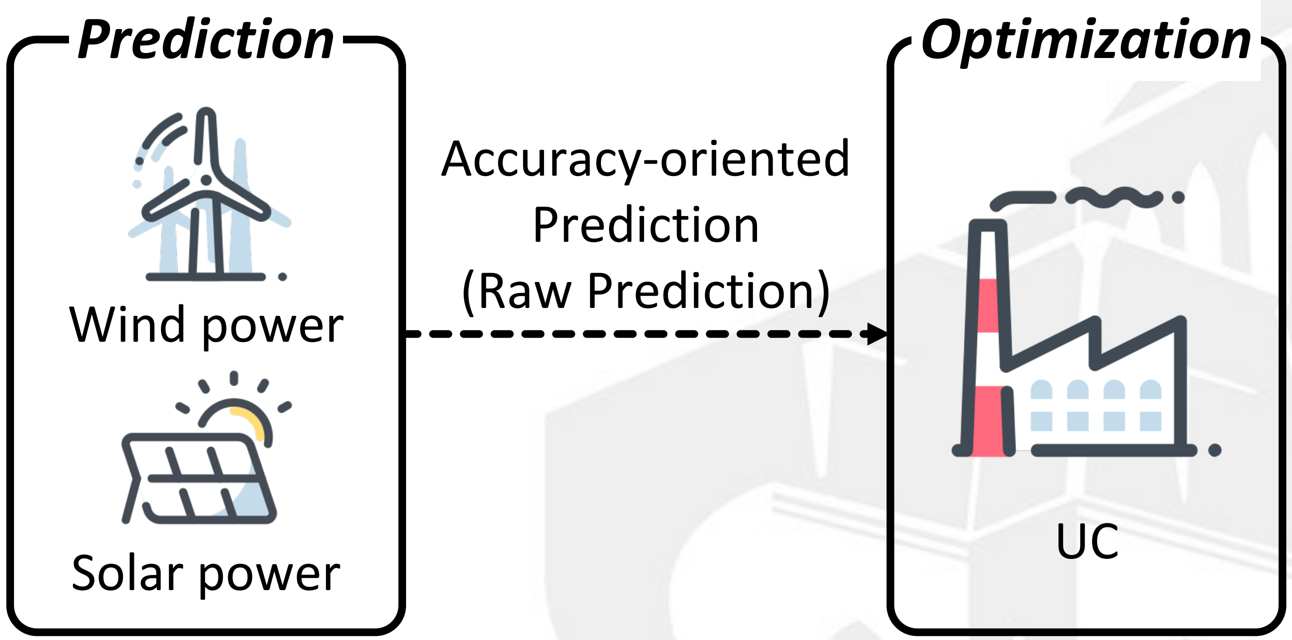


$\boldsymbol{I}$	Commitment	$\boldsymbol{P}$	Set-point generation	$\boldsymbol{P}^{RD}$	Actual generation
$\boldsymbol{U}$	Start-up	$\boldsymbol{O}^{sr}$	Spinning reserve	$\boldsymbol{U}^{RD}$	Start-up of quick generator
$\boldsymbol{D}$	Shut-down	$\boldsymbol{O}^{nr}$	Non-spinning reserve	$\boldsymbol{D}^{RD}$	Shut-down of quick generator

Preliminaries and Motivations

- ***Motivations: Flaws in Traditional Open-Loop Predict-then-Optimize Framework***

An open-loop predict-then-optimize (O-PO) framework for UC



Supported by ML

Supported by OR

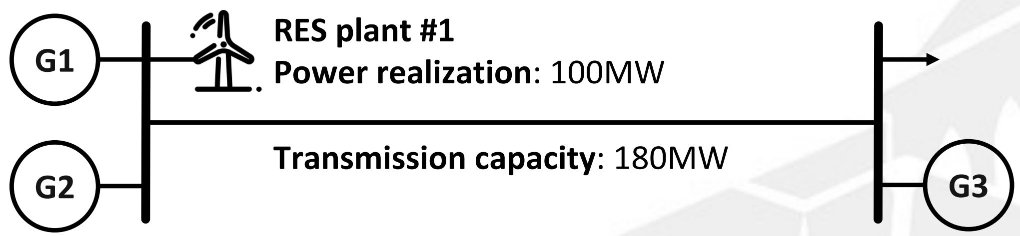
Statistically more accurate prediction ⇏ Higher UC economics

Preliminaries and Motivations

- ***Motivations: Flaws in Traditional Open-Loop Predict-then-Optimize Framework***

