

The Hidden Cost of Priority Dispatch for Wind Power

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Abstract

Renewable generation, such as wind power, is commonly considered a must-take resource in power systems. In this work we show that, given the technical capabilities of current wind turbines, this approach could lead to major economic inefficiency as wind integration levels in power systems increase. We initially provide intuition for cases in which the optimal operating point involves shedding renewable generation, even though no cost is associated with it in the optimization objective, illustrated in small power systems. We then explore the expected benefit from dispatching wind resources at a lower level than their available output in a Stochastic Unit Commitment (SUC) framework. The modeling and evaluation approach adopted are described. A decomposition technique based on recent literature that utilizes global cuts and Lagrangian penalties to achieve convergence is used to solve the resulting large scale mixed integer optimization problem, in a high performance computing environment. A reduced California system is examined as a test case.

1. Introduction

The worldwide drive towards a cleaner and sustainable electricity generation mix has led to increased renewable integration goals for the coming years. California, for example, is on track for achieving its 2020 goal of 33% of energy needs satisfied by renewable resources and now aims for 50% by 2030 [1]. Renewable resources have been traditionally treated - and are still treated by many system operators - as must-take resources (negative load), i.e. they are fully integrated in the electricity network regardless of their level or variability. Renewable curtailments only occur in cases where operational feasibility is at risk. The increased renewable integration, however, gradually brings about new operating conditions, such as steeper power ramps, overgeneration and decreased frequency response capabilities. Conventional generation by itself is unable or

extremely costly to deal with these new conditions and a paradigm shift is necessary, in which renewable generation is called upon to contribute to ancillary services and grid flexibility by systematically dispatching at levels defined by operational and cost considerations. The need for such policies is already becoming apparent in regions with increased renewable integration; the California Independent System Operator (CAISO) curtailed about 1% of the total potential renewable generation during the first quarter of 2017, with solar curtailment reaching up to 30% at specific times, while it has already adopted market based curtailment mechanisms [2]. In Europe, on the other hand, directive 2009/28/EC is currently in force and stipulates by law that “Member States shall ensure that when dispatching electricity generating installations, transmission system operators shall give priority to generating installations using renewable energy sources in so far as the secure operation of the national electricity system permits and based on transparent and non-discriminatory criteria” [3].

We focus on mobilizing the flexibility of wind dispatch. Current wind generators and power plants have advanced controls that allow them to operate practically at any point below their (maximum) available output [4,5]. However, their available output itself depends on the weather conditions, i.e. the availability of wind. Consequently, they are considered semi-dispatchable (in contrast to conventional resources for which complete control over the output point is possible). These technical capabilities, however, enable us to consider the optimization of the wind generation setpoint, instead of integrating all of the available wind generation into the system. The benefits from curtailing wind production have been examined from various perspectives. In [6] and [7], NREL provides a series of cases of wind curtailment in systems in the US or abroad. In [8] and [9] CAISO uses the software PLEXOS to simulate a rolling unit commitment problem in the presence of wind curtailment for high wind penetration. In [10] it is shown that allowing for renewable curtailment enables significant reduction of the required system storage size, in [11] the benefits

are motivated mainly through solving a Security Constrained Optimal Power Flow (SCOPF) problem, in [12] through a market coupling and a nodal pricing model of part of the European system, in [13, 14] through a Security Constraint Unit Commitment (SCUC) Problem and in [15] a dynamic interaction of wind curtailment with storage is examined when the ramping rates of power plants are considered. An overview of the motivation behind wind curtailment is given in [16], whereas in [17] wind curtailment is employed for active network management. A flexible wind dispatch margin for the joint energy and reserves market and offline policies to obtain it are examined in [18] and [19].

We decided to motivate flexible wind dispatch in the context of the Stochastic Unit Commitment (SUC) problem instead. The Unit Commitment problem is a widely studied mixed integer program [20–22] that determines the set of generators, among all the available ones, that will be committed to satisfy the load during the following day. The two stage Stochastic Unit Commitment problem (SUC) formulates the same decision in the presence of uncertainty (renewable generation, faults, load), captured by a finite set of possible realizations (scenarios) [23–27]. While wind curtailment is a usual assumption when formulating the SUC problem, in this work we explicitly focus on calculating the expected benefit from optimizing the wind output setpoint versus an approach that treats wind as a priority resource. A similar approach appears in [28], where coordination with storage is considered to illustrate the benefits from dispatchable wind. The size of the optimization problem scales linearly with the number of scenarios and for that purpose a large amount of research has been devoted to decomposition techniques to iteratively approximate the solution of the problem. Among these, in [29], the Progressive Hedging (PH) algorithm is adapted to successfully solve the SUC problem. In [30] a cutting plane algorithmic approach is used. In [31] a parallel implementation of Lagrangian relaxation in a high performance computing environment is employed. In [32] an asynchronous parallelized algorithm based on stochastic subgradient is utilized to efficiently solve the problem.

