Improving Electricity Market Economy via Closed-Loop Predict-and-Optimize

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Abstract—The electricity market clearing is usually implemented via an open-loop predict-then-optimize (O-PO) process: it first predicts the available power of renewable energy sources (RES) and the system reserve requirements; then, given the predictions, the markets are cleared via optimization models, i.e., unit commitment (UC) and economic dispatch (ED), to pursue the optimal electricity market economy. However, the market economy could suffer from the open-loop process because its predictions may be overly myopic to the optimizations, i.e., the predictions seek to improve the immediate statistical forecasting errors instead of the ultimate market economy. To this end, this paper proposes a closed-loop predict-and-optimize (C-PO) framework based on the tri-level mixed-integer programming, which trains economy-oriented predictors tailored for the market-clearing optimization to improve the ultimate market economy. Specifically, the upper level trains the economy-oriented RES and reserve predictors according to their induced market economy; the middle and lower levels, with given predictions, mimic the market-clearing process and feed the induced market economy results back to the upper level. The trained economy-oriented predictors are then embedded into the UC model, forming a prescriptive UC model that can simultaneously provide RES-reserve predictions and UC decisions with enhanced market economy. Numerical case studies on an IEEE 118-bus system illustrate potential economic and practical advantages of C-PO over O-PO, robust UC, and stochastic UC.

Index Terms—Predict-and-optimize, unit commitment, prescriptive analytics, bilevel/tri-level mixed-integer programming.

NOMENCLATURE

Sets and Indexes

| Symbol | Description |
|--------|-------------|
| B/b   | Set/index of branches. |
| E/e   | Set/index of enumerations (iterations). |
| T/i   | Set/index of units. |
| T/ns  | Set of non-start/quick-start units. |
| K/k   | Set/index of generation segments. |
| S/s   | Set/index of training scenarios. |
| J/j   | Set/index of load buses. |
| Q/q   | Set/index of load buses. |
| T/sd  | Set of hours. |
| T/nsd | Set defined as \( \{ T_i/n, \cdots, T \} \). |

Decision Variables

| Symbol | Description |
|--------|-------------|
| \( D_{it}/U_{it} \) | Unit commitment/startup status of unit \( i \) at hour \( t \). |
| \( I_{it}/O_{it} \) | Unit commitment/non-spinning reserve (NR) provision status of unit \( i \) at hour \( t \). |
| \( P_i \) | Generation schedule of unit \( i \) at hour \( t \). |
| \( P_{isk} \) | Schedule of unit \( i \) in segment \( k \) at hour \( t \). |
| \( R_{it}/R_{it}^{sr} \) | Spinning reserve (SR)/NR schedule of unit \( i \) at hour \( t \). |
| \( S_1, S_2, S_3, S_4, S_5 \) | Slack variables. |
| \( \bar{W}(\cdot)/\hat{W}(\cdot) \) | Predictor of RES power/reserve requirements. |
| \( W_{jt} \) | Generation schedule of RES \( j \) at hour \( t \). |
| \( x \) | Vector of binary decisions in UC. |
| \( y \) | Vector of continuous decisions in UC excluding \( r \). |
| \( z_{ik} \) | Vector of ED decisions. |
| \( dw, ev, gw \) | Duplicated/enumerated/generated variables. |
| \( \hat{\nu} / \bar{\nu} / \hat{\nu} \) | Predicted/actual available power of RES \( j \) at hour \( t \), whose vector is \( \hat{\nu} / \bar{\nu} \). |
| \( T \) | Total number of hours. |
| \( N / NT \) | Number of historical/training scenarios. |
| \( \hat{L}_t / \bar{L}_t \) | Predicted/actual demand of load \( q \) at hour \( t \), whose vector is \( \hat{L} / \bar{L} \). |
| \( T_{ns} / T_{sd} \) | Minimum on/off time requirement of unit \( i \). |
| \( \hat{w} / \bar{w} / \hat{w} \) | Tailored counterpart of raw prediction \( \hat{w} / \bar{w} \). |

Parameters

| Symbol | Description |
|--------|-------------|
| \( B_b \) | Transmission capacity of branch \( b \). |
| \( C_{seg} \) | Generation cost of unit \( i \) in segment \( k \). |
| \( \bar{C}_{su} / \bar{C}_{s} \) | Startup/no-load cost of unit \( i \). |
| \( \bar{C}_{sr} / \bar{C}_{s} \) | Power limit of unit \( i \) at segment \( k \). |
| \( \bar{C}_{1} \) | Upward/downward ramping capacity of unit \( i \). |
| \( \bar{C}_{2} \) | SR/NR limit of unit \( i \). |
| \( \bar{C}_{3} \) | Predicted SR/NR requirement at hour \( t \), which together form the vector \( \hat{r} / \bar{r} \). |
| \( \bar{C}_{4} \) | Predicted/actual available power of RES \( j \) at hour \( t \), whose vector is \( \hat{w} / \bar{w} \). |
| \( \bar{C}_{5} \) | Cardiogram of a set. |

I. INTRODUCTION

ELECTRICITY market clearing plays an important role in guaranteeing the operational economy of power systems. Aiming to achieve the optimal market economy (i.e., maximizing the social welfare or minimizing the system cost), the electricity markets are generally cleared by Independent System Operators (ISO) via an open-loop predict-then-optimize (O-PO) framework, as shown in Fig. 1(a):

- Available power of renewable energy sources (RES) as well as system spinning reserve (SR) and non-spinning reserve (NR) requirements are predicted.
- Taking the predictions as inputs, ISOs solve a deterministic unit commitment (UC) problem [2] to clear the day-ahead electricity market.
- Based on the UC decisions, ISOs tackle an economic dispatch (ED) problem [3] to clear the real-time electricity market, while multiple intra-day and real-time UC runs adopted in certain markets are ignored.
Although O-PO seems practically reasonable, it suffers from two flaws. First, the RES predictions simply pursue statistical accuracy, such as mean absolute error (MAE). However, due to inherent nonlinearity, a statistically more accurate prediction may not necessarily induce a higher market economy [4]. Second, the reserve requirements sized by traditional rule-of-thumb methods could be overly conservative and further worsen market economy [5]. Thus, the predictions in O-PO are regarded as raw because they are myopic to the optimization tasks.

To improve the market economy, a common way is to augment the deterministic UC to its two-stage stochastic programming (T-SP) [6] or two-stage robust optimization (T-RO) [7] counterpart. Another emerging way is to feed the optimization information back to the prediction phase, seeking for cost-oriented predictors that can fundamentally improve the economy. Pioneering methodologies have been explored in this direction, such as the prescriptive framework [8], the regression method [9], and the smart predict-then-optimize (SPO) approach [10]. In a nutshell, these approaches intend to close the loop between the prediction and the optimization through a feedback path, hence referred to as the closed-loop predict-and-optimize (C-PO).