  - ***A 2-Bus Example***

G1: [5MW, 100MW]
No-load cost: $100
Generation cost: $15/MWh
Start-up cost: $120
G2: [5MW, 80MW]
No-load cost: $60
Generation cost: $20/MWh
Start-up cost: $100



System Load: 200MW
G3: [5MW, 33MW]
No-load cost: $30
Generation cost: $40/MWh
Start-up cost: $50

  - ***Prediction term***
    RES power with 100MW realization

  - ***Measurement of Prediction Quality***
    Mean absolute error (Statistically)

Preliminaries and Motivations

- ***Motivations: Flaws in Traditional Open-Loop Predict-then-Optimize Framework***
  - ***Case 1: Our method over-predicts and O-PO under-predicts***

			Case 1	
Method			Our method	O-PO
RES power prediction/MW			130	72
Mean absolute error/MW			30 (Worse)	28 (Better)
UC	G1	Set-point generation/MW	50	97
		Reserve/MW	±6	±4
	G2	Set-point generation/MW	OFF	11
		Reserve/MW	+40	±6
	G3	Set-point generation/MW	20	20
		Reserve/MW	±0	±10
Re-dispatch		Dispatch of RES/MW	130	72
		Anticipated system cost/$	1,850	2,938
		Actual generation of G1/MW	56	93
		Actual generation of G2/MW	24	5
		Actual generation of G3/MW	20	20
		Actual utilized RES/MW	100	82
	Actual system cost/$		2,580 (Better)	2,754 (Worse)

"±": Bi-directional spinning reserve. "+": Upward only non-spinning reserve.

Preliminaries and Motivations

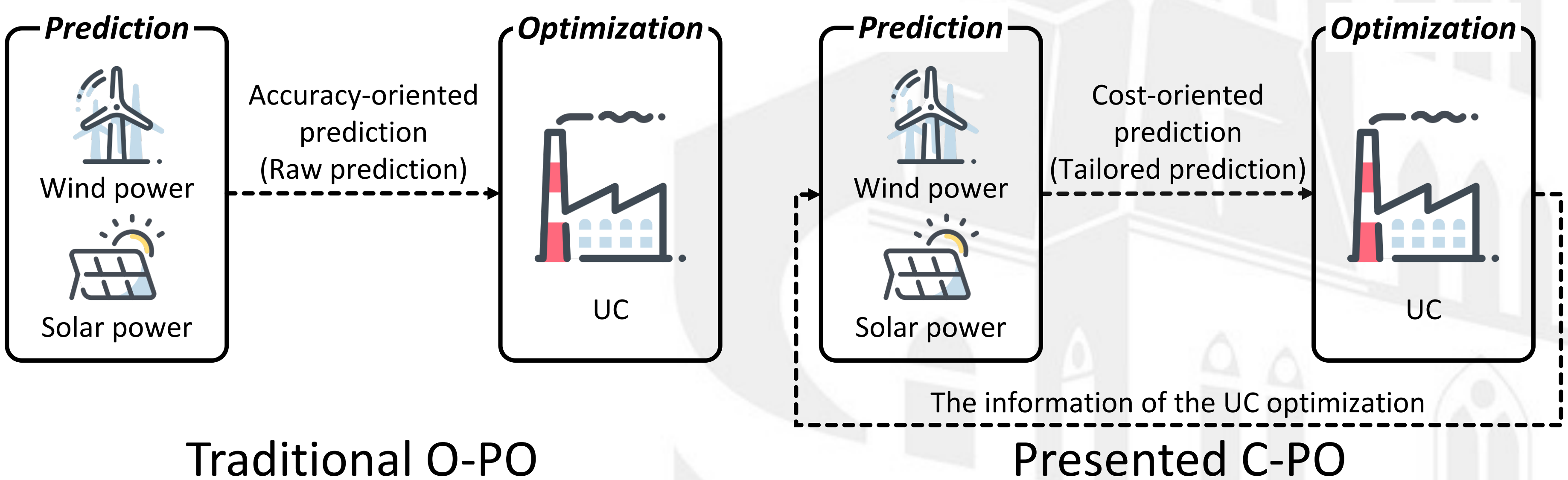
- ***Motivations: Flaws in Traditional Open-Loop Predict-then-Optimize Framework***
  - ***Case 2: Our method under-predicts and O-PO over-predicts***

			Case 1	
Method			Our method	O-PO
RES power prediction/MW			90	107
Mean absolute error/MW			10 (Worse)	7 (Better)
UC	G1	Set-point generation/MW	90	73
		Reserve/MW	±6	±0
	G2	Set-point generation/MW	OFF	OFF
		Reserve/MW	+40	+40
	G3	Set-point generation/MW	20	20
		Reserve/MW	±0	±6
Re-dispatch		Dispatch of RES/MW	90	107
		Anticipated system cost/$	2,450	2,195
		Actual generation of G1/MW	84	73
		Actual generation of G2/MW	OFF	7
		Actual generation of G3/MW	20	20
		Actual utilized RES/MW	96	100
	Actual system cost/$		2,360 (Better)	2,495 (Worse)

"±": Bi-directional spinning reserve. "+": Upward only non-spinning reserve.

