Grid Integration of Wind Generation Considering Remote Wind Farms: Hybrid Markovian and Interval Unit Commitment

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***Abstract*—Grid integration of wind power is essential to reduce fossil fuel usage but challenging in view of the intermittent nature of wind. Recently, we developed a hybrid Markovian and interval approach for the unit commitment and economic dispatch problem where power generation of conventional units is linked to local wind states to dampen the effects of wind uncertainties. Also, to reduce complexity, extreme and expected states are considered as interval modeling. Although this approach is effective, the fact that major wind farms are often located in remote locations and not accompanied by conventional units leads to conservative results. Furthermore, weights of extreme and expected states in the objective function are difficult to tune, resulting in significant differences between optimization and simulation costs. In this paper, each remote wind farm is paired with a conventional unit to dampen the effects of wind uncertainties without using expensive utility-scaled battery storage, and extra constraints are innovatively established to model pairing. Additionally, proper weights are derived through a novel quadratic fit of cost functions. The problem is solved by using a creative integration of our recent surrogate Lagrangian relaxation and branch-and-cut. Results demonstrate modeling accuracy, computational efficiency, and significant reduction of conservativeness of the previous approach.**

***Index Terms*—Branch-and-cut, interval optimization, Markov decision process, remote wind farms, surrogate Lagrangian relaxation (SLR), unit commitment.**

I. Introduction

To reduce greenhouse gas emissions and global warming caused by fossil fuels, the use of renewable energy such as wind is essential. In 2014 alone, more than 51 GW of wind capacity was installed, bringing the global wind capacity to nearly 370 GW, an increase of 14% since 2013 [1]. The U. S. Department of Energy's goal is to increase the nation's wind energy to 20% by 2030 [2]. A critical operation process of wind integration is day-ahead unit commitment (UC). In the UC process, independent system operators, which coordinate, control and monitor power system operation within a single or multiple states in the U. S., commit conventional units with wind generation to meet the forecasted demand of the following day. UC with high levels of wind integration is challenging because of the intermittent nature of wind.

To incorporate wind uncertainties in UC, the literature offers several approaches, e.g., stochastic programming, robust optimization, interval optimization, and hybrid approaches. In stochastic programming, uncertainties are modeled by representative scenarios. However, it is difficult to select an appropriate number of scenarios to balance modeling accuracy and computational efficiency. While in robust optimization, uncertainties are modeled by sets, and an optimal solution of the worst-case realization is found, feasible for all realizations, leading to conservativeness. As for interval optimization, uncertainties are modeled by intervals to capture bounds of uncertain wind generation, where other realizations within these bounds are guaranteed to be feasible. The approach is computationally efficient, but results are still conservative. There are also hybrid approaches of the above.

Recently, to solve the UC problem with uncertain wind generation, we developed a hybrid approach [3]. The basic idea is to divide power generation of conventional units into two components: a Markovian one depending on local wind states to dampen the effects of wind uncertainties, and an interval one that manages extreme non-local states to capture constraint bounds for solution feasibility. To reduce complexity, extreme and expected states are considered as interval modeling. The problem was solved by branch-and-cut. Results demonstrated that the approach is effective, computationally efficient, and less conservative as compared to other methods. However, wind farms are often located in remote locations with high-output wind resources, far from cities, where electricity demand is high [4]. For example, in Texas, most wind farms are in the windy western part, while load centers and most conventional units are in the eastern part [5], [6]. With the

Manuscript received December 3, 2015; accepted May 25, 2016. This work was supported in part by the Project Funded by ABB and U.S. National Science Foundation (ECCS-1509666). Recommended by Associate Editor Qinmin Yang.

Citation: B. Yan, H. P. Fan, P. B. Luh, K. Moslehi, X. M. Feng, C. N. Yu, M. A. Bragin, and Y. W. Yu, "Grid integration of wind generation considering remote wind farms: hybrid markovian and interval unit commitment," *IEEE/CAA Journal of Automatica Sinica*, vol. 4, no. 2, pp. 205−215, Apr. 2017.

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Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation and ABB.

Digital Object Identifier 10.1109/JAS.2017.7510505

consideration of remote wind farms, this approach could still be conservative since it degenerates to the pure interval approach.

In this paper, our idea is to pair each remote wind farm with a sufficiently large and not necessarily collocated conventional unit with high ramp rates to dampen the effects of wind uncertainties without using expensive utility-scaled battery storage. However, with wind farms and units coupled, the problem is difficult to formulate and to solve. Furthermore, weights of extreme and expected states in the objective function are difficult to tune, resulting in significant differences between optimization and simulation costs.

Section II of this paper presents a literature review. Section III establishes a novel formulation where each remote wind farm is paired with a sufficiently large conventional unit with high ramp rates. The pairing is based on heuristic rules, not optimized, since the pairing itself is a combinatorial problem. With non-local units treated as virtual local ones, the constraints are established to formulate the pairing relation and to model extreme generation. Section IV describes the solution methodology, a creative integration of our recent Surrogate Lagrangian Relaxation (SLR) and branch-and-cut [7]. Additionally, proper weights are derived through a novel quadratic fit of cost functions. Section V provides testing results that include a simple system, and the IEEE 30-bus and 118-bus systems. Numerical results demonstrate modeling accuracy, computational efficiency, and significant reduction of conservativeness of the previous approach. The formulation established is general and can be applied to real-time UC as well. This generic nature allows modeling of other intermittent resources such as solar.

II. Literature Review

To solve UC with wind uncertainties, stochastic programming, robust optimization, interval optimization, hybrid methods, and our earlier work are briefly reviewed in this section. More detailed reviews of these methods are provided in [3].

A. Stochastic Programming

In stochastic programming, uncertainties are modeled by representative scenarios [8]−[13]. To generate scenarios, wind generation is typically assumed to follow a certain probability distribution, and each scenario represents a sequenced realizations of wind uncertainties over the optimization horizon. From the modeling point of view, the locations of wind farms do not matter. In this method, optimization determines a single set of UC decisions to satisfy all the selected scenarios and multiple sets of dispatch decisions for the corresponding scenarios. The objective is to minimize the sum of the commitment cost and the expected dispatch cost with equal weights. Decomposition methods, such as Benders' decomposition [10] and Lagrangian relaxation [11], are commonly used to solve such problems. Since the number of scenarios in the method can be extremely large even with discrete probability distributions, scenario reduction is commonly used [14]−[16]. However, it is difficult to determine a proper number of scenarios to balance modeling accuracy, solution feasibility, and computational efficiency.