Indeed, the C-PO idea has been recently applied in electricity markets. References [11] and [12] train decision trees to predict available RES power for RES producers, which use the RES trading profit instead of entropy to evaluate the prediction quality. Similarly, [13]-[15] train neural networks to predict RES power for RES trading [13], load for ED [14], and electricity price for energy storage system arbitrage [15], in which the training loss functions explicitly consider the economy loss induced by the predictions. All the references [11]-[15] demonstrate that tailoring the raw predictions for targeted optimization tasks can improve the economy noticeably, although the statistical accuracy may be slightly compromised.

Rather than grounding on heuristic methods as [11]-[15], references [16]-[19] use mathematical programming as the underlying methodology to implement the C-PO. The core of [16]-[19] is to construct an empirical risk minimization (ERM) problem that integrates both the predictor training and optimization tasks, which is then solved to obtain the globally optimal predictors. By solving an ERM problem, [16] trains an extreme learning machine that can size the SR requirements economically. By solving a regression-based ERM, [17] obtains an optimal linear decision rule that maps the raw RES predictions to the profit-oriented predictions for RES trading. The same authors further use an analogous idea to train value-oriented load predictors for ED in [18]. Different from [16]-[18] which focus on linear programming (LP) tasks, our previous work [19], as shown in Fig.1(b), constructs a SPO-type ERM for the mixed-integer programming (MIP)-based UC that yields a cost-oriented RES predictor tailored for the market-clearing optimization.

Although the methods in [16]-[19] are regarded as stable and interpretable, their single-level ERM structures require the predictor training and in-sample optimization to share exactly the same objective function. As a result, this restriction would compromise the in-sample optimization model, disobeying the least-cost merit-order principle (which will be detailed in Section II-B2). Feeding these compromised optimization information back to training could lead to an over-fitted predictor.

In fact, this issue could be resolved by leveraging multi-level (e.g., bilevel and tri-level) programming to construct the ERM—modeling the predictor training in the upper level while uncompromisingly formulating the optimization tasks in the lower levels. Following this spirit, [20] and [21] respectively enhance their previous single-level ERMs in [16] and [17] via bilevel LP. Similarly, [22]-[24] utilize bilevel LP to construct ERM and train cost-oriented SR predictors for ED.

Table I summarizes the above C-PO applications [11]-[24]. It is noteworthy that those market-related applications merely utilize LP-based ED models and/or exclusively predict SR requirements, ignoring the quick-start units with NR capabilities that can support the practical ED task.

To this end, this paper presents a C-PO framework, as in Fig.1(c), to predict RES-SR-NR and optimize market operations. A tri-level MIP-based ERM problem is first constructed, in which the upper level trains the predictors for RES power as well as SR and NR requirements, while the middle and lower levels, formulated as MIP problems, mimic the UC-ED market-clearing process to calculate the optimal system cost with respect to given predictions from the upper level. The system cost is fed back to the upper level for assessing and improving the prediction quality. The ERM is converted into a bilevel MIP and then solved by a reformulation and decomposition (R&D) method [25] to deliver the optimally trained predictors of RES, SR, and NR. Finally, the predictors are embedded into the deterministic UC, forming a prescriptive UC model that delivers cost-oriented RES-SR-NR predictions and UC decisions simultaneously.

The major works in this paper are summarized as follows:

- To improve the electricity market economy, a C-PO framework is presented. The core is to leverage tri-level MIP in constructing an ERM problem, in which RES-SR-NR predictions and the market-clearing optimization are integrated in a closed-loop structure without compromise.
- The ERM problem is converted into a tractable bilevel MIP and then solved by a R&D method [25]. Solving the ERM provides the cost-oriented predictors tailored for the market-clearing optimization.
- Based on an IEEE 118-bus system with real-world data from the Belgian ISO [26], the proposed C-PO is compared to O-PO and T-SP/T-RO with MIP recourse, and sensitivity analysis is also conducted. To improve the transparency and reproducibility of this paper, all the testing data and source codes are made publicly accessible at [27].

The rest of the paper is organized as follows: Section II details the necessary preliminaries and motivations; Section III presents the core methods and concludes the paper with Section IV.
expands the C-PO framework; Section [IV] analyzes the experimental results; and Section [V] concludes this paper.

II. PRELIMINARIES AND MOTIVATIONS

A. Preliminaries

1) UC Model: The UC problem is formulated as a MIP model in [1]. The objective (1.1) is to minimize the total operation cost including startup, no-load, generation, SR, and NR costs. The generator constraints include generation limits (1.2)-(1.3), segment-based generation representation (1.4)-(1.5), SR (1.6) and NR (1.7) capacities, startup-shutdown-commitment status logic (1.8), minimum on and off requirements (1.9)-(1.10), ramping limits (1.11)-(1.12), and RES power limitation (1.13). Constraints (1.14)-(1.15) mean that only the offline quick-start units can provide NR. Constraint (1.16) is the integrality requirement. System constraints include system reserve requirements (1.17)-(1.18), power balance (1.19), and DC power flow-based transmission limits (1.20). Vector \( x \) represents UC variables \( I, U, D, \) and \( O \); vector \( r \) represents SR and NR variables \( R^r \) and \( R^nr \); and all other variables are contained in vector \( y \).

\[
\begin{align*}
\min_{x, y, r} & \quad \sum_{t \in T, i \in I} \left\{ C^u i_t U_{it} + C^ni_i I_{it} + \sum_{k \in K} C^seg_{itk} P^seg_{itk} \right. \\
& \left. + C^r i_t R^r_{it} + C^nr i_t R^nr_{it} \right\} \\
\text{Generator Constraints:} & \quad P_{it} - P^r_{it} \geq P^min_{it} \quad \forall t \in T, i \in I \\
& \quad P_{it} + P^r_{it} \leq P^{max}_{it} \quad \forall t \in T, i \in I \\
& \quad P_{it} = \sum_{k \in K} P^seg_{itk} \quad \forall t \in T, i \in I \\
& \quad 0 \leq P^seg_{itk} \leq P^{seg}_{itk} \quad \forall t \in T, i \in I, k \in K \\
& \quad 0 \leq R^r_{it} \leq R^{max}_{it} \quad \forall t \in T, i \in I \\
& \quad P^{min}_{it} O_{it} \leq R^nr_{it} \leq R^nr_{it} O_{it} \quad \forall t \in T, i \in I \\
& \quad U_{it} - D_{it} = I_{it} - I_{it-1} \quad \forall t \in T, i \in I \\
& \quad \sum_{t=t_{seg}+1}^{t_{seg}} U_{it} \leq I_{it} \quad \forall t \in T, i \in I \\
& \quad \sum_{t=t_{seg}+1}^{t_{seg}+d_{it}} D_{it} \leq 1 - I_{it} \quad \forall t \in T, i \in I \\
& \quad P_{it} - P_{it-1} \leq P^{max}_{it} (1 - I_{it-1}) \\
& \quad + R^r_{it} (I_{it} - I_{it-1}) + R^nr_{it} I_{it-1} \quad \forall t \in T, i \in I \\
& \quad P_{it-1} - P_{it} \leq P^{max}_{it} (1 - I_{it-1}) \\
& \quad + R^r_{it} (I_{it} - I_{it-1}) + R^nr_{it} I_{it} \quad \forall t \in T, j \in J \\
& \quad 0 \leq W_{jt} \leq \hat{W}_{jt} \quad \forall t \in T, j \in J \\
& \quad O_{it} + I_{it} \leq 1 \quad \forall t \in T, i \in I \\
& \quad O_{it} = 0 \quad \forall t \in T, i \in I \\
& \quad I_{it}, U_{it}, D_{it}, O_{it} \in \{0, 1\} \\
\end{align*}
\]