Preliminaries and Motivations

- ***Motivations: Flaws in Traditional Open-Loop Predict-then-Optimize Framework***
  - ***Statistically more accurate prediction $\not\Rightarrow$ Higher UC economics***
  - ***To improve the UC economics, we shall close the loop:***
    Consider the downstream UC optimization when using ML for the upstream RES prediction.



Content

Integrating Machine Learning (ML) and Operation Research(OR) for Unit Commitment (UC)

Ⅰ *Preliminaries and Motivations*

Ⅱ *Presented Closed-Loop Predict-and-Optimize Framework*

Ⅲ *References and Q&A*

Presented Closed-Loop Predict-and-Optimize Framework

- *Features of the Closed-Loop Predict-and-Optimize (C-PO) Framework*
  - ***Take advantage of available feature data. (Data-driven)***
  - ***Ability to delivery cost-oriented RES predictions for improving UC economics. (Economics benefits)***
  - ***Potential for large-scale MILP-based UC problems. (Practicality)***
  - ***Extendable to prediction tasks in other fields. (Expansibility)***

Presented Closed-Loop Predict-and-Optimize Framework

- ***Data-Driven C-PO Framework: Overview***
  - ***Data-processing module***

    1. Feature selection
    2. Selection of training scenarios

  - ***Cost-oriented modeling-and-training module***

    1. Cost-oriented empirical risk minimization (ERM) problem modeling
    2. Cost-oriented ERM problem solving (Predictor training)

  - ***Closed-loop predict-and-optimize module***

    1. Predict RES and optimize UC.

Presented Closed-Loop Predict-and-Optimize Framework

- ## *Data-Driven C-PO Framework: Data-Processing Module*

Data-processing module

Feature selection based on historical scenarios in past years: Based on historical scenarios in past years, identify the most relevant feature types using standard regression coefficient.

Training scenarios selection from the latest historical scenarios: Among the latest historical scenarios, select the most representative scenarios as training scenarios using Wasserstein distance.

Goal

- ***Feature selection:*** Avoid overfitting and underfitting issues for the prediction model.
- ***Selection of training scenarios:*** Ensure the effectiveness of the prediction model on upcoming dispatch days.

- ***Standard regression coefficient for feature selection***
- ***Wasserstein distance for training scenario selection***

Presented Closed-Loop Predict-and-Optimize Framework

- ***Data-Driven C-PO Framework: Cost-Oriented Modeling-and-Training Module***
  - ***Smart "predict-then-optimize" (SPO) loss*** $\ell^{SPO}(\widehat{\boldsymbol{w}}, \widetilde{\boldsymbol{w}}) := |z^{\star}(\widehat{\boldsymbol{w}}) - z^{\star}(\widetilde{\boldsymbol{w}})|$
    SPO: Measuring prediction quality with *UC cost loss* instead of *statistical accuracy loss*, so that the open-loop is closed.
  - ***Recalling the UC model***

$$
\begin{aligned}
z(\widehat{\boldsymbol{w}}) = &\min_{\boldsymbol{x},\boldsymbol{y}} [\boldsymbol{c}^{\top}\boldsymbol{x} + \boldsymbol{d}^{\top}\boldsymbol{y}] \\
s.t.\ &\boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y} \le \boldsymbol{g} \\
&\boldsymbol{F}\boldsymbol{y} \le \widehat{\boldsymbol{w}}, \boldsymbol{x} \in \{0,1\}^{M}
\end{aligned}
$$

  - ***Cost-oriented ERM problem of*** $|\mathcal{S}|$ ***scenarios***

$$
\begin{aligned}
&\min_{\boldsymbol{x},\boldsymbol{y},\boldsymbol{H}} \frac{1}{|\mathcal{S}|} \sum_{s\in\mathcal{S}} [\ell_s^{SPO}(\widehat{\boldsymbol{w}}_s, \widetilde{\boldsymbol{w}}_s)] + \lambda \|\boldsymbol{H}\|_1 \\
&\quad s.t.\ \boldsymbol{A}\boldsymbol{x}_s + \boldsymbol{B}\boldsymbol{y}_s \le \boldsymbol{g} \\
&\quad\quad \boldsymbol{F}\boldsymbol{y}_s \le \boldsymbol{H}\boxed{\boldsymbol{f}_s}, \boldsymbol{x}_s \in \{0,1\}^{M}
\end{aligned}
$$