B. Robust Optimization

In robust optimization, uncertainties are modeled by a predetermined set, where wind farms at different locations are treated similarly [17]−[21]. Optimization determines a single set of UC decisions to be feasible for all possible realizations and a set of dispatch decisions against the worst-case realization. Since the objective is to minimize the worst-case cost, there is no need of weights. In robust optimization, Benders' decomposition is usually combined with other methods, such as outer approximation [17] and cutting plane [18] to solve the problems. This method gives conservative solutions, and the models involve nonlinear min/max functions which require much computational effort [17].

C. Interval Optimization

In interval optimization, uncertainties are modeled by closed intervals in terms of upper and lower bounds [10], [22], where the locations of wind farms are not a concern. In this method, it requires a set of UC decisions to be feasible for all the bounds, and two sets of dispatch decisions to be feasible for the bounds of system demand and transmission capacity constraints captured by bounds of uncertain wind generation [22]. The objective is to minimize the sum of the costs associated with the minimum and maximum wind generation under equal weights. Since only the two sets of dispatch decisions and bounds of system-wide constraints are considered, the method requires less computational effort, and provides the lower and upper bounds for the total cost. However, its optimal solution is very sensitive to the uncertainty interval, which needs to be carefully selected. A narrow interval may not cover the entire uncertainty and the solution does not correspond to all possible uncertain situations. A wide interval could lead to pessimistic solutions where resources are not efficiently utilized.

D. Hybrid Methods

A hybrid stochastic and robust approach is developed in [23], where dispatch decisions and constraints from both stochastic programming and robust optimization are considered at the same time. By minimizing the weighted sum of the costs from both approaches, this hybrid approach provides more robust UC decisions than stochastic programming and a lower simulation cost than robust optimization. System operators can adjust the weights in the objective function based on their preferences for the two methods. Its robust optimization part is still nonlinear. A hybrid stochastic and interval approach is developed in [24]. In this approach, in the first few hours, stochastic programming is considered, and in the remaining hours, interval optimization is used, where their costs have equal weights. This hybrid approach provides a lower simulation cost than either of the two methods, while its interval optimization part remains conservative. For neither stochastic/robust nor stochastic/interval approaches, the locations of wind farms matter.

E. Our Previous Work

In our early work [25], without considering transmission capacities, aggregated wind generation is molded as a Markov chain instead of scenarios to reduce complexity. However, when considering transmission, wind generation at different locations cannot be aggregated and has to be modeled as a Markov chain at each node. To avoid explicitly considering all global states, interval optimization is synergistically integrated with the Markovian approach in [3]. The basic idea is to divide power generation of conventional units into two components: a Markovian one depending on local wind states to dampen the effects of wind uncertainties, and an interval one that manages extreme non-local states to capture constraint bounds for solution feasibility. In this way, the Markovian component only depends on local wind states. In the pure Markovian approach, wind generation depends on all wind states, therefore the problem is combinatorial. Consider a system with I wind farms, and assume that each one has N states. For each local conventional unit, there are N^I dispatch decisions per hour where the complexity increases exponentially with the number of wind farms. In the hybrid approach, there are only N^I dispatch decisions per hour for each local conventional unit where the complexity increases linearly with the number of wind farms, therefore the computational complexity is dramatically reduced. In addition, by making use of information provided by local states and their transitions, this approach is less conservative than pure interval optimization. The detailed complexity and conservativeness comparison among the hybrid, pure Markovian and pure interval approaches can be found in Section IV-B of [3]. With appropriate transformations, the problem is converted to a linear form and solved by using branch-and-cut. In Examples 1 and 2 of [3], a small system with three buses and the IEEE 30-bus system are tested, respectively, and results show that this approach is less conservative than pure interval optimization. In Example 3, the IEEE 118-bus system is tested, and the problem can be solved in about one minute, which shows this method is computationally efficient. Also, the lower relative difference between the simulation and optimization costs demonstrates the modeling accuracy. However, with the consideration of remote wind farms, the approach could still be conservative since it degenerates to the pure interval approach. In addition, weights of extreme and expected states in the objective function are difficult to tune, resulting in significant differences between optimization and simulation costs.

III. PROBLEM FORMULATION

Based on our early work [3], a novel formulation is developed by pairing remote wind farms and conventional units without using expensive utility-scaled battery storage in this section. It contains three major sets of constraints at unit, nodal, and system levels as presented in the first three sections. The objective is to minimize the commitment cost plus the weighted sum of the dispatch costs for the extreme and expected states as shown in the last section.

A. Unit Level Constraints

Based on [3], consider a day-ahead energy market for an independent system operator over 24 (T) hours with each hour indexed by t ($1 \le t \le T$). At node i of the power system, there are K_i (≥ 0) conventional units indexed by (i, k) ($0 \le k \le K_i$), and their properties such as cost functions and capacities are assumed known. At some nodes, there are also wind farms. The demand $p_i^L(t)$ (MW) is assumed known for node i at hour t. In the power system, there are L transmission lines indexed by l ($1 \le l \le L$), where line l has a transmission capacity $f_l^{\max}$ (MW). The UC problem is to commit conventional units to meet the forecasted demand of the following day while satisfying individual unit and node constraints as well as transmission constraints. In this section, constraints corresponding to UC decisions and dispatch decisions at the unit level are formulated as follows.

1) Generation Level: Based on [3], the generation level of a conventional unit$_{i,k}$ (dispatch decision) at time t is divided into two components: Markovian generation $p_{i,k,n_i}^M(t)$ depending on local wind state n_i, and interval generation $p_{i,k,\bar{n}_i}^I(t)$ depending on extreme non-local states $\bar{n}_i$, i.e.,

$$p_{i,k,n_i,\bar{n}_i}(t) = p_{i,k,n_i}^M(t) + p_{i,k,\bar{n}_i}^I(t) \quad \forall i; \;\; \forall k; \;\; \forall t. \tag{1}$$

In the above, the minimum possible local state of node i is denoted by min n_i, and the maximum by max n_i. Its minimum non-local state is denoted as m_i, which is a combination of possible minimum states of other nodes. The maximum non-local state is defined as M_i in a similar way. A global state g at time t is a combination of wind generation states at all nodes.

2) Startup Constraints: The binary startup variable $u_{i,k}(t)$ equals 1 if and only if the unit is turned on from offline at hour t, i.e.,

$$u_{i,k}(t) \geq x_{i,k}(t) - x_{i,k}(t-1) \quad \forall i; \;\; \forall k; \;\; \forall t \tag{2}$$

where $x_{i,k}(t)$ represents the on/off status (binary, "1" online and "0" offline), and $u_{i,k}(t)$ represents the start-up status (binary, "1" start-up and "0" otherwise).

