Grid Integration of Intermittent Wind Generation: A Markovian Approach

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Abstract—**Although the unique characteristics of intermittent wind generation have been acknowledged and drastic impacts of sudden wind drops have been experienced, no effective integration approach has been developed. In this paper, without considering transmission capacity constraints for simplicity, aggregated wind generation is modeled as a discrete Markov process with state transition matrices established based on historical data. Wind generation is then integrated into system demand with multiple net demand levels at each hour. To accommodate the uncertain net demand, a stochastic unit commitment problem is formulated based on states instead of scenarios. The objective is to minimize the total commitment cost of conventional generators and their total expected dispatch cost while satisfying all possible net demand levels. The advantage of this formulation is that the state at a time instant summarizes the information of all previous instants in a probabilistic sense for reduced complexity. With state transition probabilities given, state probabilities calculated before optimization, and the objective function and constraints formulated in a linear manner, the problem is effectively solved by using branch-and-cut. Numerical testing shows that the new Markovian approach is effective and robust through the examined cases, resembling the sudden wind drop in Texas in February 2008.**

Index Terms—**Grid integration, intermittent wind generation, Markov process, unit commitment.**

I. Introduction

WITH MAJOR initiatives promoting wind generation, effective and robust integration of wind into the grid becomes a critical issue. Wind generation cannot be dispatched as conventional generation because of its intermittent and uncertain nature. Sudden drops in wind generation may have drastic impacts on system security if the system ramping capability of dispatchable resources is not large enough to respond. One example is the event on February 26, 2008 in which the Electric Reliability Council of Texas (ERCOT) called for an Emergency Electric Curtailment Plan (EECP) because of worsening imbalance between generation and load. One of the major reasons behind was a large 3.5-hour ramp-down in wind generation from 2000 MW to 360 MW. Even though the curtailment plan resolved the imbalance issue, there was a decline in system frequency from 60 Hz to 59.85 Hz [1]. Although the intermittent and volatile characteristics of wind generation have been acknowledged and the drastic impacts of sudden drops in wind generation have been experienced, no effective integration approach has yet been developed to address these issues.

In this paper, a Markov-based stochastic unit commitment model is presented based on states instead of scenarios to integrate intermittent and uncertain wind generation in the day-ahead unit commitment process. With state transition probabilities given, state probabilities calculated before optimization, and the objective function and constraints formulated in a linear manner, the problem can be effectively solved by using the branch-and-cut method. The approach developed here can be applied to reliability assessment commitment performed in real-time. In Section II, the deterministic approach, stochastic programming approach, and robust optimization approach are reviewed. For the deterministic approach, the uncertainty of wind generation is not explicitly captured, so solutions are not robust against realizations of wind generation. On the other hand, the stochastic programming approach explicitly models uncertainty by considering the possible scenarios and the probability information. Scenario reduction techniques are commonly used to reduce the number of scenarios for computational efficiency. However, it is difficult to balance the computational effort and the ability to manage low-probability high-impact events by selecting an appropriate number of representative scenarios. The robust optimization approach models uncertainty by using a deterministic uncertainty set, rather than the probability information as is used in the stochastic programming approach. The robust optimization approach considers the worst-case realization, and it is difficult to choose an appropriate uncertainty set that balances the tradeoff between low-probability high-impact events and the resulting costs.

To overcome the above difficulties, discrete Markov processes are used in Section III to model intermittent and uncertain wind generation, with state transition matrices established based on historical data. In Section IV, discretized wind generation is aggregated into system demand, which itself is assumed to be deterministic for simplicity. The net system demand for each hour thus has many possible states, each corresponding to one wind generation level. The stochastic unit

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commitment problem is to minimize the total expected cost by selecting a single set of unit commitment decisions over a given period (e.g., 24 hours), and multiple sets of economic dispatch decisions, one per net system demand level at each hour. Constraints considered include generator capacities, ramp rates, minimum up/down times, and system demand constraints. For simplicity, transmission capacity constraints, demand bids and ancillary services are not considered. Since the performance of the branch-and-cut method depends heavily on problem linearity, the objective function, constraints and the state transitions are formulated in a linear manner. The advantage of the proposed Markovian formulation is that the state at a time instant summarizes the information of all previous instants in a probabilistic sense, resulting in reduced complexity of the overall problem.

In Section V, the problem is solved by using the branch-and-cut method. Although commercial packages such as CPLEX [2] or GUROBI [3] do not provide infrastructure to explicitly describe stochastic processes, with state transition probabilities given, state probabilities calculated before optimization, and the objective function and constraints formulated in a linear manner, the problem can be effectively solved. For reliability assessment commitment performed in real-time, wind generation may maintain an increasing (or a decreasing) trend over several consecutive timeframes. With this trend, the stochastic process representing wind generation is driven by a colored noise, and pre-whitening can be performed [4]. In Section VI, two examples are provided. In Example 1, a simple two-unit three-hour problem is used to illustrate the differences between the Markovian approach and the standard stochastic programming approach. In Example 2, a problem with 309 units based on ISO-New England data is tested to demonstrate the computational efficiency, the effectiveness to accommodate high levels of wind penetration, and the ability to capture low-probability high-impact events.

The preliminary results for a simplified unit commitment model were presented in [5]. In this paper, testing using an ISO-NE's data set is added, and the comparison with the deterministic approach and the stochastic programming approach is made through Monte Carlo simulation. The ability to capture low-probability events, resembling the sudden wind drop happened in Texas in February 2008, is also demonstrated. In addition, the overall presentation has been significantly improved.