Feature data such as raw RES predictions and regional load

Presented Closed-Loop Predict-and-Optimize Framework

- ***Data-Driven C-PO Framework: Cost-Oriented Modeling-and-Training Module***
  - ***Cost-oriented ERM problem of $|\mathcal{S}|$ scenarios***
    Regression-based problem: $\boldsymbol{H}$ linearly maps feature $\boldsymbol{f}_s$ to RES predictions. Simple and interpretable.

$$\min_{\boldsymbol{x},\boldsymbol{y},\boldsymbol{H}} \frac{1}{|\mathcal{S}|}\sum_{s\in\mathcal{S}}[\ell_s^{SPO}(\widehat{\boldsymbol{w}}_s,\widetilde{\boldsymbol{w}}_s)] + \boxed{\lambda}\|\boldsymbol{H}\|_1$$
$$s.t.\ \boldsymbol{A}\boldsymbol{x}_s + \boldsymbol{B}\boldsymbol{y}_s \le \boldsymbol{g}$$
$$\boldsymbol{F}\boldsymbol{y}_s \le \boldsymbol{H}\boldsymbol{f}_s, \boldsymbol{x}_s \in \{0,1\}^M$$

The only hyper-parameter to be tuned

  - ***Lagrangian-relaxation (LR) decomposition for solving the ERM***
    Solving ERM is essentially training the predictors.
  - ***Training result: Cost-oriented RES predictor tailored for UC.***

$$\boldsymbol{H}^{\star}$$

Presented Closed-Loop Predict-and-Optimize Framework

- ***Data-Driven C-PO Framework: Cost-Oriented Modeling-and-Training Module***

Cost-oriented modeling-and-training module

Modeling cost-oriented ERM problem: Given the selected feature types of the training scenarios, model a cost-oriented ERM problem based on SPO loss function, which considers objective and constrains of UC.

Solving cost-oriented ERM problem: Solve the cost-oriented ERM problem using LR-based decomposition, so that a cost-oriented RES power prediction model can be trained.

Goal

- ***ERM problem modeling:*** Feed the UC information (i.e., the induced costs, objective, and constraints) back to the ERM.
- ***ERM problem solving:*** Training a prediction model that can deliver cost-oriented RES predictions for UC.

- ***Modeling ERM based on SPO loss***
- ***Solving ERM via LR-based decomposition***
- ***Get a cost-oriented predictor for UC***

Presented Closed-Loop Predict-and-Optimize Framework

- ***Data-Driven C-PO Framework: Closed-Loop Predict-and-Optimize Module***

Closed-loop predict-and-optimize module

Form feature-driven UC prescription model: Integrate the cost-oriented RES power prediction model and UC model to form a feature-driven UC prescription model for the upcoming dispatch days.

Closed-loop predict and optimize: In day-ahead stage of a dispatch day, input the selected feature types of this day to the prescription model for jointly executing cost-oriented RES prediction and UC optimization.

Goal

- ***UC prescription model:*** Build a UC prescription model that can perform closed-loop predict-and-optimize for UC.
- ***Closed-loop predict and optimize:*** Execute cost-oriented RES prediction and UC optimization simultaneously.

- ***Data-driven UC prescription model:***

$$
\begin{aligned}
z(\boldsymbol{f}) = \min_{\boldsymbol{x},\boldsymbol{y}} & [\boldsymbol{c}^\top \boldsymbol{x} + \boldsymbol{d}^\top \boldsymbol{y}] \\
s.t.\ & \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y} \le \boldsymbol{g} \\
& \boldsymbol{F}\boldsymbol{y} \le \boldsymbol{H}^\star \boldsymbol{f}, \boldsymbol{x} \in \{0,1\}^M
\end{aligned}
$$

- ***Prescription: Combining prediction and decision.***
- ***Regression property: $\boldsymbol{H}^\star \boldsymbol{f}$ is essentially a weighted sum of the features $\boldsymbol{f}$.***

Presented Closed-Loop Predict-and-Optimize Framework

- ***Comparing Original UC Model and UC Prescription Model***
  - ***Original UC model***

$$z(\hat{\boldsymbol{w}}) = \min_{\boldsymbol{x},\boldsymbol{y}} [\boldsymbol{c}^\top \boldsymbol{x} + \boldsymbol{d}^\top \boldsymbol{y}]$$
$$s.t.\ \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y} \le \boldsymbol{g}$$
$$\boldsymbol{F}\boldsymbol{y} \le \hat{\boldsymbol{w}}, \boldsymbol{x} \in \{0,1\}^M$$