System Constraints:

\[
\begin{align*}
\sum_{t \in T} R^r_{it} & \geq R^r_{it} \quad \forall t \in T \\
\sum_{t \in T} (R^r_{it} + R^{red}_{it}) & \geq \hat{R}^r_{it} + \hat{R}^{red}_{it} \quad \forall t \in T \\
- B_b & \leq F_b (P_{it}, W_{jt}, \hat{L}_{qt}) \leq B_b \quad \forall t \in T, b \in B
\end{align*}
\]

The UC model (1) can be represented in a compact form (2), in which \( F(\cdot) \) and \( G(\cdot) \) respectively represent the sets of equality and inequality constraints of (1).

\[
\begin{align*}
\min_{\bar{x}, y, r} & \quad \bar{x}^T \left[ \begin{array}{c}
C^u I \bar{x} + C^ni I \bar{x} + \sum_{k \in K} C^seg_{itk} P^seg_{itk} \\
+ C^r I R^r_{it} + C^nr I R^nr_{it}
\end{array} \right] \\
\text{s.t.} & \quad (\bar{x}, y, r) \in \mathcal{X}(\hat{w}, \hat{r}) \\
& \quad \left\{ \begin{array}{c}
F(\bar{x}, y, r) = 0 \\
G(\bar{x}, y, r, \bar{w}, \bar{r}) \leq 0
\end{array} \right.
\end{align*}
\]

Taking the predictions \( \hat{w} \) and \( \hat{r} \) as inputs, UC is solved to deliver the optimal solutions of startup, commitment, base-point generation, SR schedule, and NR schedule to ED.

2) ED Model: Taking the UC solutions and the actual RES realization \( \hat{w} \) as inputs, the ED is modeled as a MIP in [3], where \( \hat{r}_* \) indicates the optimal solution from UC. The objective (3.1) is to minimize startup and no-load costs of quick-start units that are not committed in UC but scheduled for providing NR, generation costs of all units, as well as slack penalty costs. Constraints (3.2)-(3.3) mean that only the quick-start units not committed in UC may change their statuses. All units are subjected to generation limits (3.4)-(3.5), dispatch adjustment limitation (3.5), ramping limits (3.6)-(3.10), RES power limitation (3.11), and integrality requirement (3.12). The system shall satisfy real-time power balance (3.13) and transmission limits (3.14)-(3.15). Note that ISOs usually adopt slack variables (i.e., \( S^3_{bt} \) and \( S^4_{bt} \)) to ensure the ED feasibility.

\[
\begin{align*}
\min_{z \in T} & \quad \sum_{t \in T} \left\{ C^u i_t U_{it} + C^ni_i I_{it} + \sum_{k \in K} C^seg_{itk} P^seg_{itk} \right. \\
& \left. + C^r i_t R^r_{it} + C^nr i_t R^nr_{it} \right\} \\
\text{Generator Constraints:} & \quad I_{it} = I_{it} + R^ed_{it} \quad \forall t \in T, i \in I \\
& \quad U_{it} - D_{it} = I_{it} - I_{t-1} \quad \forall t \in T, i \in I \\
& \quad P^r_{it} - P_{it} \leq P^{max}_{it} - P^r_{it-1} \\
& \quad + R^r_{it} (I_{it} - I_{it-1}) + R^nr_{it} I_{it-1} \quad \forall t \in T, i \in I \\
& \quad P_{it} - P_{it-1} \leq P^{max}_{it} (1 - I_{it-1}) \\
& \quad + R^r_{it} (I_{it} - I_{it-1}) + R^nr_{it} I_{it} \quad \forall t \in T, j \in J \\
& \quad 0 \leq W_{jt} \leq \hat{W}_{jt} \quad \forall t \in T, j \in J \\
& \quad O_{it} + I_{it} \leq 1 \quad \forall t \in T, i \in I \\
& \quad O_{it} = 0 \quad \forall t \in T, i \in I \\
& \quad I_{it}, U_{it}, D_{it}, O_{it} \in \{0, 1\} \\
\end{align*}
\]
Execute UC (2) based on predictions of RES and reserve requirements.

Day-Ahead Electricity Market
Actual UC Cost

Actual UC Cost

Execute ED (4) based on UC decisions in the face of actual RES realization.

Real-Time Electricity Market
Actual ED Cost

Actual ED Cost

UC Decisions

Start-up and no-load costs of quick-start units committed in ED.

Spinning reserve and non-spinning reserve costs.

Fig. 2. Procedure to evaluate the electricity market economy.

\[
\begin{align*}
|P_{it}^d - P_{it}^r| & \leq R^{sr, *}_i I^*_{it} + P_{it}^{max} I_{it}^d \quad \forall t, i \in I \\
P_{it}^d - P_{it}^{red} & \leq P_{it}^{max} (1 - P_{it}^{red}) \\
& + R^{mp, *}_i I^*_{it} + R^{mp} (P_{it}^d - P_{it}^{red}) \quad \forall t, i \in I \\
I_{it}^d - P_{it}^{red} & \leq \frac{1}{I_{it}^{max}} (I_{it}^d - I_{it}^{red}) \quad \forall t, i \in I \\
0 & \leq W_{it}^{red} \leq W_{it} \quad \forall t, j \in J \\
I_{it}^d, I_{it}^{ed, qs}, I_{it}^{ed, qs}, P_{it}^{ed, qs} & \in \{0, 1\} \quad \forall t, i \in I
\end{align*}
\]

System Constraints:

\[
\sum_{t \in T} \sum_{j \in J} W_{it}^{ed} + S_{it}^1 = \sum_{q \in Q} \tilde{L}_{it} + S_{it}^2 \quad \forall t \in T
\]

\[
F_b (P_{it}^d, W_{it}^d, \tilde{L}_{it}) - S_{bt}^3 \leq B_b \quad \forall t \in T, b \in B
\]

\[
F_b (P_{it}^d, W_{it}^d, \tilde{L}_{it}) + S_{bt}^4 \geq -B_b \quad \forall t \in T, b \in B
\]

\[
S_{bt}^3, S_{bt}^4 \geq 0 \quad \forall t \in T, b \in B
\]

The compact form of ED is shown as in (3), where \( M(\cdot) \) and \( N(\cdot) \) respectively represent the sets of equality and inequality constraints of (3).

\[
\begin{align*}
\min & \quad d^T z \\
\text{s.t.} & \quad z \in Z(x^*, y^*, r^*, \tilde{w})
\end{align*}
\]

\[
Z(x^*, y^*, r^*, \tilde{w}) = \left\{ z \mid M(x^*, z) = 0, N(x^*, y^*, r^*, z, \tilde{w}) \leq 0 \right\}
\]

ED calculates optimal solutions to status switch of quick-start units, generation of all units, and slack variables.