II. Literature Review

Most of the practical applications, either in day-ahead or real-time market, adopt the deterministic approach. In this approach, intermittent and uncertain wind generation is represented by its mean value without explicitly considering uncertainties. The problem is then solved by existing methods, e.g., Lagrangian relaxation to exploit the separability of a formulation [6], [7], or branch-and-cut to solve linear mixed-integer formulations [8]–[10]. Since uncertainties are not explicitly considered, the solutions of deterministic models are not robust against realizations of wind generation. On the research side, stochastic programming has recently been explored by many to address the intermittent and uncertain nature of wind generation based on representative scenarios in unit commitment problems [11]–[17]. Generally, a large number of scenarios are generated based on distributions of wind generation [11], [12] or wind speed [15], [16] over a day. The number of scenarios could be prohibitively large. For example, a distribution with seven discretized values per hour over a time horizon of 24 hours will result in $7^{24}(= 1.9\times 10^{20})$ scenarios if all possible inter-hour transitions are considered [11]. Scenario reduction techniques are therefore commonly used to eliminate scenarios with very low probability, or to aggregate "close" scenarios based on probability metrics [18]–[20]. The reduced set of scenarios is then used in the unit commitment process. To mimic the operation of the day-ahead market, the scenario-based stochastic unit commitment model looks for a single set of unit commitment decisions to satisfy all scenarios, while generation levels of committed units are scenario dependent to satisfy individual net demand levels. In addition, individual unit constraints should be satisfied for all scenarios. The objective of the stochastic unit commitment problem is to minimize the expected total cost. The scenario-based stochastic unit commitment problem is non-deterministic polynomial-time hard (NP-hard) [17], i.e., it is not proved to be solvable within polynomial time and is at least as hard as NP-complete problems [21]. Thus, decomposition methods are often used for near-optimal solutions. For example, Benders' decomposition is used to decompose the problem into one master problem and multiple subproblems for each scenario [12], [17]. Subproblems are linear and can be solved by using branch-and-cut. The number of scenarios is a critical consideration. If too few scenarios are selected, low-probability but high-impact events, such as the sudden wind drop happened to ERCOT on the February 26, 2008, may not be captured, and this may lead to severe consequences. If too many scenarios are included, the computational effort will be prohibitive. In a recent study, it took 35 minutes to solve the modified IEEE 118-bus system with 54 thermal units, three wind farms, and 186 branches with 100 scenarios using CPLEX 12.1 on an Intel Core i7 2.67-GHz personal computer [17]. The stochastic programming approach thus has limited success and questionable scalability.

Robust optimization seeks the optimal solution feasible for any realization in a given uncertainty set without requiring a specific probabilistic description. This is equivalent to find the optimal solution for the worst-case realization [22], [23]. Robust optimization was investigated to address demand uncertainty in [24] and uncertainties on both demand and supply sides in power grids in [25], [26]. A two-stage robust adaptive model for the security constrained unit commitment problem with uncertain net injections was discussed in [27]. In their paper, the first stage is to find optimal unit commitment decisions feasible for any realizations in the given uncertainty set of net injections, while the second stage is to find the worst-case dispatch under the fixed unit commitment decisions obtained from the first stage. This problem is solved by using a Benders' decomposition type cutting plane algorithm. A real world system operated by ISO New England was tested. In [28], wind generation uncertainties and pumped-storage units to partially absorb the uncertainties were considered in robust unit commitment, and the problem was solved by using Benders' decomposition.

For the robust optimization approach, it is difficult to choose an appropriate uncertainty set that balances the tradeoff between low-probability high-impact events and the resulting costs.

III. Formulation of Wind Generation

In this section, to overcome the above difficulties, discrete Markov processes are used to model intermittent and uncertain wind generation, with state transition matrices established based on historical data.

In the formulation, since transmission capacity constraints are ignored, wind generation from all wind farms can be aggregated, and the resulting generation is assumed to be a discrete Markov process [29], [30]. In this Markov process, the capacity of wind generation is evenly divided into N intervals. The mean of each interval is represented by a state, and the states are arranged in the ascending order of the means. The state transition matrix, of which the elements are state transition probabilities, can be established based on historical data. The $(m,n)^{\text{th}}$ element is the ratio of the number of observed transitions from state m to state n to the number of occurrences of state m[31]:

$$\pi_{mn} = \frac{observed\ transitions\ from\ state\ m\ to\ n}{occurrences\ of\ state\ m}. \quad (1)$$

The average hourly wind generation for the year 2000 of the Lake Benton wind farm was analyzed in [29], and it was shown that the generation had a weak diurnal pattern but with noticeable changes from winter to non-winter. Furthermore, wind generation in New England over the years 2004, 2005, and 2006 had the highest values in winter seasons [31]. Therefore, a winter wind transition matrix is developed using data from winter seasons, and a non-winter wind transition matrix is constructed from non-winter seasons. The advantage of formulating aggregated wind generation as discrete Markov processes is that according to the Markov property, the state at a time instant summarizes the information of all previous instants in a probabilistic sense, resulting in reduced complexity of the stochastic unit commitment problem to be formulated in Section IV.

For example, National Renewable Energy Laboratory's Eastern Wind Dataset from April to September 2006 [32] is used to establish the summer wind transition matrix for an aggregation of 113 onshore and 666 offshore wind farms in New England with a total capacity of 24 GW. With wind generation discretized into ten equally divided states, the non-winter wind transition matrix is obtained in Table I. This transition matrix is block diagonal, indicating that the probabilities for sudden increases or decreases of wind generation are generally very small. The block diagonal characteristic is common for aggregated wind farms over large regions. The analysis from [33] shows that the reduction of wind power forecasting error is mainly determined by the size of the region, e.g., for the size of a typical large utility ($\sim$ 370 km in diameter), less than 50 sites are sufficient to obtain 63% of the error of single sites. If the wind generation is more volatile, there will be more nonzero transition rates in the off-diagonal positions. Our approach can still incorporate the transition matrix with more nonzero off-diagonal elements, since the approach is not based on the block diagonal characteristic. Also, the number of states $N =$ (10 in Table I) should be determined as a balance between modeling accuracy and computational efficiency when solving the unit commitment problem. A detailed state transition matrix, which is derived from the same data set but with a larger number of states, is used to produce random scenarios for simulating the real-time dispatch process to evaluate the performance of the new approach in Section VI.

TABLE I
Non-Winter Wind Transition Matrix for New England

State	1	2	3	4	5	6	7	8	9	10
1	0.785	0.215	0	0	0	0	0	0	0	0
2	0.115	0.711	0.168	0.006	0	0	0	0	0	0
3	0	0.167	0.652	0.169	0.012	0	0	0	0	0
4	0	0.005	0.204	0.604	0.176	0.012	0	0	0	0
5	0	0	0.016	0.204	0.599	0.174	0.007	0	0	0
6	0	0	0	0.002	0.210	0.631	0.148	0.008	0	0
7	0	0	0	0	0.007	0.187	0.679	0.126	0	0
8	0	0	0	0	0	0	0.205	0.700	0.095	0
9	0	0	0	0	0	0	0	0.184	0.776	0.041
10	0	0	0	0	0	0	0	0	0.171	0.829

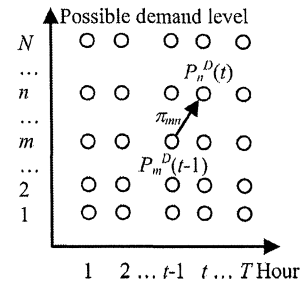

Fig. 1. Net system demand state transition.