3) Minimum up/down Time: The unit must remain online or offline for its minimum up or down time, respectively. The formulas in [27, eq. (3) and (5)] are used here.

4) Generation Capacity Constraints: If a unit is online, its generation level should be within its minimum and maximum values; otherwise, its generation level has to be zero, i.e.,

$$x_{i,k}(t)p_{i,k}^{\min} \leq p_{i,k,n_i,\bar{n}_i}(t) \leq x_{i,k}(t)p_{i,k}^{\max}$$

$$\forall i, \; \forall k, \; \forall t, \; \forall n_i \in \Omega_i(t); \; \forall \bar{n}_i \in \{m_i, M_i\} \tag{3}$$

where $p_{i,k}^{\min}$ (MW) and $p_{i,k}^{\max}$ (MW) are minimum and maximum generation levels, respectively, and $\Omega_i(t)$ is the set of possible wind states of node i at hour t, i.e., $\Omega_i(t) \equiv \{n_i | \varphi_{n_i}(t) > 0\}$, where $\varphi_{n_i}(t)$ is the probability that wind generation is at state n_i during time t. The expression $n_i \in \Omega_i(t)$ and $\overline{n}_i \in \{m_i, M_i\}$ is omitted for the rest of the paper.

5) Ramp Rate Constraints: Ramp rate constraints require that the change of the generation level cannot exceed the unit's ramp rate between two consecutive hours. Based on [22, eq. (21) and (22)], if the unit is online at hours $t-1$ and t, then for all possible state transitions and the two extreme non-local states, the variation of generation levels cannot exceed its ramp rate, i.e.,

$$p_{i,k,n_i',\bar{n}_i'}(t{-}1) - R_{i,k} \le p_{i,k,n_i,\bar{n}_i}(t) \le p_{i,k,n_i',\bar{n}_i'}(t{-}1) + R_{i,k}$$
$$\forall (n_i', n_i) \in \{(n_i', n_i) | \varphi_{n_i'}(t),\ \pi_{n_i' n_i} > 0\}$$
$$\forall \bar{n}_i;\ \ \forall \bar{n}_i';\ \ \forall\, i;\ \ \forall\, k;\ \ \forall t \tag{4}$$

where $R_{i,k}$ (MW/ hour) denotes the ramp rate; n_i' and $\bar{n}_i'$ denote the local and non-local states of node i at hour $t{-}1$; and denotes the transition probability from state n_i' to state n_i, which is established based on historical data and forecasted weather. In addition, generation limits at start-up and shut-down hours [28, eq. (11)] are merged with (4) based on [25].

The above constraints are for conventional units accompanied with local wind farms. For the units paired with remote wind farms, their Markovian generation depends on wind states of the corresponding remote wind farms. For the units not accompanied with local wind farms or paired with remote ones, their generation only has the interval components.

The dispatch decisions of the expected state E (where wind generation is at their expected values) will be also considered in the objective function to be discussed later. With the same set of commitment decisions and one set of dispatch decisions $p_{i,k,E}(t)$, the constraints for the expected state can be easily included as a set of deterministic constraints. These constraints are not presented here for conciseness.

B. Nodal Level Constraints

Based on locations of wind farms and conventional units in the system, there are five types of nodes which are associated with: wind farms and conventional units; remote wind farms; conventional units paired with remote wind farms; conventional units; and no wind farms or conventional units, respectively. Let I^{LW}, I^{RW}, I^{LU}, I^{NU} and I^{NN}denote the sets of those nodes, respectively. The nodal level constraints are presented below.

1) Load Shedding Constraints: When wind and conventional generation cannot meet the system demand, the load has to be shed, where the shed load cannot exceed the total load, i.e.,

$$p_{i,n_i,\bar{n}_i}^{LS}(t) = p_{i,n_i}^{LS,M}(t) + p_{i,\bar{n}_i}^{LS,I}(t) \le p_i^L(t)$$
$$\forall i;\ \ \forall t;\ \ \forall n_i;\ \ \forall \bar{n}_i \tag{5}$$

where $p_{i,n_i}^{LS,M}(t)$, $p_{i,\bar{n}_i}^{LS,I}(t)$ and $p_{i,n_i,\bar{n}_i}^{LS}(t)$ denote the Markovian, interval and total load shedding of node i at time t, respectively. The above constraints are for all nodes, while there are no Markovian components for I^{NU} and I^{NN}.

2) Wind Curtailment Constraints: When wind and conventional generation exceeds the system demand, wind generation has to be curtailed, where the curtailed wind power should be less than the total, i.e.,

$$p_{i,n_i}^{WC}(t) \le p_{i,n_i}^{W},\quad i \in I^{LW} \cup I^{RW};\ \ \forall t;\ \ \forall n_i \tag{6}$$

where $p_{i,n_i}^{WC}(t)$ and $p_{i,n_i}^{W}(t)$ denote the curtailed and total wind generation of node i under state n_i at time t, respectively. Based on [3], wind generation at different nodes is treated separately and assumed to be modeled as independent Markov chain for simplicity. At each node, wind generation is discretized into N states, arranged in the ascending order.

3) Nodal Injections: The nodal injection for the node with wind farms and conventional units equals wind generation (after curtailment) plus conventional generation and minus the demand (after load shedding), i.e.,

$$P_{i,n_i,\bar{n}_i}(t) = p_{i,n_i}^{W}(t) - p_{i,n_i}^{WC}(t) + \sum_k p_{i,k,n_i,\bar{n}_i}(t) + p_{i,n_i,\bar{n}_i}^{LS}(t)$$
$$- p_i^L(t),\quad i \in I^{LW};\ \ \forall t;\ \ \forall n_i;\ \ \forall \bar{n}_i. \tag{7}$$

For node $i \in I^{RW}$, there is no conventional generation; for node $i \in I^{LU}$, there is no wind generation or curtailment; for node $i \in I^{NU}$, there are no wind related terms or Markovian components; and for node $i \in I^{NN}$, there are no wind or unit related terms.

C. System Level Constraints

System level constraints consist of system demand and transmission capacity constraints as follows.