3) Evaluation of Electricity Market Economy: As shown in Fig. 2 the market economy is evaluated by solving the day-ahead UC and the real-time ED in a queue.

Specifically, since \( \tilde{w} \) remains unknown in the day-ahead stage, UC is first conducted to clear the day-ahead market using \( \tilde{w} \) and \( \tilde{r} \), providing the actual UC cost (i.e., startup and no-load costs \( a^T x^* \) plus SR and NR costs \( c^T r^* \)). After \( \tilde{w} \) is revealed in the real-time stage, ED is executed to clear the real-time market, providing the actual ED cost \( d^T z^* \) (i.e., startup and no-load costs of quick-start units additionally committed in ED, generation cost of all units, and slack penalties).

Finally, the actual system cost \( \epsilon^{sys} \) is calculated via (5), which is utilized to evaluate the electricity market economy.

\[
\epsilon^{sys} = \sum_{t \in T} \sum_{i \in I} \left( C_{su} U_{it}^d + C_{il} I_{it}^d \right) + \sum_{t \in T} \sum_{i \in I} \left( C_{sr} P_{it}^{sr,*} + C_{ir} P_{it}^{nr,*} \right) + \sum_{t \in T} \sum_{i \in I} \left( C_{su} P_{it}^{ed,*} + C_{il} I_{it}^{ed,*} \right) + \sum_{t \in T} \sum_{i \in I} \sum_{k \in K} C_{sk} P_{it}^{ed,seg,*} + C_{bs} \sum_{b \in B} \left( S_{bt}^3 + S_{bt}^4 \right) \right)
\]

\[
= a^T x^* + c^T r^* + d^T z^*
\]

(5)

B. Motivations

1) Asymmetric Impact of RES Prediction MAE on Market Economy: To show this motivation, multiple raw predictions \( \tilde{w} \) on Feb. 16, 2020 are generated based on the Belgian ISO data. These raw predictions are applied on an IEEE 118-bus system to conduct the market clearing, i.e., the OPO process. Finally, the market economy loss is evaluated by (6), where \( \epsilon^{sys}_{\tilde{w}} \) and \( \epsilon^{sys}_{\tilde{w}} \) are actual system costs induced by \( (\tilde{w}, \tilde{r}) \) and \( (\tilde{w}, \tilde{r}) \), respectively. Fig. 3 shows the results of all raw predictions.

Market Economy Loss = \( \epsilon^{sys}_{\tilde{w}} - \epsilon^{sys}_{\tilde{w}} \times 100\% \)

(6)

Two motivating cases are highlighted as follows:

Case 1: Raw predictions of the same MAE may lead to different economies. Note that points A and B in Fig. 3 have the same MAE (61.8MW) but different economy losses (3.2% vs 3.6%). This is because the under-prediction of point A merely causes downward generation adjustment and RES curtailments in real-time ED; in comparison, the over-prediction of point B requires expensive NR deployment from quick-start units in real-time ED. Indeed, the asymmetric impacts inspire that the predictions should consider the ultimate economic consequence out of the UC-ED optimization.

Case 2: Raw predictions of a worse MAE may even lead to a better economy. Although MAE of point C is noticeably high (150.2MW), it still achieves the lowest economy loss (2.3%) among all raw predictions. This is because each \( \tilde{w} \) shall associate with a just-enough reserve level \( \tilde{r} \) in the face of \( \tilde{w} \) (e.g., a proper \( \tilde{r} \) depends on the difference between \( \tilde{w} \) and \( \tilde{w} \), and \( \tilde{r} = 0 \) if \( \tilde{w} = \tilde{w} \)). Consequently, if \( (\tilde{w}, \tilde{r}) \) is taken as input to (2), the induced UC decisions can ensure just-enough reserve to enable the full utilization of available RES in real time, delivering the best market economy. Thus, simultaneously predicting cost-oriented \( \tilde{w} \) and \( \tilde{r} \) by assessing their joint impacts on the ultimate market economy would be beneficial.

2) Limitations in Our Previous Work [19]: This paper is also motivated by overcoming these limitations of [19].

Underutilization of information. As shown in Fig. 1 [19] only feeds the UC information back to the prediction, while this paper feeds both UC and ED information back to optimizations for boosting the ultimate market economy.

Rule-of-thumb reserve requirements. Only the RES predictions are tailored in [19], while the reserve requirements are still rule-of-thumb. Instead, this paper tailors both the RES and reserve predictions, seeking for the just-enough reserve requirements paired with RES predictions to deliver the best market economy.
Compromised UC modeling in the single-level ERM. In the single-level ERM \( (7) \), the UC objective has to be packed into objective function of the predictor training model as in \( (7.1) \), in which \( c_w^{uc,s} \) is the UC cost \( (7.1) \) induced by \( (\hat{w}_s, \hat{r}_s) \). Thus, the UC model in \( (7) \) is regarded as compromised.

\[
\min_{W,x,s,y_r,s} \frac{1}{|S|} \sum_{s \in S} \left[ a^T x_s + b^T y_s + c^T r_s - c_w^{uc,s} \right] \quad (7.1)
\]

s.t. \( (x_s, y_r, r_s) \in \mathcal{X}(\hat{W}(\hat{w}_s), \hat{r}_s); \mathcal{W}(\cdot) \in \mathcal{P}^w \forall s \in S \) \( (7.2) \)

Indeed, since \( (7) \) minimizes the in-sample training loss \( (7.1) \) instead of system cost \( (7.1) \), its in-sample UC solutions (i.e., \( x_s \) and \( y_s \)) may violate the least-cost merit-order principle (i.e., using more expensive units to pursue the minimum loss function \( (7.1) \)), leading to compromised UC decisions. Using these compromised UC solutions in the training would derive a predictor \( \mathcal{W}^* \) that fails to generalize well, i.e., overfitting \( (7) \).

Instead, this paper uses tri-level MIP to construct ERM, in which UC is exactly modeled in the middle level without compromise. In this way, the in-sample UC solutions always minimize the system cost \( (7.1) \), and the least-cost principle is strictly followed. With this, the accuracy of the feedback information can effectively avoid the overfitting issue.

III. Closed-Loop Predict-and-Optimize Framework

This section first constructs the tri-level MIP-based ERM problem and introduces its solution approach, followed by the prescriptive UC model that integrates the trained predictors into the UC model to simultaneously deliver the RES-reserve predictions and UC decisions with the enhanced market economy.

A. Constructing ERM Problem

Based on a preselected scenario set \( S \) (the scenario selection will be detailed in Section IV), the tri-level ERM problem is constructed as in \( (8) \). Solving \( (8) \) can provide cost-oriented predictors \( \mathcal{W}^* \) and \( \mathcal{R}^* \).