In this work, we provide a complete framework to understand and evaluate the expected benefit from flexible wind dispatch in a SUC setting, while also introducing innovations in the implementation of the various components of the model. To begin with, since wind generation is not associated with any fuel costs in the objective, it is not self evident why we could be better off curtailing it and using costly conventional generation in its place. For this reason, we present small motivating examples to offer intuition regarding the most

common setups where such benefit may occur: operation during oversupply, ramping requirements, technical minima of generators and congestion. We then proceed to describe the complete evaluation framework, by introducing its basic components: the Uncertainty and Optimization Modules.

The Uncertainty Module is responsible for generating sample scenarios that capture the underlying uncertainty for renewables and system faults. It is based on existing wind speed modeling techniques, which we extend by using a non parametric modeling methodology for the aggregate power curve, i.e. the mapping of wind speed to wind generation, utilizing local polynomial regression [33]. The Optimization module, on the other hand, is responsible for solving the SUC problem given a set of scenarios. It specializes an algorithm presented in [34] for general two stage stochastic programs with binary first stage variables. The intuition behind the algorithm is that, if the different scenarios of a stochastic program are similar, then it is possible that a good (first stage) solution to the full problem will come from solving the significantly smaller subproblems that only look at scenarios in isolation. By solving the scenarios in isolation in the first phase of the algorithm, we obtain lower bounds to the SUC optimal objective. Then, by testing the various first stage solutions we got from the individual scenario subproblems to the full problem, we get feasible solutions to the full problem (upper bounds) in the second phase of the algorithm. We proceed to eliminate these solutions from consideration in the next iterations, when we resolve the individual scenario subproblems. The algorithm is executed until the desired optimality guarantee is obtained.

In the experimental results of [34, 35], the algorithm is tested without implementing dual updates (just employing cuts to eliminate solutions already tested). Even though SUC satisfies the technical requirements of the algorithm, the cuts employed fail to efficiently reduce the gap for the SUC problem on their own. To remedy that, we combine the use of cuts with Lagrangian penalties in the objective of the individual scenario subproblem to convey information from other scenarios, so as to obtain scenario specific solutions that perform well in the full problem. The exact penalties we use are the same as the Progressive Hedging Lower Bounds [36], in a way that the lower bounding property of the first phase of the algorithm is preserved, and lead to a projected subgradient descent optimization scheme at every iteration (an update that lies within the general framework of the algorithm in [34]). One advantage of the algorithm from [34] is that termination of the algorithm with any desired optimality gap is (at least in theory) guaranteed, in contrast to a simple subgradient optimization scheme

for the dual where the achievable accuracy is limited by the duality gap between the primal and dual problems at best.

We test our framework on a reduced model of the Western Electricity Coordinating Council (WECC) system from 2010 [37], consisting of 130 thermal generators, 225 nodes and 371 lines for three wind penetration scenarios (low, medium and high). After the SUC problem is solved, we utilize its optimal solutions to compare the cost of policies that treat wind as a must-take resource versus ones that allow flexible wind dispatch. Regarding the value of wind flexibility, our results indicate negligible cost benefit in the low and medium integration case, but a 15% cost improvement in the high integration case, supporting the argument that flexible wind dispatch should be directly integrated in the operation of the power market.

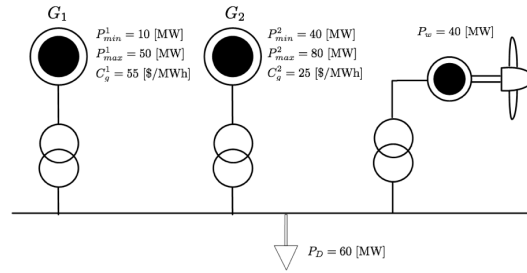
The paper is structured as follows: In section 2, the motivating examples are provided, in section 3, the general modeling is described, in section 4 simulation results are shown, and in section 5 we conclude and discuss policy implications of the work.