1) System Demand Constraints: These constraints require that the total wind generation plus the total conventional generation equals the total system demand (after wind curtailment and load shedding) at each hour, i.e., the sum of nodal injections of all nodes, equals zero. Based on [22, eq. (20)], the lower bound of the total wind generation happens at the minimum global state m (when the outputs of all wind farms are at their lower limits), while the upper bound happens at the maximum global state M. As long as the minimum and maximum states are satisfied, system demand is satisfied for all other states. At the minimum state m, system demand constraints are described as follows:

$$\sum_i P_{i,\min n_i,m_i}(t) = 0 \quad \forall t. \tag{8}$$

Similarly, the constraints at the maximum state M are:

$$\sum_i P_{i,\max n_i,M_i}(t) = 0 \quad \forall t. \tag{9}$$

2) Transmission Capacity Constraints: These constraints imply that the power flow through a line at each hour cannot exceed its transmission capacity. In DC power flow, a line flow is a linear combination of nodal injections weighted by generation shift factors (GSFs). Since GSFs could be positive or negative, the nodal injection terms of (7) are regrouped to a Markovian nodal injection consisting of those related to local states:

$$P_{i,n_i}^{M}(t) \equiv p_{i,n_i}^{W}(t) - p_{i,n_i}^{WC}(t) + \sum_k p_{i,k,n_i}^{M}(t)$$
$$+ p_{i,n_i}^{LS,M}(t) - p_i^L(t) \quad \forall i;\ \ \forall t;\ \ \forall n_i \tag{10}$$

and an interval nodal injection related to non-local states:

$$P_{i,\bar{n}_i}^{I}(t) \equiv \sum_k p_{i,k,\bar{n}_i}^{I}(t) + p_{i,\bar{n}_i}^{LS,I}(t) \quad \forall i;\ \ \forall t;\ \ \forall \bar{n}_i. \tag{11}$$

The above two equations are for nodes with wind farms and conventional units. For other types of nodes, their nodal injections are regrouped with the corresponding components as discussed at the end of Section III-B.

Bounds of Markovian flow levels are calculated based on GSF signs and the corresponding extreme Markovian nodal injections, i.e.,

$$\begin{aligned}&\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i>0}[a_l^i\cdot\min_{n_i}P_{i,n_i}^M(t)]\\&\quad+\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i<0}[a_l^i\cdot\max_{n_i}P_{i,n_i}^M(t)]\\&\le\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}}[a_l^i\cdot P_{i,n_i}^M(t)]\\&\le\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i>0}[a_l^i\cdot\max_{n_i}P_{i,n_i}^M(t)]\\&\quad+\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i<0}[a_l^i\cdot\min_{n_i}P_{i,n_i}^M(t)]\quad\forall t.\end{aligned}\tag{12}$$

Bounds of interval flow levels can be obtained from the two sets of interval nodal injections directly, i.e.,

$$f_{l,m}^I(t)=\sum_i[a_l^i\cdot P_{i,m_i}^I(t)]\quad\forall l;\quad\forall t\tag{13}$$

$$f_{l,M}^I(t)=\sum_i[a_l^i\cdot P_{i,M_i}^I(t)]\quad\forall l;\quad\forall t.\tag{14}$$

The above two interval flow levels are required to satisfy the two extreme Markovian flow levels in transmission capacity constraints as formulated in (15) and (16), so that other states also satisfy transmission capacity constraints, i.e.,

$$\begin{aligned}&\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i>0}[a_l^i\cdot\min_{n_i}P_{i,n_i}^M(t)]\\&\quad+\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i<0}[a_l^i\cdot\max_{n_i}P_{i,n_i}^M(t)]+f_{l,g}^I(t)\\&\qquad\ge-f_l^{\max}(t)\qquad\forall l;\ \forall t;\ \forall g\in\{m,M\}\end{aligned}\tag{15}$$

$$\begin{aligned}&\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i>0}[a_l^i\cdot\max_{n_i}P_{i,n_i}^M(t)]\\&\quad+\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i<0}[a_l^i\cdot\min_{n_i}P_{i,n_i}^M(t)]+f_{l,g}^I(t)\\&\qquad\le f_l^{\max}(t)\qquad\forall l;\ \forall t;\ \forall g\in\{m,M\}.\end{aligned}\tag{16}$$

In the above, the min/max operations for the nodes with wind farms and conventional units can be linearized based on the monotonicity conjecture obtained in [3]. Consider two possible local states at node i: state n_i, and state n_i-1. The local state with lower wind generation provides a less or equal Markovian nodal injection at the optimum, i.e.,

$$\begin{aligned}&P_{i,n_i-1}^M(t)\le P_{i,n_i}^M(t),\quad i\in I^{LW}\\&\forall t;\ \forall n_i;\ \forall(n_i-1)\in\{n_i-1|\varphi_{n_i-1}(t)>0\}\end{aligned}\tag{17}$$

where $\varphi_{n_i-1}(t)$ is the probability that wind generation is at state n_i-1 during time t. Based on the above conjecture, the minimum Markovian nodal injection happens at the minimum local wind state at the optimum, i.e.,

$$\min_{n_i}P_{i,n_i}^M(t)=P_{i,\min n_i}^M(t)\quad\forall i;\ \forall t\ .\tag{18}$$

Similarly, the maximum Markovian nodal injection happens at the maximum local wind state at the optimum, i.e.,

$$\max_{n_i}P_{i,n_i}^M(t)=P_{i,\max n_i}^M(t)\quad\forall i;\ \forall t\ .\tag{19}$$

After including (17) as constraints and substituting the min/max operations with min/max states of nodal injections as (18) and (19), the terms associated with the nodes with wind farms and conventional units in (15) and (16) become linear.

To linearize the min/max operations associated with other types of nodes, our idea is to treat non-local conventional units which are paired with remote wind farms as virtual local units of the wind farms. In this way, the Markovian nodal injections of the nodes with remote wind farms and paired units have the following relationships, similar to (17):

$$\begin{aligned}&P_{i,n_i-1}^M(t)+P_{j,n_i-1}^M(t)\le P_{i,n_i}^M(t)+P_{j,n_i}^M(t),\quad i\in I^{RW}\\&j=I_i^{\text{Paired}};\ \forall t;\ \forall n_i;\forall(n_i-1)\in\{n_i-1|\varphi_{n_i-1}(t)>0\}\end{aligned}\tag{20}$$

where I_i^{Paired} denotes the node with a conventional unit that is paired with the remote wind farm at node i. Since Markovian nodal injections of the node with a remote wind farm and the node with the paired unit are coupled together, their extreme nodal injections may not happen at extreme wind states and extra efforts are needed. With continuous decision variables $p_{i,}^{M,\min}(t)$/$p_{i,}^{M,\max}(t)$ and binary ones $x_{i,n_i}^{M,\min}(t)$/$x_{i,n_i}^{M,\max}(t)$, the min/max operations can be linearized as follows,

$$\begin{aligned}&P_i^{M,\max}(t)\ge P_{i,n_i}^M(t)\\&P_i^{M,\max}(t)\le P_{i,n_i}^M(t)+\left(1-x_{i,n_i}^{M,\max}(t)\right)\cdot N\\&\sum_{n_i}x_{i,n_i}^{M,\max}(t)\ge1\\&P_i^{M,\min}(t)\le P_{i,n_i}^M(t)\\&P_i^{M,\min}(t)\ge P_{i,n_i}^M(t)-\left(1-x_{i,n_i}^{M,\min}(t)\right)\cdot N\\&\sum_{n_i}x_{i,n_i}^{M,\min}(t)\ge1,\quad i\in I^{RW};\ \forall t;\ \forall n_i\end{aligned}\tag{21}$$

where N is a large number [29].