Upper Level (Predictor Training):

\[
\mathcal{E}^{rnm,s} = \min_{W,R} \frac{1}{|S|} \sum_{s \in S} \left[ a^T x_s + c^T r_s + d^T z_s \right] \quad (8.1)
\]

\[
\hat{w}_s = \mathcal{W}(\hat{w}_s); \hat{r}_s = \mathcal{R}(\hat{w}_s, \hat{I}_s) \quad \forall s \in S \quad (8.2)
\]

\[
\mathcal{W}(\cdot) \in \mathcal{P}^w; \mathcal{R}(\cdot) \in \mathcal{P}^r; r_s \leq \hat{r}_s \quad \forall s \in S \quad (8.3)
\]

Middle Level (UC for Day-Ahead Market Clearing):

\[
x_s, y_s, r_s \in \arg \min_{x_s, y_s, r_s \in \mathcal{X}(\hat{w}_s, \hat{I}_s)} a^T x_s + b^T y_s + c^T r_s \quad \forall s \in S \quad (8.4)
\]

Lower Level (ED for Real-Time Market Clearing):

\[
z_s \in \arg \min_{z_s \in \mathcal{Z}(x_s, y_s, r_s, \hat{w}_s, \hat{r}_s)} d^T z_s \quad \forall s \in S \quad (8.5)
\]

The upper level \( (8.1)-(8.3) \) trains the RES predictor \( \mathcal{W} \) and reserve (including SR and NR) predictor \( \mathcal{R} \). The training objective \( (8.1) \) is to minimize the weighted sum of actual system costs for all scenarios. Constraint \( (8.2) \) defines \( \mathcal{W} \) and \( \mathcal{R} \), respectively taking \( \hat{w}_s \) and \( (\hat{w}_s, \hat{I}_s) \) as inputs; \( (8.3) \) limits the predictor parameters within their feasible regions, and the last inequality ensures the non-triviality of \( \mathcal{R} \). In this paper, the predictors take the form of affine linear functions as in \( (8.3) \), because of their interpretability and numerical stability. With this, the training is essentially to determine the optimal vectors \( h, m, \) and \( n \).

\[
\mathcal{W}(\hat{w}_s) = h^T \hat{w}_s \quad \forall h \in \mathcal{P}^w \quad (9.1)
\]

\[
\mathcal{R}(\hat{w}_s, \hat{I}_s) = m^T \hat{w}_s + n^T \hat{I}_s \quad \forall (m, n) \in \mathcal{P}^r \quad (9.2)
\]

The middle level \( (8.4) \) and the lower level \( (8.5) \) respectively model UC \( (2) \) and ED \( (4) \) following their original models exactly without compromise.

Fig. 4 depicts how the tri-level ERM \( (8) \) closes the loop between the predictions and optimizations. The upper level generates the tailored predictions \( \hat{w}_s^* \) and \( \hat{r}_s^* \), but cannot directly assess their ultimate economic consequence. Thus, \( \hat{w}_s^* \) and \( \hat{r}_s^* \) are first passed to the middle-level day-ahead UC \( (8.4) \). Solving \( (8.4) \) provides the actual UC cost \( a^T x^* + c^T r^* \) to the upper level as well as the UC decisions \( (x^*, y^*, r^*) \) to the lower-level real-time ED. Then, ED \( (8.5) \) is solved to provide the actual ED cost \( d^T z^* \) to the upper level. With this, the upper level can assess the prediction quality via actual system cost \( a^T x^* + c^T r^* + d^T z^* \), and tune the predictor parameters accordingly. This process repeats until the optimally trained predictors \( \mathcal{W}^* \) and \( \mathcal{R}^* \) are obtained. Since \( \mathcal{W}^* \) and \( \mathcal{R}^* \) trained to optimize the market economy, they are economy-oriented (i.e., cost-oriented) and tailored for the market-clearing optimizations.

B. Solving ERM Problem

1) Convert \( (8) \) to Bilevel MIP \( (10) \): By leveraging special structure of the tri-level ERM \( (8) \), we convert it into a more tractable bilevel MIP \( (10) \). Solving \( (10) \) provides the optimal solution of the original ERM \( (8) \), as indicated in Proposition 1.

Proposition 1: The optimal solution of the bilevel MIP \( (10) \) is also optimal to the original tri-level MIP \( (8) \).

\[
\begin{align*}
\min_{W,R,z} & \quad \frac{1}{|S|} \sum_{s \in S} \left[ a^T x_s + c^T r_s + d^T z_s \right] \\
\text{s.t.} & \quad \hat{w}_s = \mathcal{W}(\hat{w}_s); \hat{r}_s = \mathcal{R}(\hat{w}_s, \hat{I}_s) \quad \forall s \in S \\
& \mathcal{W}(\cdot) \in \mathcal{P}^w; \mathcal{R}(\cdot) \in \mathcal{P}^r; r_s \leq \hat{r}_s \quad \forall s \in S \\
& \mathcal{Z}(x_s, y_s, r_s) \quad \forall s \in S \\
& \mathcal{X}(\hat{w}_s, \hat{I}_s) \quad \forall s \in S
\end{align*}
\]

Proof: See the Appendix.

2) Solve \( (10) \) by Reformulation and Decomposition: The bilevel MIP \( (10) \) is solved by a column-and-constraint generation (C&CG) type algorithm \( (25) \) which iterates between two subproblems SP1, SP2 and one master problem MP. The procedure is summarized in Algorithm 1.

Subproblem SP1 is shown as \( (11) \). It is a duplication of the UC problem \( (10.5) \) while taking the incumbent predictors \( \mathcal{W}_c \) and \( \mathcal{R}_c \) as inputs. Solving SP1 can reveal the UC cost \( c_w^{uc,s} \) induced by the incumbent predictors.

\[
\begin{align*}
\min_{x,y_r,r_s} & \quad a^T x_s + b^T y_s + c^T r_s \\
\text{s.t.} & \quad \hat{w}_s = \mathcal{W}_c(\hat{w}_s); \hat{r}_s = \mathcal{R}_c(\hat{w}_s, \hat{I}_s) \\
& \mathcal{F}(x_s, y_s) = 0 \\
& \mathcal{G}(x_s, y_s, r_s) = 0
\end{align*}
\]

Note that multiple optimal UC solutions for SP1 may exist, which however could lead to different system costs evaluated.
via (10.1). To tackle this issue, the second subproblem SP2 is modeled as in (12) with \( c^{\text{uc}}_s \) from SP1 as input. Essentially, solving SP2 is to select one of the multiple optimal UC solutions of SP1 in the favor of the objective (10.1). This is referred to as optimistic bilevel programming (25).

**SP2:**

\[
\begin{align*}
\min_{x, y, r_s, z_s} & \quad a^T x_s + c^T r_s + d^T z_s \\
\text{s.t.} & \quad \hat{w}^s = W_\nu(x_s, \hat{x}_s); \quad \hat{r}^s = R_c(x_s, \hat{I}_s) \\
& \quad a^T x_s + b^T y_s + c^T r_s \leq c^{\text{uc}}_s
\end{align*}
\]

(12.1)

Based on the selected UC decisions from SP2, the master problem MP is formulated as in (13).