    - Predict-then-optimize
    - Use accuracy-oriented prediction
    - The loop between RES prediction and UC optimization is wide-open

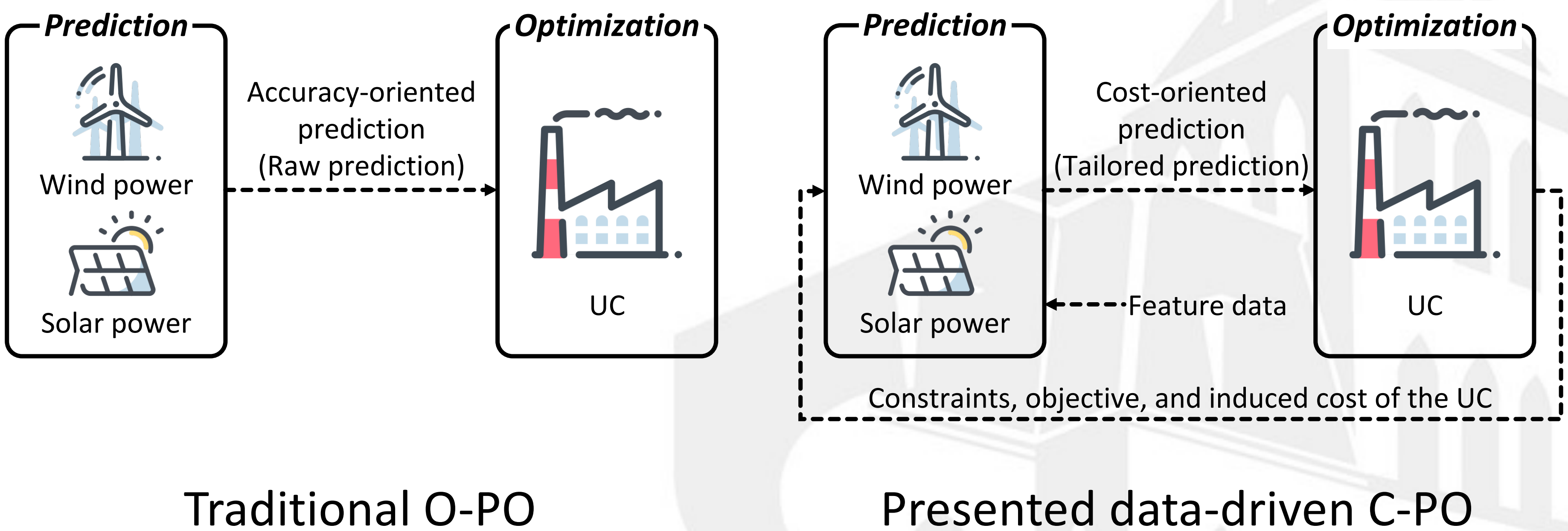
  - ***Data-driven UC prescription model***

$$z(\boldsymbol{f}) = \min_{\boldsymbol{x},\boldsymbol{y}} [\boldsymbol{c}^\top \boldsymbol{x} + \boldsymbol{d}^\top \boldsymbol{y}]$$
$$s.t.\ \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y} \le \boldsymbol{g}$$
$$\boldsymbol{F}\boldsymbol{y} \le \boldsymbol{H}^\star \boldsymbol{f}, \boldsymbol{x} \in \{0,1\}^M$$

    - Predict-and-optimize (Prescription)
    - Use Cost-oriented prediction (Driven by feature data $\boldsymbol{f}$)
    - The loop between RES prediction and UC optimization is closed