Based on the above equations, for nodes with remote wind farms, the minimum (maximum) Markovian nodal injection can be represented by $p_{i,}^{M,\min}(t)$ ($p_{i,}^{M,\max}(t)$) at the optimum, i.e.,

$$\min_{n_i}P_{i,n_i}^M(t)=P_i^{M,\min}(t),\quad i\in I^{RW};\ \forall t\tag{22}$$

$$\max_{n_i}P_{i,n_i}^M(t)=P_i^{M,\max}(t),\quad i\in I^{RW};\ \forall t\tag{23}$$

After including (20) and(21) as constraints and substituting the in/max operations with new variables as shown in (22) and (23), the terms associated with the nodes with remote wind farms in (15) and(16) become linear. For nodes with conventional units paired with remote wind farms, their minimum (maximum) Markovian nodal injections can be modeled in a similar way. Since the linear constraints are equivalent to min/max operations based on [29], the solution to the linearized problem will be feasible to the original problem.

D. The Objective Function and Overall Problem

The goal of the optimization problem is to minimize the commitment cost plus the expected dispatch cost. To avoid computational complexity, a weighted sum of the costs for the extreme and expected states is used to approximate the expected cost following the interval approach. The details of weight determination will be discussed in Section IV-B. The resulting total cost to be minimized is the weighted dispatch cost plus the commitment cost, i.e.,

$$f(x) \equiv w_m \sum_t \sum_i \sum_k \phi_{n_i} C_{n_i}^m(t) + w_M \sum_t \sum_i \sum_k \phi_{n_i} C_{n_i}^M(t) + w_E \sum_t \sum_i \sum_k C_i^E(t) + \sum_t \sum_i \sum_k (u_{i,k}(t) S_{i,k} + x_{i,k}(t) S_{i,k}^{NL}) \tag{24}$$

where

$$C_{n_i}^m(t) = C_{i,k} p_{i,k,n_i,m_i}(t) + P^{LS} p_{i,n_i,m_i}^{LS}(t)$$
$$C_{n_i}^M(t) = C_{i,k} p_{i,k,n_i,M_i}(t) + P^{LS} p_{i,n_i,M_i}^{LS}(t)$$
$$C_i^E(t) = C_{i,k} p_{i,k}^E(t) + P^{LS} p_i^{LS,E}(t). \tag{25}$$

In the above, x represents all the decision variables (both UC and dispatch decisions); $C_{i,k}$, $S_{i,k}$ and $S_{i,k}^{NL}$ are generation, start-up and no-load costs, respectively; P^{LS} is load shedding penalty; and ω_m, ω_M, and ω_E are weights for dispatch costs of the minimum, maximum and expected states, respectively. The overall problem is to minimize the total cost by selecting a single set of UC decisions and multiple sets of dispatch decisions of conventional units over 24 hours.

The above stochastic UC problem (1)−(11), (13)−(25), and minimum up/down time constraints is a mixed-integer linear optimization problem with binary decision variables $\{u_{i,k}(t)\}$ and $\{x_{i,k}(t)\}$, and continuous decision variables $\{p_{i,k,n_i}^M(t)\}$, $\{p_{i,k,\bar{n}_i}^I(t)\}$, $\{p_{i,n_i}^{LS,M}(t)\}$, $\{p_{i,\bar{n}_i}^{LS,I}(t)\}$, $\{p_{i,n_i}^{WC}(t)\}$, $\{p_{i,k}^E(t)\}$, $\{p_i^{LS,E}(t)\}$ and $\{p_i^{WC,E}(t)\}$. While wind farms and conventional units are coupled through system demand constraints (8) and (9) and transmission capacity constraints (15) and (16).

IV. Solution Methodology

The above mixed-integer linear problem with coupling constraints is solved by integration of our recent surrogate Lagrangian relaxation and branch-and-cut as presented in Section IV-A. To approximate the expected cost, proper weights are derived based on a simplified quadratic function in Section IV-B.

A. Surrogate Lagrangian Relaxation and Branch-and-cut [7], [30], [31]

The main idea of our surrogate Lagrangian relaxation approach is decomposition and coordination. After relaxing system-wide coupling constraints, i.e., system demand (8) and (9) and transmission capacity constraints (15) and (16) by introducing Lagrange multipliers, the relaxed problem is to minimize the following Lagrangian function L as,

$$\begin{aligned} L(\lambda,\mu,x) &\equiv f(x) + \sum_t \lambda^m(t)\left(\sum_i P_{i,n_i,m_i}(t)\right) + \sum_t \lambda^M(t)\left(\sum_i P_{i,n_i,M_i}(t)\right) + \sum_t \lambda^E(t)\left(\sum_i P_i^E(t)\right) \\ &+ \sum_t\sum_l\sum_g \mu_{l,g}^N(t)\Bigg\{-\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i>0}\left[a_l^i\cdot\min_{n_i} P_{i,n_i}^M(t)\right] - \sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i<0}\left[a_l^i\cdot\max_{n_i} P_{i,n_i}^M(t)\right] - f_{l,g}^I(t) - f_l^{\max}(t)\Bigg\} \\ &+ \sum_t\sum_l\sum_g \mu_{l,g}^P(t)\Bigg\{\sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i>0}\left[a_l^i\cdot\max_{n_i} P_{i,n_i}^M(t)\right] + \sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i<0}\left[a_l^i\cdot\min_{n_i} P_{i,n_i}^M(t)\right] + f_{l,g}^I(t) - f_l^{\max}(t)\Bigg\} \\ &+ \sum_t\sum_l\sum_g \mu_{l,g}^{E,N}(t)\left\{-f_l^{\max}(t) - \sum_i\left[a_l^i\cdot P_i^E(t)\right]\right\} + \sum_t\sum_l\sum_g \mu_{l,g}^{E,P}(t)\left\{-f_l^{\max}(t) + \sum_i\left[a_l^i\cdot P_i^E(t)\right]\right\} \end{aligned} \tag{26}$$

subject to (1)−(7), (10), (11), (13), (14), (17)−(25), and minimum up/down time constraints. In the above, λ represents multipliers relaxing system demand constraints, and μ represents multipliers relaxing transmission capacity constraints.