**MP:**

\[
W(\cdot), R(\cdot); \quad m \in 3^{s, e} \\
\Xi = \{W(\cdot), R(\cdot), \hat{w}^s, \hat{r}^{\text{uc}}_s, z_s, x^d_s, y^d_s, r^d_s, y^g, r^g_s\}
\]

(13.1)

**Original Constraints (10.2)-(10.4):**

\[
\begin{align*}
W(\cdot) & \in \mathcal{P}^W; \quad R(\cdot) \in \mathcal{P}^R \\
\hat{w}^s = W(\hat{x}^s); \quad \hat{r}^s = R(\hat{w}^s, \hat{I}^s); \quad r_s \leq \hat{r}^s \\
M(x^d_s, z_s) = 0; \quad N(x^d_s, y^d_s, r^d_s, z_s, \hat{w}^s) \leq 0; \quad \forall s \in S
\end{align*}
\]

(13.2)

**Duplication of UC Constraints:**

\[
F(x^d_s, y^d_s) = 0; \quad G(x^d_s, y^d_s, r^d_s, \hat{w}^s, \hat{r}^{\text{uc}}_s) \leq 0; \quad \forall s \in S
\]

(13.3)

**Stationary of KKT (Optimality Cut):**

\[
\nabla L(y^g, \mu, \nu, \nu^{\text{uc}}) = 0 \quad \forall s \in S
\]

(13.5)

**Primal and Dual Feasibilities of KKT (Optimality Cut):**

\[
F(x^e_s, y^e_s) = 0; \quad G(x^e_s, y^e_s, r^e_s, \hat{w}^s, \hat{r}^{\text{uc}}_s) \leq 0; \quad \nu^e_s \geq 0; \quad \forall s \in S, e \in \mathcal{E}
\]

(13.6)

**Complementary Slackness of KKT (Optimality Cut):**

\[
\nu^e_s \perp G(x^e_s, y^e_s, r^e_s, \hat{w}^s, \hat{r}^{\text{uc}}_s) \quad \forall s \in S, e \in \mathcal{E}
\]

(13.7)

**Objective Cut (Optimality Cut):**

\[
a^T x^e_s + b^T y^e_s + c^T r^e_s \leq a^T x^e_s + b^T y^e_s + c^T r^e_s \quad \forall s \in S, e \in \mathcal{E}
\]

(13.8)

Three variants of the original UC variables \( \{x_s, y_s, r_s\} \) are used in MP, including duplicated \( \{x^d_s, y^d_s, r^d_s\} \), enumerated \( \{x^e_s\} \), and generated \( \{y^g, r^g_s\} \). The duplicated variables serve as the proxy of the original variables, but with a larger feasible region; the enumerated and generated variables and their associated cutting planes (13.5)-(13.9) serve to gradually cut the feasible region of duplicated variables. Finally, MP is built in three parts:

- The first part is (13.1)-(13.4) based on the duplicated variables. The objective function (13.1) also includes a regularization term \( \lambda \|W\|_1 \) with hyper-parameter \( \lambda \) to avoid overfitting. Constraints (13.2)-(13.4) correspond to the original constraints (10.2)-(10.4).
- The second part (13.5) is a duplication of UC constraints to ensure feasibility of the duplicated variables.
- The third part (13.6)-(13.9) serves as the optimality cuts for the duplicated variables. Note that \( x^e_s \) is a constant vector enumerated by SP2 for scenario \( s \) in iteration \( e \). When \( x_s \) is fixed as \( x^e_s \), (10.5) degenerates to a LP that can be equivalently substituted by the Karush–Kuhn–Tucker (KKT) condition (13.6)-(13.8).

Here, \( L(\cdot) \) denotes the Lagrangian function; \( \mu \) and \( \nu \) are dual variables of equalities and inequalities. The KKT (13.6)-(13.8) ensures the optimality of the generated variables given \( x^e_s \). Finally, (13.9) links the duplicated variables with their optimality cuts. By linearizing the complementary slackness (13.8) using Big-M method, MP can be directly solved via MIP solvers.

### C. Forming Prescriptive UC Model

The prescriptive UC model (14) can be formed by integrating the trained cost-oriented predictors \( W^* \) and \( R^* \) into the deterministic UC model (2). It presents two major favorable features as compared to the deterministic UC model (2):

- Integrating the predictors enables (14) to simultaneously deliver the RES-reserve predictions and UC decisions, referred to as prescription. In comparison, (2) exclusively focuses on the UC decision, and most existing forecasting works mainly focus on the prediction.
- \( W^* \) and \( R^* \) are affine linear functions (9). Therefore, the tailored predictions are essentially the linear scaling of the raw predictions, which will not introduce significantly extra computation burden in solving (14).

\[
\begin{align*}
\min_{x, y, r_s, \hat{w}^s, \hat{r}^s} & \quad a^T x + b^T y + c^T r \\
\text{s.t.} & \quad \hat{w}^s = W^*(\hat{w}); \quad \hat{r}^s = R^*(\hat{w}, \hat{I}) \\
& \quad (x, y, r) \in \mathcal{X}(\hat{w}^s, \hat{r}^s)
\end{align*}
\]

(14.1)

(14.2)

(14.3)

### IV. CASE STUDIES

#### A. Experimental Setting

1) C-PO Implementation Design: By leveraging adaptation to the ISO’s market-clearing practice and solution quality of (14), the proposed C-PO is implemented via a weekly rolling scheme, i.e., for each week, the predictors are retrained to update (14) using information of the past \( NH \) days.

Specifically, for the dispatch week of Days (\( D+1 \)) to (\( D+7 \)), before the first dispatch Day (\( D+1 \)), norm-2 distance of the net-load error (15) is calculated for each of the most recent \( NH \) days (i.e., Days (\( D-NH \)) to (\( D-1 \))). Among these \( NH \) historical days, \( NT \) days with the largest \( dist \) are selected to build the training scenario set \( S \). Then, the ERM (10) is solved to provide the cost-oriented predictors \( W^* \) and \( R^* \), which are used to form
the prescriptive UC model (14) used for Days \((D+1)\) to \((D+7)\). At the end of this period, the above process repeats to update the predictors and solve (14) for the next week (i.e., Days \((D+8)\) to \((D+14)\)).

\[
dist = \| I^\text{net} - \hat{I}^\text{net} \|_2 (15)
\]

2) Testing System Setup: All the cases are conducted on a modified IEEE 118-bus system (as shown in Fig. 5) and solved by Gurobi 9.1 on a 3.5 GHz PC. Based on the Belgian ISO data [26], eight weeks in 2020 are selected as in Table II each of which covers a seasonal peak/valley load. The Belgian data are properly scaled to build the RES and load data for the system.