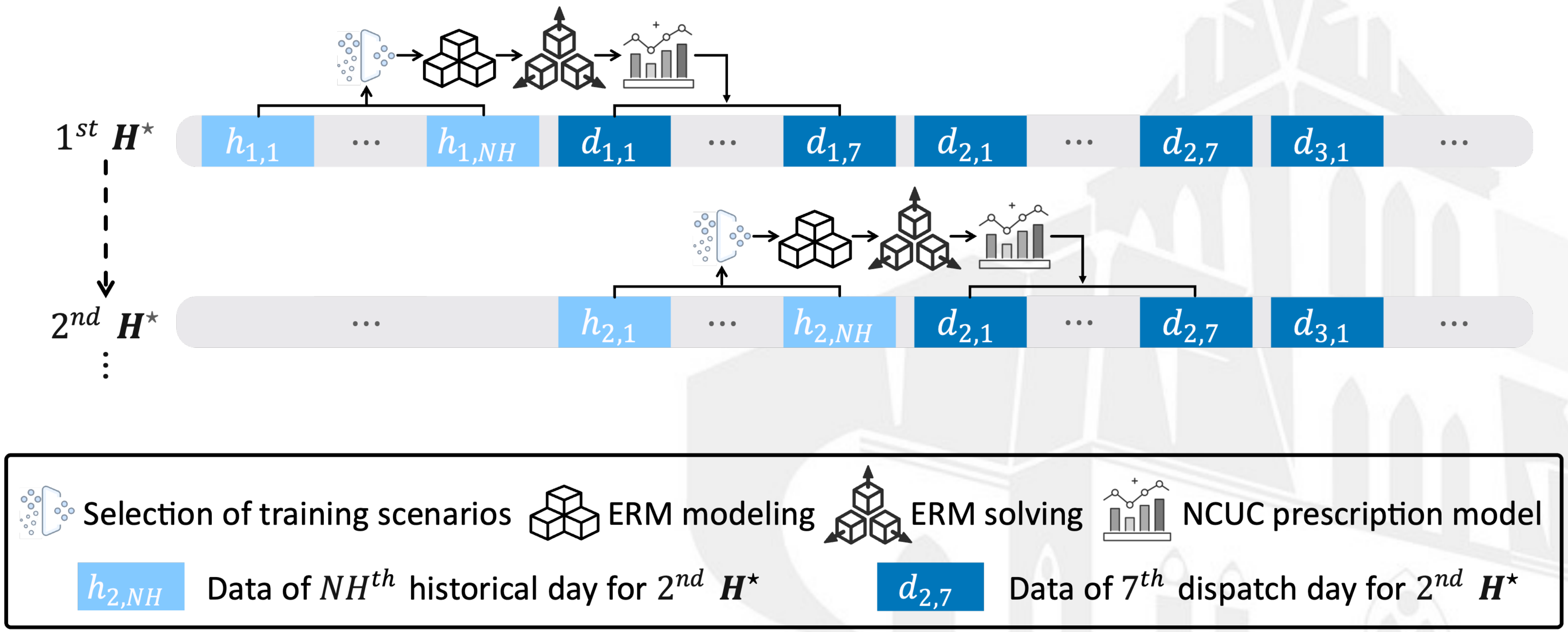
Presented Closed-Loop Predict-and-Optimize Framework

- ***Comparing Traditional O-PO and Presented C-PO***



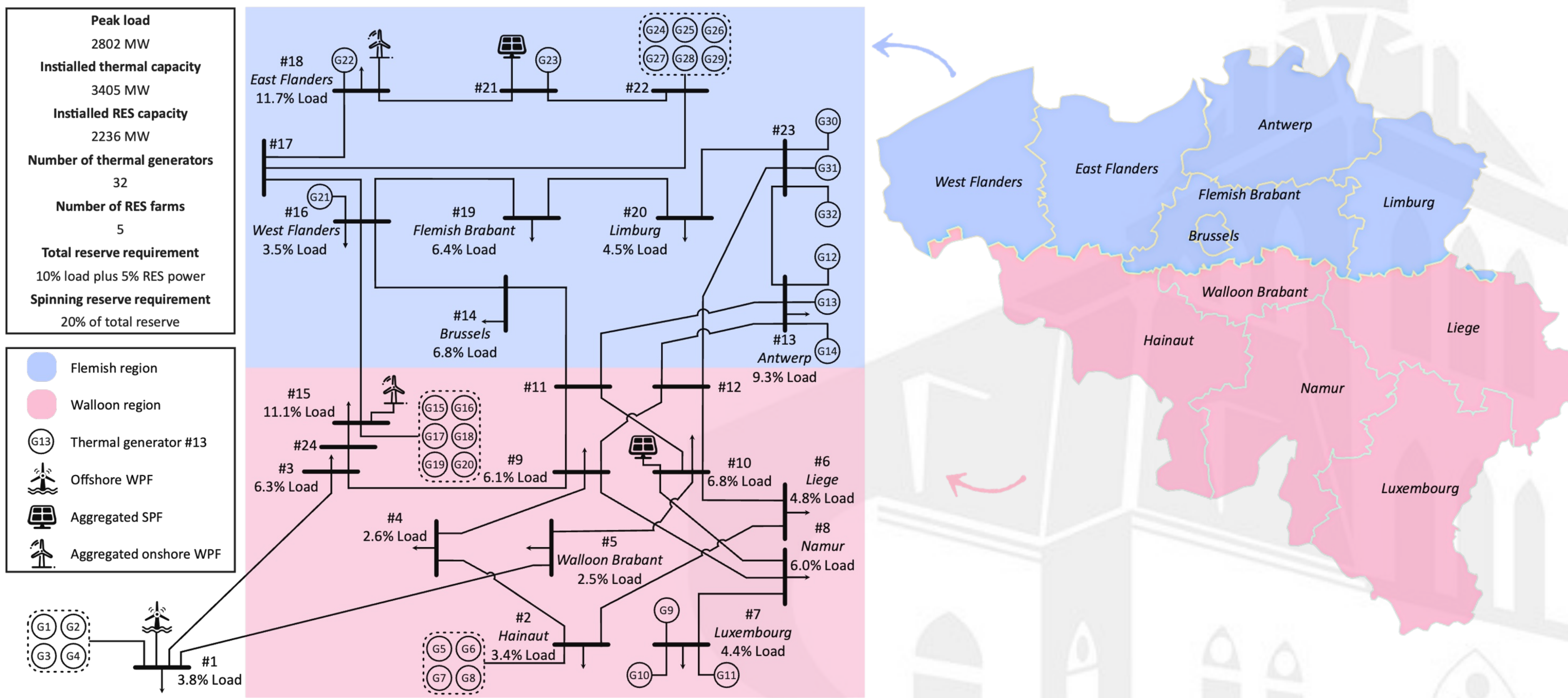
Presented Closed-Loop Predict-and-Optimize Framework