The relaxed problem is still inseparable into nodal subproblems because of (20). To overcome this, the nodal subproblem with a remote wind farm (a conventional unit paired with a remote wind farm) will be solved with the decisions of other subproblems fixed as values obtained at the previous iteration. Now there are totally I subproblems (each one corresponding to one node) and will be solved by branch-and-cut [32], [33].

By solving the relaxed problem, the dual function q becomes:

$$q(\lambda,\mu) = \min_x L(\lambda,\mu,x). \tag{27}$$

Within SLR, instead of obtaining the dual value (27), a surrogate dual value is obtained as follows,

$$\tilde{L}(\lambda^k,\mu^k,x^k) = f(x^k) + \lambda^k\tilde{g}(x^k) + \mu^k\tilde{h}(x^k). \tag{28}$$

In the above, x^k is any feasible solution of the relaxed problem at iteration k, and $\tilde{g}(x^k)$ and $\tilde{h}(x^k)$ are the surrogate subgradient vectors consisting of the following,

$$\begin{aligned} \tilde{g}^m(x^k) &= \sum_i P_{i,n_i,m_i}^k(t) \\ \tilde{g}^M(x^k) &= \sum_i P_{i,n_i,M_i}^k(t) \\ \tilde{g}^E(x^k) &= \sum_i P_i^{E\,k}(t) \\ \tilde{h}_{g,l}^N(x^k) &= -f_l^{\max}(t) - \sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i>0}\left[a_l^i\cdot\min_{n_i} P_{i,n_i}^M(t)\right] - \sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i<0}\left[a_l^i\cdot\max_{n_i} P_{i,n_i}^M(t)\right] - f_{l,g}^I(t) \\ \tilde{h}_{g,l}^P(x^k) &= -f_l^{\max}(t) + \sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i>0}\left[a_l^i\cdot\max_{n_i} P_{i,n_i}^M(t)\right] + \sum_{i\in I^{LW}\cup I^{RW}\cup I^{LU}:a_l^i<0}\left[a_l^i\cdot\min_{n_i} P_{i,n_i}^M(t)\right] + f_{l,g}^I(t) \\ \tilde{h}_l^{E,N}(x^k) &= -f_l^{\max}(t) - \sum_i\left[a_l^i\cdot P_i^E(t)\right] \\ \tilde{h}_l^{E,P}(x^k) &= -f_l^{\max}(t) + \sum_i\left[a_l^i\cdot P_i^E(t)\right]. \end{aligned} \tag{29}$$

Since SLR does not require the relaxed problem to be fully optimized, surrogate subgradient directions may not form acute angles with directions toward optimal multipliers, leading to divergence. To guarantee that surrogate directions form acute angles with directions toward the optimal multipliers, the relaxed problem has to be sufficiently optimized, such that surrogate dual values (28) satisfy the following surrogate optimality condition:

$$\tilde{L}(\lambda^k,\mu^k,x^k) < \tilde{L}(\lambda^k,\mu^k,x^{k-1}) \tag{30}$$

where λ^k and μ^k are multipliers at the iteration k, and x^{k-1} is a feasible solution at the iteration $k-1$. Since the relaxed problem is not fully optimized and subgradient directions do not change much at each iteration, computational requirements and zigzagging of multipliers are much reduced as compared to traditional subgradient methods.

In the method, multipliers are updated as

$$\lambda^{k+1} = \lambda^k + c^{SD,k}\tilde{g}(x^k), \mu^{k+1} = \max\left(0, \mu^k + c^{TC,k}\tilde{h}(x^k)\right). \tag{31}$$

In the above, $c^{SD,k}$ and $c^{TC,k}$ are the two step sizes.

It has been proven in [7] that the multipliers converge to the optimum if the step sizes are updated as,

$$c^{SD,k} = \alpha^k \frac{c^{SD,k-1}\left\|\tilde{g}(x^{k-1})\right\|}{\left\|\tilde{g}(x^k)\right\|}, c^{TC,k} = \alpha^k \frac{c^{SD,k-1}\left\|\tilde{h}(x^{k-1})\right\|}{\left\|\tilde{h}(x^k)\right\|} \tag{32}$$

where

$$\alpha^k = 1 - \frac{1}{Mk^p}, \quad p = 1 - \frac{1}{k^r} \quad M \geq 1; \quad 0 < r < 1. \tag{33}$$

The optimization stops when CPU time or the number of iterations reach the pre-set stop time or the pre-set number. Then, heuristics may be used to obtain feasible solutions while a dual value provides a lower bound on the optimal cost. A duality gap can then be calculated by using the best available feasible cost and the largest available dual value. Since the complexity of the new hybrid approach is similar to the previous one, it will be more computationally efficient than the pure Markovian approach based on the analysis in Section II.

B. Weight Determination

As mentioned earlier, the goal is to minimize the expected cost, i.e., commitment cost plus the expected dispatch cost. To avoid computational complexity, a weighted sum of the costs for the minimum, maximum and expected states is used as the optimization cost to approximate the expected cost. To evaluate the optimal UC decisions, Monte Carlo simulation runs are needed, and the simulation cost, the average cost of all scenarios with UC decisions fixed at the optimal solution, represents the expected cost. Modeling accuracy can be measured by the difference between the optimization and simulation costs. Therefore it is crucial to determine proper weights ω_m, ω_M, and ω_E in (24), where the approximated expected cost is obtained by optimization over 24 hours with wind uncertainties. Our idea is to use a simplified quadratic function under a simple distribution and only one hour to derive the weights, since the aggregated cost function of conventional units are approximately quadratic.

Consider an optimized cost function $f(x) = ax^2 + bx + c$ $(a > 0,\ x > 0)$ where conventional generation x follows a certain distribution within a known range $[x_{\min},\ x_{\max}]$. The expected conventional generation x_E is also known based on the initial wind states and state transaction matrices. The values of $f(x_{\min})$, $f(x_{\max})$, and $f(x_E)$ are assumed known as in the UC problem, representing the costs for the maximum, minimum, and expected wind states. Based on the generation distribution and the cost function, proper weights can be determined by rewriting the unknown expected value $f_E(x)$, the expected cost in the UC problem, by the three known values.