2. Motivating Examples

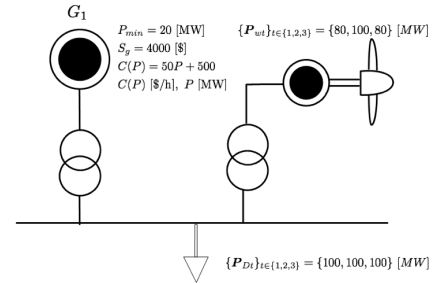
In order to motivate the discussion and provide some intuition on the cost benefits from allowing wind generation to deviate from the available wind power output, four stylized examples are examined. These examples try to illustrate that, even though wind generation is not associated with any cost in the objective, it can still be beneficial to spill wind resources for a cost efficient allocation of conventional generation. Fig. 1 outlines the parameters for these examples.

In example 1, if the 40MW of wind power are treated as a must-take resource, the total residual load that needs to be satisfied by conventional generation would be 20MW. Due to the technical minimum 40MW of generator G_2 , we need to use the expensive G_1 , resulting in a 1100 \$/h cost of operation. If instead the output of the wind generator is adjusted to 20MW, G_1 can be used and the cost drops to 1000 \$/h.

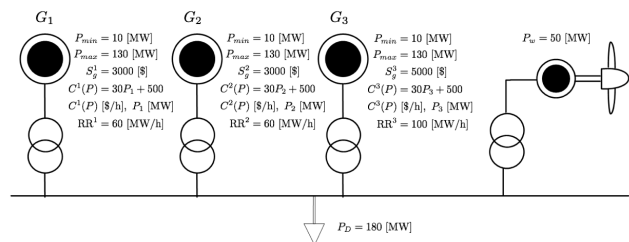
In example 2, if wind power is a must-take resource, it can fully satisfy demand for time period 2. A residual load of 20MW should be satisfied by conventional generation in periods 1 and 3. That, however, means that generator G_1 must restart at period 3 and the startup costs are incurred twice, leading to a total cost of 11000\$ for the three periods. If, instead, 20MW of wind are spilled during the second time period, G_1 can stay on and the total cost is now 8500\$. Note that this intuition could be extended for more time periods or for instances with more conventional generators.



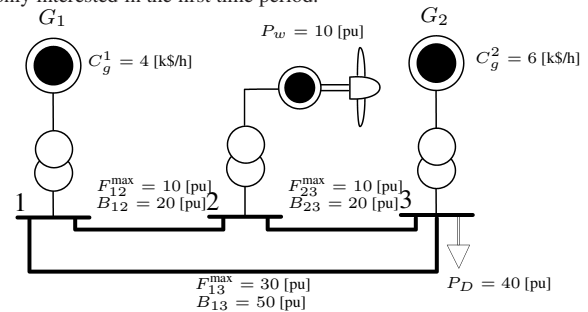
(a) Example 1. The generator specifications in this case are minimum and maximum generation limits (P_{\min} , P_{\max}) and marginal costs C_g . The available (maximum) wind power generation is P_w and the load is P_D .



(b) Example 2. The generator specifications are the minimum generation limit (P_{\min}), the startup cost S_g and the operating cost $C(P)$ as a function of the generation level P . The available (maximum) wind power generation $P_{w,t}$ and load $P_{D,t}$ are given for three consecutive time periods, $t = 1, 2, 3$. G_1 is assumed turned off at the beginning.



(c) Example 3. The generator specifications are minimum and maximum generation limits (P_{\min} , P_{\max}), the startup cost S_g , the operating cost $C(P)$ as a function of the generation level P and the ramping rate RR . The available (maximum) wind power generation is P_w and the load is P_D . The generators are initially assumed turned off and we are only interested in the first time period.



(d) Example 4. The system consists of three buses and three branches with susceptances B and capacities F^{\max} as provided in the figure. The generator specifications are the marginal costs C_g , the maximum available wind production is P_w and the load is P_D .

Figure 1: Small examples to illustrate potential benefits of wind power spilling.