The reserve prices \(C^r_t\) and \(C^p_t\) are set as 10% and 2% of the generation price at the nominal operating point [28]. The slack penalty prices \(C^s\), \(C^2\), and \(C^{\text{hos}}\) are $2,000/MWh, $1,750/MWh, and $1,500/MWh. The rule-of-thumb reserve requirement \(\hat{r}\) is set as 30% of raw net load predictions, of which at least 50% is for SR. Other data can be referred to from [27].

Table III lists all the models to be analyzed in this paper. Threshold on the optimality gap of all models is set as 1%.

### B. C-PO vs O-PO

This section compares C-PO and O-PO via two metrics: economy improvement (EI) (16) that evaluates the improvement in the market economy, and value of information (VoI) (17) that quantifies the value of the feedback information.

\[
EI = \left( e^{\text{sys},o-PO} - e^{\text{sys},c-PO} \right) / e^{\text{sys},o-PO} \times 100\% 
\]

\[
VoI = \left( e^{\text{sys},o-PO} - e^{\text{sys},c-PO} \right) / e^{\text{sys},c-PO} - e^{\text{sys},p-PO} \times 100\% (17)
\]

1) Results: Fig. 6 shows that all C-PO-NTs with \(NT = 1\) to 7 outperform O-PO economically. Moreover, C-PO-NTs with \(NT > 5\) generally outperform those with \(NT < 5\), in which C-PO-5 renders the best performance (0.82% EI and 30.85% VoI). Considering that even the ideal P-PO with an 100% VoI can only achieve 2.65% EI, the 0.82% EI of C-PO-5 would be regarded as non-trivial.

Table IV further shows the breakdown of actual system costs (no-load and slack costs are relatively small and thus not listed individually). Note that the main difference between O-PO and C-PO-A stems from the reserve schedules, implying that \(\hat{r}^o\) is generally redundant, and (17) in the real-time market.

Finally, Table VII evaluates RES prediction accuracy via four commonly used metrics, including MAE, root mean square error (RMSE), and mean over-/under-prediction percentage error (MUPE/MOPE). C-PO performs worse in MAE and RMSE. In addition, C-PO has a better MOPE but a worse MUPE, which indicates that C-PO tends to conservatively predict RES power (i.e., \(\hat{w}^o\) is statistically smaller than \(w\)).

2) Discussions: The above results clearly indicate that C-PO outperforms O-PO economically. Still, the reasons behind this conclusion deserve further discussion.

As shown in Table VII, the economy difference mainly stems from the reserve schedules. Specifically, SR and NR schedules of C-PO-A are 43.5% and 29.7% lower than those of O-PO, respectively. This is because C-PO learns that (i) the rule-of-thumb \(\hat{r}\) is generally redundant, and (ii) \(C^r_t\) is five times \(C^p_t\). Therefore, C-PO properly lowers \(\hat{r}^o\) and increases the utilization of NR, as shown in Table VII.

However, decreasing the reserve schedules may trigger load shedding in the face of \(\hat{w}\). To avoid this, C-PO leverages lower \(\hat{w}^o\) and higher base-generation \(P^o\) in the day-ahead market, allowing ISOs to flexibly dispatch RES and avoid load shedding when faced with \(\hat{w}^n\) in the real-time market.

In summary, by effectively learning the UC-ED optimization information, C-PO simultaneously tailors raw (\(\hat{w}, \hat{r}\)) to cost-oriented (\(w^o, r^o\)) for improving market economy. Even though the tailored predictions are slightly worse in accuracy, they enable ISOs to use various resources more economically, leading to a better electricity market economy than O-PO.
C. C-PO vs Two-Stage Optimization with MIP Recourse

The following points are adopted for the sake of comparisons:

- Load and RES are regarded as uncertainty factors, whose prediction and actual realization are denoted by \( \hat{u} \) and \( u \), respectively. The day-ahead point forecast and the 90% confidence interval for \( \hat{u} \) are available from [26].
- T-SP is modeled as a scenario-based SP [6] via (18). To construct the scenario set \( \mathcal{H} \), 3,000 scenarios are generated via Latin Hypercube sampling within the 90% confidence interval, and then reduced to NS scenarios via a scenario-tree method [29]. The probability of scenario \( h \) is denoted by \( p_h \). For the sake of comparison, (18) is solved directly.

\[
\begin{align*}
\min_{x, y, r, s_h} & \quad a^T x + b^T y + c^T r + p_h \sum_{h \in \mathcal{H}} d^T z_h \\
\text{s.t.} & \quad (x, y, r) \in \mathcal{X}(\hat{u}) \quad (18.1) \\
& \quad z_h \in Z(x, y, r, \hat{u}_h) \quad \forall h \in \mathcal{H} \quad (18.2) \\
& \quad \mathcal{U} \text{-scenario} \\
\end{align*}
\]

- T-RO is modeled as an adjustable RO [7] via (19). The box uncertainty set \( \mathcal{U} \) is constructed using the 90% confidence intervals, and the budget parameter \( \Gamma \in [0, 48] \) controls the robustness degree. A nested C&CG algorithm [7] is applied to solve (19).

\[
\begin{align*}
\min_{x, y, r} & \quad a^T x + b^T y + c^T r + \max_{u \in \mathcal{U}} \min_{z} d^T z \\
\text{s.t.} & \quad (x, y, r) \in \mathcal{X}(\hat{u}) \quad (19.1) \\
& \quad z \in Z(x, y, r, \hat{u}, \Gamma) \quad (19.2) \\
\end{align*}
\]

The reserve schedules are implicated in the second-stage ED of (18) and (19) (i.e., (18.3) and (19.3)), thus the reserve requirement constraints (1.17)–(1.18) are not included.

1) C-PO vs T-SP: Fig. 7(a) sketches the economy comparison of C-PO and T-SP on the four peak-load days. The following points are observed:

- T-SP-NSs require dozens of scenarios to perform well, thus leaving a wide cost gap among different NS values. Relatively, C-PO-NTs need fewer scenarios, with a narrower cost gap among different NT values. It indicates that the tri-level ERM enables C-PO to effectively mine the value of information, thus ensuring its performance in case of limited scenarios.
- Except for the winter day, the costs of T-SP-NSs finally fall within the cost gap (i.e., red shadows) of C-PO. It implies that the economy efficiencies of T-SP and C-PO are mutually reachable with larger NS values.
- On the winter day, even with \( NS = 100 \), T-SP-NS still performs poorly. This is because the confidence intervals cannot exactly cover the underlying distributions of \( \hat{u} \) and T-SP-NSs would encounter tremendous slack penalties.

2) C-PO vs T-RO: Fig. 7(b) further compares the reserve schedules in fall. It shows that T-RO-NBs outperform the C-PO-NTs in spring and summer, are outperformed by C-PO-NTs in winter, and are comparable to C-PO-NTs in fall. Additionally, several T-RO-NBs fall within the red shadows, e.g., T-RO-16 in spring and T-RO-32 in fall. It implies that T-RO and C-PO could achieve similar economy performance with properly tuned parameters.
3) Discussions: The above comparisons indicate that the market economy of C-PO is comparable to T-SP and T-RO. Although a clear-cut economic benefit of C-PO is yet to be observed, C-PO does present certain practical advantages.