It should be noted that more refined state transition matrices can be established as needed, e.g., based on monthly patterns, and incorporated in our approach. Also, to describe daily wind generation probabilities more accurately, day-ahead wind power forecasts can be considered. However, this is beyond the scope of this paper. Also, although battery storage technology can help reduce the uncertainty of wind generation, large-scale battery storage remains expensive [34], and no practical solution to completely eliminate the uncertainty of wind generation is expected [35].

IV. Unit Commitment Problem Formulation

Since wind generation cannot be dispatched as conventional generation, it is integrated into system demand following [11]–[16] in Section IV-A. In Section IV-B, the Markovian stochastic unit commitment problem is formulated based on states instead of scenarios, considering generator capacities, ramp rates, minimum up/down time, and system demand. For simplicity, demand bids and ancillary services (e.g., regulation and reserves) are not considered. The objective function, constraints and state transitions are formulated in a linear manner so that branch-and-cut can be effectively used.

A. Integration of Wind Generation Into System Demand

It is known that day-ahead load forecasting is much more accurate than wind forecasting. For example, the mean absolute error (MAE) of day-ahead load forecasts is 1% to 3% of the load, while the MAE of the state-of-the-art day-ahead wind forecasts is 15% to 20% of wind generation [31]. Therefore, for simplicity, the uncertainty of load forecasting is ignored. The resulting net system demand is the forecasted system demand minus the aggregated wind generation, and is a discrete Markov process with N states at each hour. For this Markov process, state transitions are illustrated in Fig. 1.

The range of power levels at the same net system demand state can vary at different hours, given that the forecasted system demand is time varying. For convenience, the order of net demand states is reversed from that of wind generation states. The probability that the net system demand is at state n at time t, denoted as $\varphi_n(t)$, is the sum of probabilities at time $t-1$ weighted by different transitions:

$$\varphi_n(t) = \sum_{m=1}^{N} \pi_{mn} \varphi_m(t-1). \tag{2}$$

The probabilities of net demand levels for future time instants can thereby be derived based on the initial wind generation state and the transition matrix obtained in Section III.

B. The Markovian Stochastic Unit Commitment Problem Formulation

The stochastic unit commitment problem is to minimize the total expected cost by selecting a single set of unit commitment decisions over a 24-hour period and multiple sets of economic dispatch decisions depending on net system demand levels. Building on our previous formulation [5], [6], consider a day-ahead energy market with I conventional units indexed by $i (1 \leq i \leq I)$ over $T (=24)$ operational hours indexed by $t (1 \leq t \leq T)$. Unit i submits a multi-block bid that includes bid block price $C_{i,b}$ (\$/MWh) for block $b (1 \leq b \leq B)$ with size $p_{i,b\max}$ (MW), no-load cost S_i^{NL} (\$/hr), startup cost S_i (\$/Start), and minimal and maximal generation levels $p_{i\min}$ (MW) and $p_{i\max}$ (MW), respectively. The bid block price is monotonically increasing. For unit i, the ramp rate is denoted as Δ_i (MW/h), the minimum-up time $\bar{\tau}_i$ (h), and the minimum-down time $\underline{\tau}_i$ (h). The net system demand at state n of hour t is $P_n^D(t)$ (MW) with probability $\varphi_n(t)$. As for decision variables, the startup decision is denoted by a binary decision variable $u_i(t)$, with "1" representing the starting up of the unit and "0" otherwise. The commitment status is denoted by a binary variable $x_i(t)$, with "1" meaning online and "0" offline. The generation level is denoted by $p_{i,n}(t)$ (MW) when the net system demand is at state n at time t, with $p_{i,b,n}(t)$ (MW) representing the generation of block b. As a Markov decision problem, the dispatch decision at time t depends on the state at time t only.

Constraints include individual unit constraints (startup, generator capacities, ramp rates, and minimum up/down times) and system demand constraints as presented below.

Startup constraints. The binary startup variable $u_i(t)$ equals 1 if and only if the unit is turned on from offline at hour t, i.e.,

$$u_i(t) \geq x_i(t) - x_i(t-1), \forall i, \forall t. \tag{3}$$

Generation limits for each block. The generation level for each block of unit i cannot exceed the block size, i.e.,

$$0 \leq p_{i,b,n}(t) \leq p_{i,b\max}, \forall i, \forall b, \forall n, \forall t. \tag{4}$$

The sum of generation levels for all the blocks is equal to the generation level of this unit, i.e.,

$$\sum_{b=1}^{B} p_{i,b,n}(t) = p_{i,n}(t), \forall i, \forall n, \forall t. \tag{5}$$

Generator capacities. The generation level of a unit is limited by its minimum and maximum values if the unit is committed. Otherwise, the generation level should be zero, i.e.,

$$x_i(t) p_{i\min} \leq p_{i,n}(t) \leq x_i(t) p_{i\max}, \forall i, \forall n, \forall t. \tag{6}$$

Ramp rates. If unit i is online at both $t-1$ and t hours, then the change of generation levels of the unit cannot exceed its ramp rate. Since the net system demand can be at different states at these two hours, ramp rates should be satisfied for all possible state transitions, i.e.,

$$\begin{aligned} &p_{i,m}(t-1) - \Delta_i \leq p_{i,n}(t) \leq p_{i,m}(t-1) + \Delta i, \forall i, \forall n, \forall t, \\ &\forall m \in \{m | \pi_{mn} \neq 0\}, \text{ if } x_i(t-1) = 1 \text{ and } x_i(t) = 1. \end{aligned} \tag{7}$$