For simplicity, it is assumed that wind generation follows a uniform distribution, so does conventional generation x. Based on the definition of $f(x)$, $f_E(x)$ can be rewritten by using $f(x_{\min})$ and $f(x_{\max})$ as follows:

$$\begin{aligned} f_E(x) &= \frac{a\left(x_{\min}^2 + x_{\max}^2 + x_{\min}x_{\max}\right)}{3} + \frac{b(x_{\min} + x_{\max})}{2} + c \\ &= \frac{1}{3}\left(ax_{\min}^2 + bx_{\min} + c\right) + \frac{1}{3}\left(ax_{\max}^2 + bx_{\max} + c\right) \\ &\quad + \frac{1}{3}ax_{\min}x_{\max} + \frac{1}{6}(bx_{\min} + bx_{\max} + 2c) \\ &= \frac{1}{3}f(x_{\min}) + \frac{1}{3}f(x_{\max}) + \frac{1}{3}ax_{\min}x_{\max} \\ &\quad + \frac{1}{6}(bx_{\min} + bx_{\max} + 2c). \end{aligned} \tag{34}$$

The expected conventional generation x_E can be described by $x_{\min}$ and $x_{\max}$ as follows:

$$x_E = \alpha x_{\min} + (1 - \alpha)x_{\max} \quad x_{\min} \leq x_E \leq x_{\max}; \quad 0 \leq \alpha \leq 1. \tag{35}$$

For our UC problems, α can be determined by system load, and the minimum, maximum and expected wind generation for each hour. Then by representing $ax_{\min}x_{\max}$ by $f(x_{\min})$, $f(x_E)$, $f(x_{\max})$ as follows:

$$\begin{aligned} ax_{\min}x_{\max} = \frac{1}{2\alpha(1-\alpha)}&\left[f(x_E) - \alpha^2 f(x_{\min}) - (1-\alpha)^2 f(x_{\max})\right. \\ &\left. - \alpha(1-\alpha)\left(bx_{\min} + bx_{\max} + 2c\right)\right] \end{aligned} \tag{36}$$

and substituting $ax_{\min}x_{\max}$ in (34) by (36), it can be obtained that

$$\begin{aligned} f_E(x) = &\left[\frac{1}{3} - \frac{\alpha}{6(1-\alpha)}\right] f(x_{\min}) + \frac{1}{6\alpha(1-\alpha)} f(x_E) \\ &+ \left[\frac{1}{3} - \frac{1-\alpha}{6\alpha}\right] f(x_{\max}). \end{aligned} \tag{37}$$

Therefore, the weights for $f(x_{\min})$, $f(x_E)$, $f(x_{\max})$ to approximate $f_E(x)$ are determined. In our UC problem, for simplicity, the average α of 24 hours is used.

V. Numerical Results

The method presented above has been implemented by using the optimization package IBM ILOG CPLEX Optimization Studio V 12.6.0.0 [33]. Testing has been performed on a PC with 2.90 GHz Intel Core (TM) i7 CPU and 16 GB RAM. Three examples are presented in this section. The first one is a small system to demonstrate the new approach is less conservative than our previous approach (hybrid Markovian and interval), and to illustrate dispatch decisions. The second test example uses the IEEE 30-bus system to demonstrate computational efficiency and modeling accuracy of our approach. And finally the IEEE 118-bus system is used to demonstrate scalability of our approach.

A. Example 1: Small System

Consider a 2-bus problem with one wind farm and one conventional unit for one hour as shown in Fig. 1. The figure also shows: 1) the generation values and probabilities of wind generation states; 2) the minimum and maximum generation levels and generation cost of the unit; 3) the load at the two nodes. Since only one hour is considered, time-coupling constraints such as ramp rate constraints and unit commitment costs are ignored, and the time index is omitted. In our previous hybrid Markovian and interval approach, the wind farm and conventional unit are independent, while in our new approach they are paired. Given $x_{\min}$, $x_{\max}$ and x_E, based on (37), the value of α is 0.45, and the values of ω_m, ω_M, and ω_E are 0.2, 0.13, and 0.67. To compare the conservativeness of the two approaches, optimization results are provided in Table I.

Since the remote wind farm is paired with a conventional unit, the paired conventional unit works like expensive utility-scaled battery storage to dampen the effects of wind uncertainties. With stochastic wind generation, the costs of extreme states can be reduced through the pairing to dampen the wind uncertain effects by using the new approach compared to the previous approach as shown in Table I. As for the expected state, the problem is deterministic, and the cost is not expected to be reduced by the pairing. Generally, the costs with the expected wind generation obtained by using our new approach and the previous approach may be not the same since the solutions depend on wind states, properties of conventional units, weights in the objective function, etc. In this example, the two costs with the expected wind generation happen to be the same. By using the previous approach, the total cost, the weighted sum of the costs for the extreme and expected wind generation, is \$1051. The total cost by using our new approach is \$987. The results demonstrate that the new approach is less conservative than the previous approach. Dispatch decisions are also shown in Table I. Before pairing, $\text{Unit}_{2,1}$ does not depend on wind states of the wind farm, so there is no Markovian generation. After pairing, its Markovian generation depends on local state n_1 of the wind farm at Node 1.

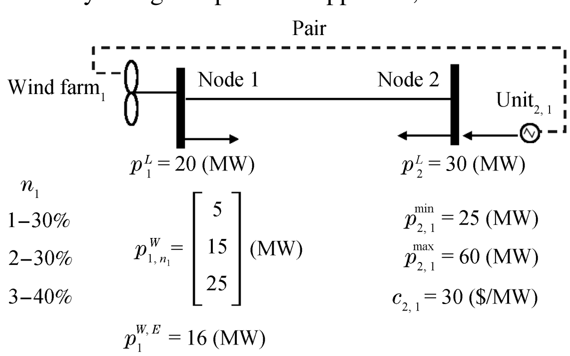

Fig. 1. The two-bus transmission network for Example 1.

TABLE I
OPTIMIZATION RESULTS FOR EXAMPLE 1

Approach		New	Previous
Cost (\$)	$Cost^{\text{Total}}$	987.15	1,050.9
	$Cost^m$	1080	1350
	$Cost^E$	1020	1020
	$Cost^M$	675	750
Dispatch decisions (MW)	$p_{2,1,1}^M$	30	/
	$p_{2,2,3}^M$	20	/
	$p_{2,1,3}^M$	25	/
	$p_{2,1,m_i}^I$	15	45
	$p_{2,1,M_i}^I$	0	25
	$p_{2,1}^E$	34	34

B. Example 2: IEEE 30-bus System

In this example, the IEEE 30-bus system is used in a 24-hour unit commitment based on the same parameters as in [3]. It is assumed that there are 10 wind farms at Nodes 1−10, and 10 conventional units at Nodes 1−8 and 11−12. The remote wind farms at Nodes 9 and 10 are paired with the units at Nodes 11 and 12, respectively. As in [3], 10 states are used for individual wind farms, and their state transition matrices are established based on measured hourly generation data of 10 wind sites between April and September in 2006 (non-winter season) selected from National Renewable Energy Laboratory's Eastern Wind Dataset [34]. The distributions of wind generation at steady states can be obtained based on the 10-state transition matrices. In the simulation, initial wind states are randomly generated based on these distributions. With the expected state calculated based on 50-state transition matrices, the wind penetration level, calculated as the ratio of the total expected wind generation to the total demand without wind curtailment and load shedding, is 5%.