Computational affordability to ISOs: The day-ahead market clearing has been widely regarded as one of the most computationally challenging tasks [5]. Concerning that T-SP/T-RO is much more computationally taxing than its deterministic counterpart, most ISOs still utilize the deterministic UC model (2) to clear the markets. In comparison, C-PO is trained offline and the prescriptive UC model (4) keeps a similar online computation burden as O-PO, thus is more affordable to ISOs.

Compatibility with the current market designs: The markets are designed to achieve maximum social welfare. Thus, ISOs are required to identify the economically optimal UC decisions given the predictions, which is vital to derive fair market signals for incentivizing the market participants. However, UC decisions of T-SP/T-RO may not follow the least-cost principle in the short term due to the uncertainty consideration. Although better social welfare may be reached in a long-term view, the short-term financial deficit would demotivate the market participants [23].

While pursuing short- and long-term social welfare maximization, ISOs in a transparent market also focus on the fairness and interpretability of market-clearing results to market participants, on which T-SP and T-RO could expose intrinsic obstacles in practical application. For T-SP, a stable market-clearing result mathematically requires a sufficiently large number of scenarios, which, however, will undoubtedly magnify the existing computational challenge and ultimately end up with a trade-off between the number of scenarios and result stability; while for T-RO, subject to the availability of tractable reformulation, adaptable uncertainty budget forms are usually simple, abstract, and heavily parameter-dependent. These together lead to volatility and poor interpretability of market-clearing results.

Specifically, different scenario sets and uncertainty budget settings, even with tiny differences, could lead to noticeable unit commitment changes that may significantly affect the revenues of certain market participants, especially those who are committed/decommitted from one case to another. Scenario generation inevitably introduces randomness, which practically will arouse complaints and misgivings of market participants on the market-clearing results. An immediate question is why a scenario set is employed instead of others as all are randomly generated.

Analogously, uncertainty budget settings will suffer from the same issue. Moreover, an abstract uncertainty budget lacks a way to be intuitively linked with the market-clearing result. That is, the impacts of budget forms and settings on the market-clearing results are difficult to be interpreted and quantified, causing suspicions to market participants, especially those whose economic interests are not in line with the expectations.

In comparison, the prescriptive UC (4) presents the same model structure as (2), thus following the least-cost principle and remaining strong interpretability. In addition, the results have clearly illustrated that efficiencies of T-SP/T-RO and C-PO are mutually reachable. Thus, it is promising to harness the compatibility of C-PO in bridging the gap between T-SP/T-RO and the current market practice.

D. Sensitivity Analysis

Sensitivity analysis on predictors of the C-PO is further conducted. The results are listed in Table VII in which C-PO-NT-R/C-PO-NT-W only predicts reserves/RES and keeps raw RES/reserves. It shows that C-PO-NTs have a slightly better accuracy than C-PO-NT-Ws, and also achieve the best EI. This observation supports our motivation—simultaneously predicting RES and reserves to assess their joint ultimate economic consequence out of the UC-ED optimization is beneficial.

Regarding the reserve schedules, both SR and NR are lower than the raw schedules. SR decreases as NT goes up but NR saturates at 272MW. This is because C-PO can properly reduce SR schedule. As NR is an important safeguard against load shedding, it saturates at a relatively high threshold.

It is also observed that C-PO-NT-Ws result in negative EI, indicating that the closed-loop learning may cause an adverse impact on market economy. Indeed, C-PO possesses the common issue existing in wide machine learning methods—there is no absolute guarantee that learning will always bring in extra benefits. Nevertheless, this issue could be relieved with sufficient training scenarios and well-tuned hyper-parameters.

V. Conclusion

The electricity market economy suffers from the traditional O-PO framework. To this end, this paper proposes a tri-level based C-PO framework for improving the market economy. The core is to train the RES and reserve predictors that can generate cost-oriented predictions for the market-clearing optimization task. Numerical case studies on an IEEE 118-bus system lead to the following conclusions:
APPENDIX

Proof: To prove Proposition 1, problem (20) is built to serve as a bridge between (8) and (10), which is constructed by adding (20.4) to (8) or adding (20.6) to (10).

\[
\min_{W \in \Omega, z^\ast} \sum_{s \in S} [a^\top x_s + c^\top r_s + d^\top z_s] / |S| \\
\text{s.t. } \hat{w}^s = W(\hat{w}_s), \quad \hat{r}_s = R(\hat{w}_s, \hat{L}_s) \quad \forall s \in S \tag{20.1}
\]

\[
W(\cdot) \in \Omega^\ast; \quad R(\cdot) \in \Omega^\ast; \quad r_s \leq \hat{r}_s \quad \forall s \in S \tag{20.2}
\]

\[
z_s \in Z(\{x_s, y_s, r_s, \hat{w}_s\}) \tag{20.3}
\]

\[
x_s, y_s, r_s \in \arg\min_{(x_s, y_s, r_s) \in \mathcal{X}(\hat{w}^s, \hat{r}_s^s)} a^\top x_s + b^\top y_s + c^\top r_s \tag{20.4}
\]

\[
z_s \in \arg\min_{z_s \in Z(x_s, y_s, r_s, \hat{w}_s)} d^\top z_s \tag{20.5}
\]

First, we claim that optimal solutions of (8) and (20) are the same because of their identical objective functions and feasible regions. They have the same feasible regions because: (i) a feasible solution of (8) satisfies all constraints of (20) and thus is feasible to (20); and (ii) a feasible solution of (20) also meets all constraints of (8) and thus is feasible to (8). Thus, it is direct to conclude that (8) and (20) have the same optimal solutions.

Second, we claim that the optimal solution of (10) is also optimal for (20). Note that as (10) is equivalent to (20.1)-(20.5), we only need to show that the optimal solution of (10) also satisfies (20.6). Specifically, if \(\Omega^\ast\) (including \(x^s, y^s, r^s, z^s\)) is an optimal solution of (10), \(z^s\) must be optimal for (21) that is constructed by fixing all variables in (10) to their optimal except \(z_s\). Problem (21) is equivalent to (20.6). Thus, because \(\Omega^\ast\) is optimal for (20.1)-(20.5) and its \(z^s\) also satisfies (20.6), \(\Omega^\ast\) must be optimal for (20).

\[
\min_{z_s \in Z(x_s, y_s, r_s, \hat{w}_s)} \sum_{s \in S} [a^\top x^s + c^\top r^s + d^\top z^s] / |S| \tag{21.1}
\]

\[
\text{s.t. } z_s \in \arg\min_{z_s \in Z(x_s, y_s, r_s, \hat{w}_s)} d^\top z_s \quad \forall s \in S \tag{21.2}
\]

From the above two claims, it is direct to conclude that the optimal solution of (10) is optimal for (20), and thus is also optimal for (8).

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