Upon starting up or at shutting down, the generation level cannot exceed its $p_{i\min}$ plus 30-minute ramp rate. i.e.,

$$\begin{aligned} p_{i,n}(t) \leq & p_{i\min} + \frac{\Delta_i}{2}, \forall i, \forall n, \forall t, \\ \text{if } x_i(t-1) =& 0 \text{ and } x_i(t) = 1, \\ \text{or if } x_i(t) =& 1 \text{ and } x_i(t+1) = 0. \end{aligned} \tag{8}$$

The above constraints (7) and (8) contain logical conditions, and are transformed into linear constraints (9) and (10) by following [8]:

1) *Ramp-Up Constraints:* :

$$\begin{aligned} &p_{i,n}(t) - p_{i,m}(t-1) \leq \Delta_i x_i(t-1) \\ &\quad + \left(p_{i\min} + \frac{\Delta_i}{2}\right) (x_i(t) - x_i(t-1)), \\ &\forall i, \forall n, \forall t, \forall m \in \{m | \pi_{mn} \neq 0\}. \end{aligned} \tag{9}$$

Upon starting up, (9) becomes (8); when the unit is kept online, (9) becomes (7); and (9) is redundant otherwise.

2) *Ramp-down Constraints:* :

$$\begin{aligned} &p_{i,m}(t-1) - p_{i,n}(t) \leq \Delta_i x_i(t) \\ &\quad + \left(p_{i\min} + \frac{\Delta_i}{2}\right) (x_i(t-1) - x_i(t)), \\ &\forall i, \forall n, \forall t, \forall m \in \{m | \pi_{mn} \neq 0\}. \end{aligned} \tag{10}$$

Minimum Up/Down Time. Unit i must be kept online until its minimum up time is reached, or be kept offline until the minimum down time is reached. A linear formulation from [8] (21)–(26) is used.

System demand constraints. Net system demand needs to be satisfied at every hour for each state of which the probability is nonzero, i.e.,

$$\sum_{i=1}^{I} p_{i,n}(t) = P_n^D(t), \forall t, \forall n \in \{n | \varphi_n(t) \neq 0\}. \tag{11}$$

If net demand cannot be satisfied, penalties will be added based on convex piecewise linear penalty functions for load shedding or over generation/wind curtailment.

Objective Function. The objective is to minimize the total expected cost, which consists of dispatch cost, no-load cost and startup cost, i.e.,

$$J=\sum_{t=1}^{T}\sum_{i=1}^{I}\left\{\sum_{n=1}^{N}\sum_{b=1}^{B}\varphi_n(t)C_{i,b}p_{i,b,n}(t)+x_i(t)S_i^{NL}+u_i(t)S_i\right\}. \tag{12}$$

The above stochastic unit commitment problem (3)–(6), (9), (10), minimum up/down time, (11), (12) is a linear mixed-integer optimization problem with binary decision variables $\{u_i(t)\}$ and $\{x_i(t)\}$ and continuous variables $\{p_{i,b,n}(t)\}$, with uncertainty described by the net demand levels $\{P_n^D(t)\}$, state probabilities $\{\varphi_{\rm n}(t)\}$, and transition probabilities $\{\pi_{\rm mn}\}$.

V. Solution Methodology

The above problem is solved by using the branch-and-cut method in Section V-A. Monte Carlo simulation is used to evaluate the solution quality as presented in Section V-B. To effectively simulate rare events, importance sampling is used as presented in Section V-C. Our Markovian approach is then compared with the deterministic approach as well as the stochastic programming approach as presented in Section V-D.

A. Solving the Markovian Problem by Using Branch-and-Cut

The branch-and-cut method combines the branch and bound algorithm and the cutting-plane method. After relaxing integrality constraints, branch-and-cut starts with cuts trying to obtain the convex hull of feasible solutions of the original problem. After the convex hull is obtained, the linear programming simplex method then efficiently optimizes the relaxed problem over the convex hull and obtains an optimal solution, which is also the optimal solution to the original problem. Since obtaining the convex hull itself is NP-hard for NP-hard problems, branching operations may be needed to decompose the problem as in the branch and bound algorithm.

The branch-and-cut method is efficient in solving deterministic linear mixed-integer problems, and has been widely used by ISOs, utility companies and semiconductor manufacturers. Also, the existence of commercial packages such as CPLEX [2] or GUROBI [3] reduces the time to code and the time to debug. However, these packages do not provide infrastructure to explicitly describe stochastic processes. For our formulation, note that state probabilities are included in the objective function (12) as weights, and system demand constraints (11) only have to hold for those states with nonzero probabilities. Also, ramp rate constraints (9) and (10) only have to hold for those transitions with nonzero probabilities. With state transition probabilities given, state probabilities calculated before optimization based on (2), and the objective and constraints formulated in a linear manner, the overall problem is a linear mixed-integer problem and can be effectively solved by using branch-and-cut.

B. Monte Carlo Simulation

After the problem is solved, the optimization cost can be calculated according to (12). The cost for a particular scenario can also be evaluated by solving the dispatch problem with commitment decisions fixed by optimization. Monte Carlo simulation runs can be conducted to obtain the simulation cost, which is the ensemble average of simulated costs. In the process, a scenario can be produced by sampling from the detailed transition matrix sequentially from Hour 1 to Hour T. The dispatch problem uses the deterministic counterpart of (4)–(6) and (9)–(12) following [14], [27] for simplicity instead of solving dispatch problems sequentially for each hour as in the real-time dispatch process, and is a linear programming problem with dispatch decisions as decision variables. Since the simulation is based on scenarios and the optimization is based on states, there are discrepancies between the simulation cost and the optimization cost. Moreover, since a simplified state transition matrix is used in optimization as presented in Section III, the simulation cost for scenarios obtained from the detailed transition matrix could be further different from the optimization cost.