In example 3, the goal is to satisfy $N - 1$ security. More specifically, if any of the generators fail, we should be able to recover the lost generation within the next time unit (an hour is used here, but a smaller time resolution could be considered). Generators G_1 and G_2 are identical and have a lower startup cost than generator G_3 , however their ramping rates are limited to 60MW/h, whereas G_3 has a ramping rate of 100MW/h. In the case where no wind spill is allowed, utilizing only the cheap generators does not yield a feasible solution, since assuming they share the residual load of 130MW by generating 65MW each, the ramping capabilities of G_1 are not sufficient in case G_2 fails (in case they share the load unevenly, the same problem arises if the highest generating unit fails). So the costly generator G_3 needs to be utilized, leading to a total cost of \$12900. Now, if instead we dispatch the wind unit at 40MW, by spilling 10MW of wind power, we can satisfy the residual load of 140MW by evenly sharing between G_1 and G_2 , i.e. 70MW each. In case G_2 suffers a fault, we can cover 60MW of its generation by G_1 and the remaining 10MW we can obtain by ramping up the wind generation to its available output. For that, we exploit the fact that wind turbine controls allow for very fast ramping. The second dispatch amounts to a lower cost of \$11200.

Finally, in example 4, a DC optimal power flow problem is solved to illustrate how allowing for flexible wind dispatch may lead to a more economical allocation by alleviating congestion. In the case where the 10pu of wind power are treated as a must-take resource, in the optimum they all pass through branch 2 – 3 to satisfy the load of bus 3, binding the phase angle difference between buses 2 and 3 as well. That means the flow of branch 2 – 3 is at its capacity, so the flow on the line 1 – 2 must be zero. Because of that, the phase of bus 1 has to equal that of bus 2 and that constrains the flow on line 1 – 3 to 25pu. We observe that both line 1 – 2 and line 1 – 3 are not utilized close to their full capacity, whereas line 2 – 3 is congested. Also, 5pu of the load is satisfied by the expensive generator G_2 , leading to a total cost of \$130000/h. If we instead dispatch wind at 8pu, we can satisfy the load without using the expensive generator, by generating 32pu with G_1 and the remaining 8pu through wind, leading to a lower total cost of \$128000/h. The flows are in this case $P_{12} = 2pu$, $P_{23} = 10pu$ and $P_{13} = 30pu$, which also corresponds to a better utilization of the line capacities.

3. Model Outline

The examples of the previous section constitute favorable scenarios in which introducing flexible wind dispatch allows for a lower cost of operation, due to

technical minima of conventional generation, efficient scheduling, ramping requirements or congestion. In order to make an argument for a more general case, however, we need to consider a large set of scenarios, generated based on a model of the underlying uncertainty of an actual system. For that purpose, the procedure depicted in Fig. 2 is adopted. The developed model comprises of two basic components, the Uncertainty Module and the Optimization Module. The Uncertainty Module tries to capture the underlying uncertainty of the system, which in our case is assumed to come from wind generation and line or generator faults. The module is trained based on a data set and then used to generate scenarios whenever these are necessary. The Optimization Module, on the other hand, takes as input a set of scenarios and solves a stochastic unit commitment problem, providing in its output a commitment schedule of the slow generators for the next day. The Optimization Module can be treated as a black box that a system operator uses to make the day ahead scheduling based on a set of available scenarios. Furthermore, it has two settings; in the first setting the optimization treats wind generation as a must-take resource, whereas in the second setting wind generation is allowed to dispatch at lower levels.

Based on these modules, the testing process is the following: Initially, the Uncertainty Module generates a set of scenarios. These scenarios are treated as the uncertainty information the system operator utilizes to make the scheduling decision. Based on this information, the Optimization Module makes one scheduling decision for each of two cases: the one in which wind is a must-take resource, and the one that it is not. In the final step, we wish to evaluate the difference between the costs associated with each case. To that end, we generate a new set of scenarios from the Uncertainty Module, representing possible actual realizations of the uncertainty the next day, and compare the expected costs of each of the two cases (Test Optimal Commitment Block).

3.1. Uncertainty Module

The underlying uncertainty of the problem considered consists of three main components: the wind model, the power curve model and the reliability model. The purpose of the wind model is to generate synthetic wind speed time series with hourly resolution, representative of the wind sites under consideration. Subsequently, the power curve model takes as input the wind speed time series and outputs a wind power generation series for every wind site. Finally, the reliability model is a discrete (Bernoulli) distribution from where faults of lines and generators are drawn, as in [23].