For SLR, the stopping criterion is the number of iterations, e.g., 500 iterations. The total computational time includes data and model loading, subproblem solving, subgradient and multiplier updating, and feasible solution searching time, while solving time excludes the data and model loading time. For branch-and-cut, the stopping criterion is to stop when the total time or the MIP gap reaches its respective preset limit.

To evaluate optimal UC decisions, 1000 Monte Carlo simulation runs are performed with 50-state transition matrices. Modeling accuracy is measured by the absolute percentage error (APE), the ratio of the absolute difference between optimization and simulation costs to the simulation cost. The standard deviation (STD) of scenario costs reflects its variation. Results with a 5% wind penetration level are summarized in Table II (ω_m, ω_M, and ω_E are 0.05, 0.05, and 0.9).

Compared with our previous approach, the feasible cost of the new one is reduced by 0.8% with less wind curtailment, indicating that our approach is less conservative. By using SLR and branch-and cut, a near-optimal solution with a 1.1% duality gap is obtained in about 505 seconds. A solution with a much higher mixed-integer programming (MIP) gap is found after 1200 seconds by pure branch-and-cut, thereby indicating that our approach is more computationally efficient. In addition, our approach is also accurate, as its absolute percentage error is about 0.3%.

C. Example 3: IEEE 118-bus System

In this example, the IEEE 118-bus system [35] with 54 conventional units is tested. It is assumed that there are 10 wind farms, 6 of which are accompanied with conventional

TABLE II
RESULTS FOR EXAMPLE 2: IEEE 30-BUS WITH A 5% WIND PENETRATION LEVEL

Approach		New		Previous
		SLR+ B & C	Pure B & C	Pure B & C
Optimization	Cost (k$)	305.728	460.296	308.149
	Penalty (k$) ($5000/MWh)	0	/	0.14
	Curtailed wind (MWh)	8.11	/	15.93
	Total time (s)	505	1200	122
	Solving time (s)	283.6	/	/
	Lower bound (k$)	302.634	286.710	307.906
	Gap (%)	1.01	37.71	0.08
	UC cost (k$)	95.41	/	97.66
Simulation	Cost (k$)	306.715		309.176
	APE	0.32		0.33
	STD (k$)	1.51		1.5
	Penalty (k$) ($5000/MWh)	0		0
	Curtailed wind (MWh)	0		0

TABLE III
RESULTS FOR EXAMPLE 3: IEEE 118-BUS

Wind penetration level		5%	15%	25%
Optimization (New by SLR)	Cost (k$)	929.425	809.119	707.601
	Penalty (k$) ($5000/MWh)	0.036	0.025	0
	UC cost (k$)	12.56	12.50	11.92
	Curtailed wind (MWh)	38.58	1583.28	4361.33
	Total time (s)	935	1195	1525
	Solving time (s)	786	1054	1400
	Lower bound (k$)	927.347	802.874	699.407
	Gap (%)	0.22	0.77	1.15
Optimization (Previous by B&C)	Cost by (k$)	936 936	815 931	711 604
	Reduced by the new approach (%)	0.8	0.83	0.63
	Total time (s)	1500	2000	2000
	Gap by (%)	N/A	19	29.7
Simulation (New)	Cost (k$)	926.988	808.601	705.068
	APE	0.26	0.064	0.36
	STD (k$)	12.64	37.80	51.02
	Penalty (k$) ($5000/MWh)	0	0	0
	Curtailed wind (MWh)	0	4.71	776.62

units and 4 are at remote locations. Each of the remote wind farms is paired with a sufficiently large unit with high ramp rates out of the 54 units. Wind state transition matrices are obtained similarly as in Example 2. As in [3], the quadratic cost curves of conventional units are approximated by piecewise linear cost curves with three blocks. The hourly system demand values in percent of peak system demand are calculated based on corresponding factors for summer weekdays of the IEEE Reliability Test System [36]. The stopping iteration number is 1300. The results with three levels of wind penetration, i.e., 5%, 15% and 25%, are summarized in Table III as follows ω_m, ω_M, and ω_E are: 0.05, 0.05, and 0.9; 0.05, 0.15, and 0.8; and 0.06, 0.24, and 0.7, respectively).

As compared with our previous approach, the total costs obtained by the new approach are reduced by 0.6% to 0.8% for each level of wind penetration. For practical power systems, such as the market for Midcontinent Independent System Operator, the total cost of a typical winter day is \$42 m to \$63 m, while \$52 m to \$73 m for a typical summer day [37]. In addition, absolute percentage errors are all within 0.5%, demonstrating the modeling accuracy. Compared with branch-and-cut, our approach can obtain near-optimal solutions in acceptable amount of time, demonstrating that our approach is computationally efficient. It is also shown that the higher the level of wind penetration, the longer the computational time. For the IEEE 118-bus system with a 5% wind penetration level, the total computational time is about 935 seconds, while it is 505 seconds for the IEEE 30-bus system in Example 2. With the same level of wind penetration, the computational time is nearly linear to the number of wind farms and conventional units. Therefore our new approach is scalable for large systems.

VI. CONCLUSION

This paper develops a new hybrid Markovian and interval approach to solve the UC problem with the consideration of remote wind farms. Since major wind sites are often located in remote locations without accompanying conventional units, our idea is to pair each remote wind farm with a sufficiently large unit with high ramp rates to dampen the effects of wind uncertainties without using expensive utility-scaled battery storage. Extra constraints are established for pairing and proper weights are derived through a simple quadratic function. The problem is solved by integration of our recent surrogate Lagrangian Relaxation and branch-and-cut for near-optimal solutions. Numerical results demonstrate that the new approach is effective in terms of solution feasibility, modeling accuracy, and computational efficiency. The formulation established is general and can model real-time UC as well. Its generic nature allows for modeling of wind and other intermittent resources such as solar.

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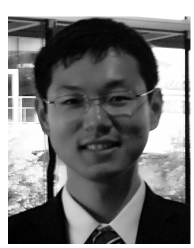

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