C. Simulating Rare Events by Using Importance Sampling

If there are low-probability events captured by the state transition matrix, a very large number of scenarios will be needed in the Monte Carlo simulation for the results to be meaningful. To increase simulation efficiency, *Importance Sampling* [36], [37] is used to make rare events occur more frequently. This technique modifies the transition probability distributions, and then adjusts the cost of each scenario. More specifically, let j be the index of scenarios ranging from 1 to J. For scenario j, let cost (j) be the cost, $p_{\rm ori}(j)$ the scenario probability calculated as the product of a sequence of original state transition probabilities, $p_{\rm new}(j)$ the scenario probability calculated based on the new transition matrix with importance sampling. The expected cost based on the original transition matrix, E[cost], is:

$$E[\text{cost}] = \frac{1}{J}\sum_{j=1}^{J}\text{cost}(j)\frac{p_{ori}(j)}{p_{new}(j)}. \tag{13}$$

Similarly, the original variance of costs, *var*[cost], is:

$$\text{var}[\text{cost}] = \frac{1}{J}\sum_{j=1}^{J}\left[\left(\text{cost}(j)-\frac{1}{J}\sum_{j=1}^{J}\text{cost}(j)\right)\frac{p_{ori}(j)}{p_{new}(j)}\right]^2 \tag{14}$$

and the standard deviation is the square root of the variance.

D. Comparison of Different Approaches

Our Markovian approach is compared with the deterministic approach as well as the stochastic programming approach. The deterministic formulation can be viewed as a special case of the Markovian formulation with only one state at each time instant, and can be efficiently solved by using branch-and-cut [8]–[10]. As shown in the first two columns in Table II, the numbers of decision variables and constraints of the Markovian formulation are not drastically larger than those of the deterministic formulation. More importantly, the Markovian formulation does not change the fundamental linear mixed-integer programming problem structure of the deterministic formulation. According

TABLE II
COMPARISON OF THE MARKOVIAN FORMULATION, THE DETERMINISTIC FORMULATION AND THE STOCHASTIC PROGRAMMING FORMULATION

	Deterministic	Markovian	Stochastic programming
Generation levels	$I\times T$	$I\times T\times N$	$I\times T\times J$
Demand constraints	T	$T\times N$	$T\times J$
Ramp Constraints	$2\times I\times T$	$2\times I\times[N+(T-1)\times N^2]$	$2\times I\times T\times J$

to Section III of [10], the branch-and-cut method is efficient to solve deterministic unit commitment problems of different sizes. The Markovian formulation can therefore be effectively solved by using the branch-and-cut method as will be demonstrated in the next section.

For the stochastic programming formulation, there are $J = N^T$ total number of possible scenarios, and the numbers of decision variables and constraints are shown in the third column of Table II. When J is reduced by using scenario reduction techniques, say to N for easy comparison, the numbers of decision variables and system demand constraints are equal to those of the Markovian formulation. However, since only a limited number of scenarios are considered in making unit commitment decisions, high penalties may incur during simulation, and the simulation cost may not be significantly lower than that of the Markovian formulation as will be shown in Case 3 of Example 2 in the next section.

It is interesting to note that with J reduced to N, the number of ramp constraints for the stochastic programming formulation is smaller than that of the Markovian formulation, since ramp rate constraints are enforced differently. For the stochastic programming formulation, since state transition from hour $t-1$ to t is fixed for each scenario, a unit should satisfy only two ramp constraints, and the total number of constraints is $2\times I\times T\times J$. For the Markovian formulation, from each state, N possible transitions can occur from hour $t-1$ to t, and the total number of constraints is about $2\times I\times T\times N^2$. With more ramp rate constraints considered, the Markovian approach is more conservative, and can result in higher optimization cost than that of the stochastic programming approach.

In above, wind generation in the day-ahead unit commitment process is modeled as a Markov process driven by a white noise. For the reliability assessment commitment process performed in real-time, however, wind generation may maintain an increasing (or a decreasing) trend over several consecutive timeframes. With this trend, the stochastic process representing wind generation is driven by a colored noise. Nevertheless, the colored noise can be pre-whitened and treated as the output of a pre-whitening system driven by a white noise. This augmented state is a Markov process [4], and the method presented above can be applied without major conceptual difficulties.

VI. NUMERICAL RESULTS

The Markovian approach has been implemented by using the commercial solver CPLEX 12.4 [2] and run on a PC laptop with an Intel Core(TM) i7–2820QM 2.30 GHz CPU and 8 GB memory. The deterministic formulation is a special case of the Markovian formulation with only one state at each time instant. The stochastic programming approach with a small number of scenarios has also been directly implemented as a linear mixed-integer programming problem by using CPLEX for comparison purposes.

TABLE III
UNIT PARAMETERS FOR EXAMPLE 1

Unit	p_{imin} (MW)	p_{imax} (MW)	Ramp rate	c_i (\$/MWh)	S_i(\$)	Initial
1	0	80	10	65	50	On/40
2	0	80	160	30	8000	Off

Two examples are provided. In Example 1, a simple two-unit three-hour problem is used to demonstrate the differences between the Markovian approach and the stochastic programming approach in terms of optimization costs, simulation costs, and impacts from different numbers of ramp rate constraints. In Example 2, a problem with 309 units over 24 hours of ISO-New England is tested to demonstrate the computational efficiency, the robustness with respect to the number of states, the impact of the number of nonzero elements in the state transition matrix, the effectiveness to accommodate different levels of wind penetration, and the ability of capturing low-probability high-impact events of the Markovian approach.

Example 1. Consider a two-unit three-hour problem without minimum up/down time for simplicity. The parameters of the two units are provided in Table III.

Assume that the three possible net demand levels are 70, 100 and 130 for all the three hours with the following state transition matrix for both optimization and simulation:

$$\pi = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} \\ \pi_{21} & \pi_{22} & \pi_{23} \\ \pi_{31} & \pi_{32} & \pi_{33} \end{bmatrix} = \begin{bmatrix} 80\% & 20\% & 0 \\ 10\% & 80\% & 10\% \\ 0 & 20\% & 80\% \end{bmatrix}.$$

The probabilities of net system demand at 70, 100 and 130 at Hour 1 are given as 0.1, 0.8, and 0.1, respectively. The probabilities of demand levels at Hours 2 and 3 can be calculated from (2). The stopping criterion is the relative mixed integer programming (MIP) gap 0.01%.

The results of the new approach are summarized in Table IV. The optimization cost is \$21 200. Both units are online, since a single unit's capacity alone is not sufficient for demand levels 100 and 130. One thousand Monte Carlo simulation runs are conducted. The simulation cost is \$19 892, which is less than the optimization cost. This is because the simulation process is simplified as discussed in Section V-B.