- ***Rolling-based C-PO Implementation for Daily UC***



Presented Closed-Loop Predict-and-Optimize Framework

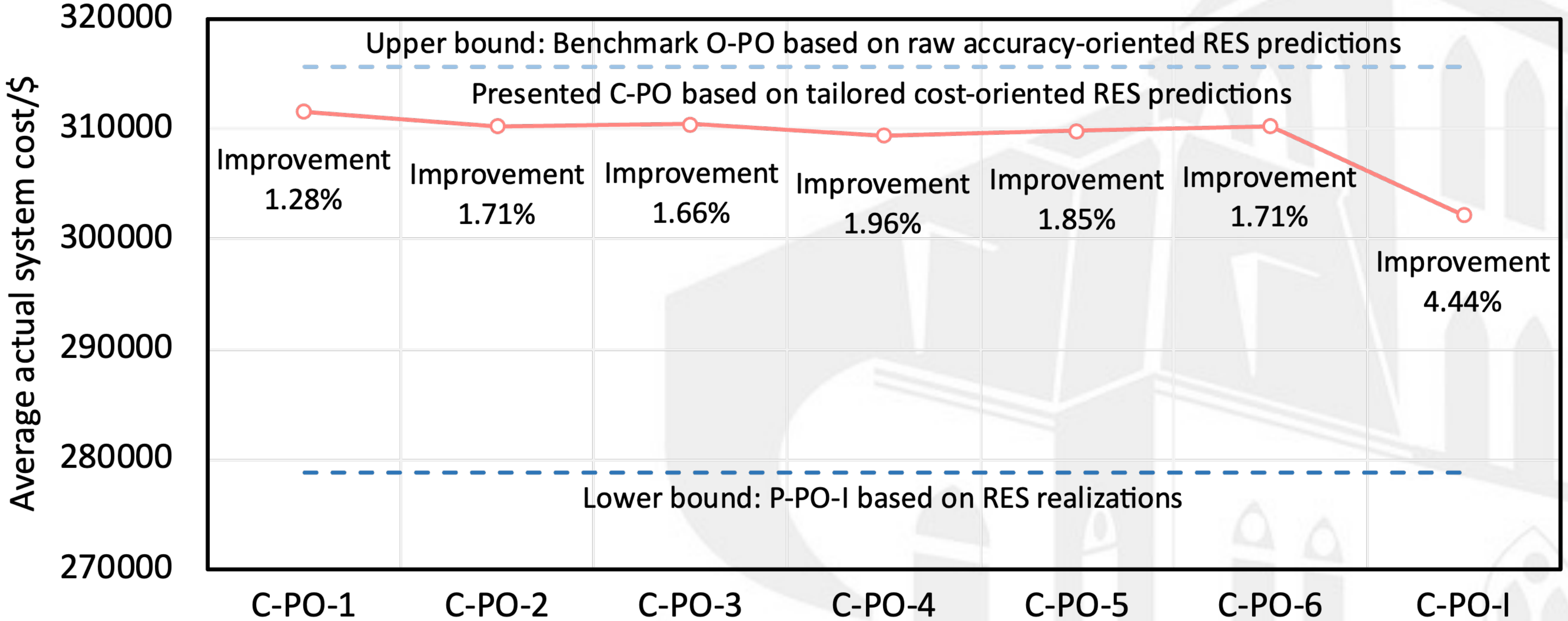
- *Cases on 24-Bus System: Simulating Belgian System*