The stochastic programming approach considers all 17 possible scenarios ($= 3^3$ minus 10 scenarios with zero probability). Even though the commitment decisions obtained by using the stochastic programming approach turn out to be the same as those obtained by using the Markovian approach, cheaper dispatch decisions are obtained under several scenarios, e.g., Scenario 10 as shown in Table V, with less ramp rate constraints binding than the Markovian approach. Consequently, the optimization cost, \$19 943, is smaller than that of the Markovian approach as discussed in the third paragraph of Section V-D.

TABLE IV
RESULTS FOR EXAMPLE 1 BY USING THE MARKOVIAN APPROACH

Optimization cost		$21,200		CPU time		0.52s	
Net demand		u_1	u_2	x_1	x_2	p_1	p_2
Hour 1	70	0	1	1	1	30	40
	100					40	60
	130					50	80
Hour 2	70	0	0	1	1	30	40
	100					40	60
	130					50	80
Hour 3	70	0	0	1	1	30	40
	100					40	60
	130					50	80

TABLE V
DISPATCH DECISIONS IN SCENARIO 10 FOR EXAMPLE 1 BY USING THE STOCHASTIC PROGRAMMING APPROACH

Scenario		Net demand	p_1	p_2
10	Hour 1	100	30	70
	Hour 2	100	20	80
	Hour 3	100	20	80

TABLE VI
PENALTY CURVES FOR LOAD SHEDDING AND OVER GENERATION FOR EXAMPLE 2

Load shedding	0~1,000MWh	After 1,000MWh	
Penalty	$1,000/MWh	$85,000/MWh	
Over generation	0~100MWh	100~1,100MWh	After 1,100MWh
Penalty	$0/MWh	$1,000/MWh	$85,000/MWh

The simulation cost turns out to be the same as that of the Markovian approach.

Example 2. Consider ISO-New England's 24-hour problem with 309 units. The bid information of units and forecasted system demand values over 24 hours are taken from a summer day of ISO-NE's day-ahead energy market. All wind farms in New England are lumped together into one aggregated wind farm, and the total wind capacity is scaled to the corresponding values from [31] for different levels of wind penetration. Three cases are tested. The nominal case uses the 10-state transition matrix of Table I with the initial wind generation at State 5 (0.4 to 0.5 of the wind capacity) for optimization, and a detailed 50-state transition matrix based on the same data set with the initial wind generation at State 25 (0.48 to 0.50 of the wind capacity) for simulation. It also considers 5% wind penetration with wind generation capacity 2.3 GW without rare events. For all the cases, if net system demand cannot be satisfied, penalties will be incurred for load shedding and over generation based on convex piecewise linear penalty functions as shown in Table VI without considering wind curtailment for simplicity. The stopping criterion in optimization is the relative MIP gap 0.01% for Cases 1 and 3, and 0.2% for Case 2.

Case 1. The robustness with respect to the number of discretized states and the impact of the number of nonzero elements in the state transition matrix on the computational efficiency are tested. To demonstrate the robustness with respect to the number of discretized states in our approach, 10 states and 20 states are tested. In simulation, 1000 Monte Carlo runs are conducted based on the 50-state detailed transition matrix.

The results are summarized in Table VII. It can be seen that the CPU time for solving the 20-state problem is longer than that of 10-state problem. Welch's t-test verifies the hypothesis that simulation costs of using 10 and 20 states are the same at the 0.05 level of significance, and F-test verifies that standard deviations are the same at the 0.05 level of significance. Thus 10 states are used in Cases 2 and 3.

TABLE VII
RESULTS FOR CASE 1

		10 states	20 states
Optimization	CPU time	1min4s	6min2s
	Cost (k$)	11,838	11,854
Simulation	Cost (k$)	11,803	11,802
	STD (k$)	513	520

To test the impact of the number of nonzero elements in the state transition matrix on the computational efficiency, one hypothetical case with a 10-state transition matrix where each element equals to 0.1 is tested. The state probabilities are calculated based on the hypothetical state transition matrix. The CPU time turns out to be 7 minutes and 18 seconds and is longer than the corresponding CPU time in Table VII by using the block diagonal matrix. The main reason is that more ramp rate constraints are considered with more nonzero elements in the transition matrix.

Case 2. Different levels of wind penetration, 9%-24% from [31], are tested beyond the nominal 5%. The same transition matrix is used for different penetration for simplicity. The system demand is increased from that of Case 1 to avoid negative net demand and is the same for all penetration levels.

The results are summarized in Table VIII. When the wind penetration level increases, the CPU time increases, since more ramp rate constraints (9) and (10) become (7), making the convex hull more difficult to obtain, as explained below. For the tested dataset, ramp constraints of units with small dispatch range ($p_{i\max} - p_{i\min}$) are mostly eliminated during preprocessing before optimization, since the dispatch range is even smaller than the ramp rate (Δ_i). Oppositely, ramp constraints of units with large dispatch range are often included in optimization. After eliminating obviously redundant ramp constraints, the number of possible ramp constraints (9) and (10) considered in optimization is the same 34608 among different penetration levels, since the same transition matrix is used. When penetration level increases, units with ramp constraints considered are committed for more hours, so more ramp constraints (9) and (10) become (7), as shown in the fifth row of Table VIII. Since constraints (7) are time-coupling and couple different states in two consecutive hours, more constraints (7) will make the convex hull more difficult to obtain. According to CPLEX log files, the stopping criterion is reached immediately after cuts are added for 5%, 9%, and 14% penetrations. However, for 20% and 24% penetrations, branching is needed after adding cuts.

The simulation cost and the standard deviation of costs are also shown in Table VIII, including the breakdown into the expected unit commitment and economic dispatch (UCED) cost and the expected penalty costs (all in $\$10^3$). It can be seen that the Markovian approach is effective to accommodate up to 20% penetration of wind generation efficiently, since UCED costs decrease and penalty costs do not increase much. However, UCED

TABLE VIII
RESULTS FOR CASE 2

Penetration		5%	9%	14%	20%	24%
Wind Capacity (GW)		2.3	4.17	6.6	9	11
Opt	CPU	1min02s	1min11s	2min41s	7min30s	38min19s
	Total (k$)	15,251	13,923	12,690	12,918	16,397
	Con-straints (7)	14,066	14,066	14,140	16,918	23,212
Simulation	Total (k$)	15,188	13,803	12,473	12,276	15,909
	STD	729	1,006	1,308	2,050	11,759
	UCED	15,182	13,803	12,458	12,185	14,496
	Penalty	6	0	15	91	1,413

costs and penalty costs increase drastically from 20% to 24% of penetration with more expensive UCED decisions and more load shedding or over generation. Also, with increasing wind penetration, the standard deviations of total costs increase.

Case 3. The Markovian approach is compared with the stochastic programming approach and the deterministic approach in terms of cost efficiency. Special attention is paid to the ability of capturing low-probability high-impact events, resembling the sudden wind drop in Texas in February 2008. For the Markovian approach, the initial wind state is State 9 (0.8 to 0.9 of the wind capacity) to make sudden wind drops more likely to happen in the experiment. For the stochastic programming approach, wind generation at each hour is assumed to follow a normal distribution with mean and standard deviation established based on the corresponding detailed 50-state transition matrix. Three thousand scenarios are produced. Scenario reduction is performed by using GAMS/SCENRED [18], [19]. The problem is solved with the reduced 10 scenarios as well as with 20 scenarios. For the deterministic approach, the net system demand uses the average demand plus 10% at each hour to secure more online generation capacity.

Results without considering rare events are summarized in Table IX. It can be seen from the CPU time that the Markovian approach is more computationally efficient than the stochastic programming approach with 20 scenarios. The optimization cost of our approach is higher than those of the stochastic programming approach with 10 and 20 scenarios as explained before. However, the simulation cost as well as the number of simulated scenarios with penalties of our approach is smaller than those of the stochastic programming approach. This demonstrates that 10 states can capture more information of wind generation than 10 or 20 scenarios. The simulation cost of the deterministic approach is much higher than others, indicating that the additional 10% online generation capacity is not as useful as stochastic models.

Considering rare events Rare events can be captured in the transition matrix. Consider a hypothetical case where the transition probability from State 50 to State 1 of the detailed transition matrix is adjusted from 0 to 0.00001. The transition probability from State 50 to State 50 is correspondingly reduced by 0.00001. In optimization, the transition probability from State 10 to State 1in Table I is adjusted to 0.00001. In simulation, importance sampling is used as discussed in Section V-C.

TABLE IX
RESULTS FOR CASE 3 WITHOUT RATE EVENTS

		Marko-vian	SP		Deter-ministic
			10 scenarios	20 scenarios	
Opt	CPU	2min29s	1min57s	6min1s	4s
	Total (k$)	10,856	10,475	10,504	13,206
Simulation	Penalty Scenarios	3	178	175	997
	Total (k$)	10,593	10,795	10,795	12,659
	STD (k$)	354	1,813	1,928	459

TABLE X
RESULTS FOR CASE 3 WITH RATE EVENTS

		Marko-vian	SP		Deter-ministic
			10 scenarios	20 scenarios	
Opt	CPU	1min57s	1min57s	6min1s	4s
	Total (k$)	10,857	10,475	10,504	13,206
Simulation	Penalty Scenarios	80	253	250	997
	Total (k$)	10,474	10,676	10,676	12,523
	STD (k$)	477	6,449	5,080	491

The results are summarized in Table X. The simulation cost, the standard deviation, and the number of simulated scenarios with penalties of the Markovian approach are smaller than those of other approaches, demonstrating that the solutions of the Markovian approach are more robust than those of other approaches. The reason is that for the stochastic programming approach, the scenarios with high-impact rare events are likely to be eliminated during the scenario reduction procedure. Also, it is difficult to specifically include such high-impact scenarios since which scenarios will cause harmful impacts cannot be identified before unit commitment decisions are made. In contrast, for the Markovian approach, multiple rare events can be captured in the state transition matrix with only one nonzero element in an off-diagonal position, and the adjusted transition matrix can be directly used in the unit commitment process.

VII. CONCLUSION

In this paper, the aggregated wind generation is modeled as discrete Markov processes with state transition matrices established based on historical data. A stochastic unit commitment problem is formulated based on states instead of scenarios. With state transition probabilities given, state probabilities calculated before optimization, and the objective function and constraints formulated in a linear manner, the linearly formulated problem can be effectively solved by using the branch-and-cut method. Numerical results demonstrate that the Markovian approach is computationally efficient, effective under 20% of wind penetration, and is able to capture low-probability high-impact events. The approach thus represents a new and effective way to address stochastic problems without scenario analysis.

REFERENCES

[1] E. Ela and B. Kirby, "ERCOT event on February 26, 2008: Lessons learned," NREL, CO, Tech. Rep. NREL/TP-500–43373, 2008.

[2] IBM ILOG, "Introducing IBM ILOG CPLEX Optimization Studio V12.4," 2012 [Online]. Available: http://pic.dhe.ibm.com/infocenter/cosinfoc/v12r4/index.jsp? topic=\%2Filog.odms.studio.help%2FOptimization_Studio%2Ftopics%2FCOS_home.html

[3] O. I. Gurobi, *UROBI Optimizer Reference Manual, Version 5.0,* Gurobi Optimization, Inc., 2012 [Online]. Available: http://www.gurobi.com/documentation/5.0/reference-manual

[4] Y. Bar-Shalom, X. R. Li, and T. Kirubarajan, *Estimation with Applications to Tracking and Navigation: Theory Algorithms and Software*. Hoboken, NJ, USA: Wiley, 2001.

[5] B. Zhang, P. B. Luh, E. Litvinov, T. Zheng, F. Zhao, J. Zhao, and C. Wang, "Electricity auctions with intermittent wind generation," in *Proc. IEEE Power Energy Soc. 2011 Gen. Meet.*, Detroit, MI, USA, Jul. 2011.

[6] X. Guan, P. B. Luh, H. Yan, and J. A. Amalfi, "An optimization-based method for unit commitment," *Int. J. Electr. Power Energy Syst.*, vol. 14, no. 1, pp. 9–17, 1992.

[7] S. J. Wang, S. M. Shahidehpour, D. S. Kirschen, S. Mokhtari, and G. D. Irisarri, "Short-term generation scheduling with transmission and environmental constraints using an augmented Lagrangian relaxation," *IEEE Trans. Power Syst.*, vol. 10, no. 3, pp. 1294–1301, 1995.