- *Cases on 24-Bus System: Data from Belgian System[3] (01/01/2018-12/31/2020)*

Presented Closed-Loop Predict-and-Optimize Framework

- ***Cases on 24-Bus System: Results of Economics Improvements***
  - ***C-PO enables noticeable economics improvements (1.28%-4.44%) over the daily UCs over entire 2020.***



Presented Closed-Loop Predict-and-Optimize Framework

- ***Cases on 5655-Bus System: Whether LR-based Decomposition Works?***
  - ***C-PO-LR computationally outperforms C-PO-SD without optimality loss.***

Case	Training time/s		Optimality gap	
	C-PO-SD	C-PO-LR	C-PO-SD	C-PO-LR
1	1273.6	593.2	0.32%	0.62% (4 Iterations)
2	1111.7	1029.2	0.59%	0.89% (3 Iterations)
3	1655.8	927.5	0.51%	0.69% (3 Iterations)
4	828.6	619.2	0.86%	0.64% (4 Iterations)
5	685.9	512.3	0.81%	0.69% (4 Iterations)
6	3686.1	1364.1	0.93%	0.77% (4 Iterations)
7	1581.5	1312.6	0.33%	0.35% (4 Iterations)
8	1803.8	1215.9	0.74%	0.99% (4 Iterations)
9	1266.1	1211.8	0.67%	0.17% (4 Iterations)
10	1140.8	1086.3	0.36%	0.73% (4 Iterations)
11	2632.4	1089.1	0.49%	0.82% (3 Iterations)
12	1462.7	1321.3	0.31%	0.76% (4 Iterations)
13	1436.4	834.7	0.72%	0.74% (4 Iterations)
14	1138.9	714.8	0.98%	0.89% (4 Iterations)
15	1810.2	767.6	0.87%	0.99% (4 Iterations)
16	2146.1	290.8	0.92%	0.88% (1 Iteration)

Presented Closed-Loop Predict-and-Optimize Framework

- *Conclusions*
  - ***The data-driven (or feature-driven) C-PO can improve UC economics by generating cost-oriented RES predictions tailored for UC.***
  - ***The LR-based decomposition method enables C-PO to be applicable to the practical system.***
  - ***From perspective of machine learning, the C-PO essentially utilizes the linear regression: simple yet effective.***

Content

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Ⅲ References and Q&A

References and Q&A

- *References*

[1] Yafei Yang and Lei Wu, "Machine Learning Approaches to the Unit Commitment Problem: Current Trends, Emerging Challenges, and New Strategies," *The Electricity Journal*, 2020.

[2] Xianbang Chen, Yafei Yang, Yikui Liu, and Lei Wu, "Feature-Driven Economic Improvement for Network-Constrained Unit Commitment: A Closed-loop Predict-and-optimize Framework ," *IEEE Transactions on Power Systems*, 2021.

[3] Dataset of Closed-loop Predict-and-Optimize NCUC. [Online]. Available: github.com/asxadf/Closed_Loop_NCUC_Dataset.

- *Open-Access Dataset and Codes*

  Our dataset and codes have been uploaded at [3], including RES, load, feature, and system data. Please feel free to use them.

References and Q&A

- ***Opening: Join Us!***
  Professor Lei Wu is looking for **highly motivated Post Doc and PhD students**.
  If you are interested in our research areas, please feel free to send your resume to Lei.Wu@stevens.edu

- ***About Professor Lei Wu***

  - ***Professor in ECE Department at Stevens Institute of Technology***
  - ***Fellow of IEEE (Class of 2022)***
  - ***Research Focus: Applying mathematical optimization and machine learning on power system operation and planning.***
  - ***Group: 4 PhDs & 4 Post Doctors***
  - ***Homepage: https://sites.google.com/site/leiwupes***

References and Q&A

- *About Stevens Institute of Technology*
  - ***Nearby New York but quiet***
  - ***Possess excellent views of Manhattan***
  - ***Nice neighborhoods comfortable environment for living and studying***
  - ***Solid environment for researching***
  - ***Enjoy high security (Rank top 10 in USA)***


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RISE

Thank you

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For OR Talk
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