[8] M. Carrión and J. M. Arroyo, "A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem," *IEEE Trans. Power Syst.*, vol. 21, no. 3, pp. 1371–1378, Aug. 2006.

[9] G. Morales-España, J. M. Latorre, and A. Ramos, "Tight and compact MILP formulation of start-up and shut-down ramping in unit commitment," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1288–1296, May 2013.

[10] D. Rajan and S. Takriti, "Minimum up/down polytopes of the unit commitment problem with start-up costs," IBM Res. Rep., 2005.

[11] F. Bouffard and F. D. Galiana, "Stochastic security for operations planning with significant wind power generation," *IEEE Trans. Power Syst.*, vol. 23, no. 2, pp. 306–316, 2008.

[12] J. Wang, M. Shahidehpour, and Z. Li, "Security-constrained unit commitment with volatile wind power generation," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1319–1327, Aug. 2008.

[13] V. S. Pappala, I. Erlich, K. Rohrig, and J. Dobschinski, "A stochastic model for the optimal operation of a wind-thermal power system," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 940–950, May 2009.

[14] P. Ruiz, P. C. Philbrick, E. Zak, K. W. Cheung, and P. Sauer, "Uncertainty management in the unit commitment problem," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 642–651, May 2009.

[15] A. Papavasiliou, S. Oren, and R. P. O'Neill, "Reserve requirements for wind power integration: A scenario-based stochastic programming framework," *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2197–2206, Nov. 2011.

[16] C. Weber, P. Meibom, R. Barth, and H. Brand, "Wilmar: A stochastic programming tool to analyze the large-scale integration of wind energy," in *Optimization in the Energy Industry*. Berlin, Germany: Springer, 2009, ch. 19, pp. 437–458.

[17] L. Wu, M. Shahidehpour, and Z. Li, "Comparison of scenario-based and interval optimization approaches to stochastic SCUC," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 913–921, May 2012.

[18] J. Dupacový, N. Gröwe-Kuska, and W. Römisch, "Scenario reduction in stochastic programming: An approach using probability metrics," *Math. Program.*, vol. 95, no. 3, pp. 493–511, 2003.

[19] H. Heitsch and W. Römisch, "Scenario reduction algorithms in stochastic programming," *Comput. Optim. Appl.*, no. 24, pp. 187–206, 2003.

[20] N. Growe-Kuska, H. Heitsch, and W. Romisch, "Scenario reduction and scenario tree construction for power management problems," in *Proc. Power Tech Conf. 2003 IEEE Bologna*, Jun. 2003.

[21] M. R. Garey and D. S. Johnson, *Computers and Intractability: A Guide to the Theory of NP-Completeness*. New York: W. H. Freeman, 1979.

[22] A. Ben-Tal and A. Nemirovski, "Robust optimization-methodology and applications," *Math. Program.*, vol. 92, no. 3, pp. 453–480, 2002.

[23] D. Bertsimas and S. Melvyn, "The price of robustness," *Operations Res.*, vol. 52, no. 1, pp. 35–53, 2004.

[24] M. Zhang and Y. Guan, "Two-stage robust unit commitment problem," Arizona State Univ., Tempe, AZ, USA, Tech. Rep., 2009.

[25] R. Jiang, M. Zhang, G. Li, and Y. Guan, "Two-stage robust power grid optimization problem," Univ. Florida, Gainesville, FL, USA, Tech. Rep., 2010.

[26] L. Zhao and B. Zeng, "Robust unit commitment problem with demand response and wind energy," Univ. South Florida. Tampa, FL, USA, Oct. [Online]. Available: http://www.optimization-online.org/DB_FILE/2010/11/2784.pdf

[27] D. Bertsimas, E. Litvinov, X. A. Sun, J. Zhao, and T. Zheng, "Adaptive robust optimization for the security constrained unit commitment problem," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 52–63, Feb. 2013.

[28] R. Jiang, J. Wang, and Y. Guan, "Robust unit commitment with wind power and pumped storage hydro," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 800–810, May 2012.

[29] D. Brooks, E. Lo, R. Zavadil, S. Santoso, and J. Smith, "Characterizing the impacts of significant wind generation facilities on bulk power system operations planning," Xcel Energy, Arlington, VA, USA, North Case Study Final Rep., prepared for Utility Wind Integration Group, May 2003.

[30] J. Mur-Amada and A. A. Bayod-Rújula, "Wind power variability model," in *Proc. 9th Int. Conf. Elect. Power Quality Util.*, Barcelona, Spain, Oct. 2007.

[31] "New England wind integration study," Final Report, Prepared for ISO New England , Dec. 5, 2010 [Online]. Available: http://www.iso-ne.com/committees/comm_wkgrps/prtcpnts_comm/pac/reports/2010/newis_report.pdf

[32] The National Renewable Energy Laboratory, "Eastern wind dataset," 2010 [Online]. Available: http://www.nrel.gov/electricity/transmission/eastern_wind_methodology.html

[33] U. Focken, M. L. K. Mönnich, H. Waldl, H. G. Beyer, and A. Luig, "Short-term prediction of the aggregated power output of wind farms-a statistical analysis of the reduction of the prediction error by spatial smoothing effects," *J. Wind Eng. Ind. Aerodyn.*, vol. 90, no. 3, pp. 231–246, Mar. 2002.

[34] "'The grid scale battery storage market to be worth $1.2bn in 2013,' says Visiongain report," 2013 [Online]. Available: http://www.visiongain.com/Press_Release/381/'The-grid-scale-battery-storage-market-to-be-worth-1-2bn-in-2013'-says-visiongain-report

[35] "The energy storage breakthrough we've been waiting for?" *Smart Grid News*, 2013 [Online]. Available: http://www.smartgridnews com/artman/publish/Technologies_Storage/The-energy-storage-breakthrough-we-ve-been-waiting-for-5654.html#.UWRK4jBceNo

[36] M. Denny, "Introduction to importance sampling in rare-event simulations," *Eur. J. Phys.*, vol. 22, no. 4, pp. 403–411, 2001.

[37] P. W. Glynn and D. L. Iglehart, "Importance sampling for stochastic simulation," *Manage. Sci.*, vol. 35, no. 11, pp. 1367–1392, Nov. 1989.

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