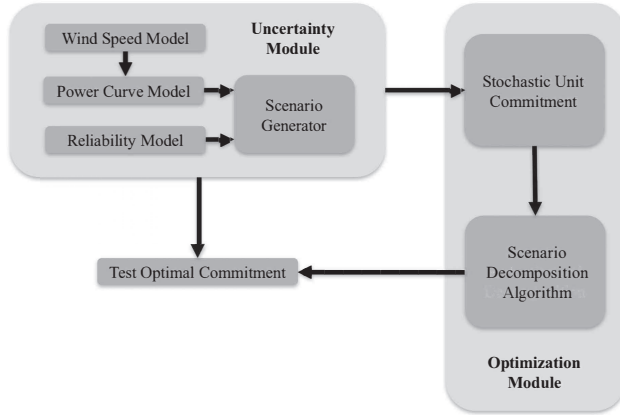


Figure 2: General model outline. The Uncertainty Module generates scenarios to be used as input for the Optimization Module, which defines an optimal commitment. It also generates a new set of scenarios to test this optimal commitment.

3.1.1. Wind Speed Model A wind model that captures the characteristics of wind speed from multiple wind sites is implemented. The approach follows the steps from [38], which builds upon work from [39] and [40]. The input data used to train the model are wind speed measurements ξ_{gk}^{train} , where $g \in G_W$ indicates the different wind sites and $k \in \{1, 2, \dots, T_{\text{train}}\}$ indicates the T_{train} hourly measurements that are available at every wind location. The goal is to train a model based on these measurements and then use it to generate artificial wind series. The steps employed are divided in two phases; in the first one (Learning Phase) the model is trained using the time series data, whereas in the second one (Time Series Generation Phase) randomly generated wind time series to be used in a Monte Carlo simulation are created based on the model. The output of the process is a wind time series $\xi_{gts}^{\text{sample}}$ with $g \in G_W$ (for the various wind sites), $t \in T$ (for the desired time steps of the SUC problem), and $s \in S$ (different scenarios/samples used to capture the stochastic nature of the problem).

3.1.2. Power Curve Model For every site of wind generation an aggregate power curve that will provide an estimate of the wind power generation given the wind speed needs to be constructed. For that purpose, wind data and the corresponding wind power generations are used to train a power curve model. The power generation data points come from an aggregation of multiple wind turbines in each site, with potentially different individual power curves and characteristics. Therefore, the use of the standard parametric power curve model of a single wind turbine to describe the wind

speed and power relationship [41] would not be a satisfactory approximation and a data driven non-parametric fit is more suitable. The model should also be able to capture the nonlinear behavior of the power curves, that is dependent on the wind speed operating point. For the aforementioned reasons, a local polynomial regression scheme is proposed.

More specifically, for every fixed $g \in G_W$ the wind speed and wind power measurement data $(\xi_{gk}^{\text{train}}, P_{gk}^{\text{train}})$, $k \in \{1, \dots, T_{\text{train}}\}$ are sorted (based on the lexicographical ordering) in L_g wind speed intervals $[a_{gi}, b_{gi}]$, where $i \in \{1, 2, \dots, L_g\}$, with approximately equal number of measurements, represented by a central wind speed point c_{gi} . We locally approximate the power curve mapping for this site with a polynomial of degree p , i.e. $m_{gi}(x) \approx \beta_{gi0} + \beta_{gi1}(x - c_{gi}) + \beta_{gi2}(x - c_{gi})^2 + \dots + \beta_{gip}(x - c_{gi})^p$. The coefficients $\beta_{gi0}, \dots, \beta_{gip}$ are trained for each interval based on a weighted least squares problem, where the weights are kernel functions of the distance of a point from the center of its interval. After an initial fit is obtained, the procedure in [33] is adopted to ensure the fit is robust to outliers.

Following that process, we feed the wind speed samples $\xi_{gts}^{\text{sample}}$, obtained by the wind speed model, to the trained power curve model, to obtain available wind power samples P_{Wgts} , for $g \in G_W, t \in T, s \in S$:

$$P_{Wgts} = \sum_{i=1}^{L_g} m_{gi}(\xi_{gts}^{\text{sample}}) \mathbb{I}_{[a_{gi}, b_{gi}]}(\xi_{gts}^{\text{sample}}) \quad (1)$$

3.2. Optimization Module

3.2.1. Stochastic Unit Commitment The generating units available to the system operator are divided into slow and fast, based on how long prior to operation a commitment decision for that unit has to be made. The output of the SUC problem is the commitment of slow generating units. The challenge is that the commitment decision for slow units has to be made a day before operation, when the underlying uncertainty is still unknown, i.e. the commitment decisions (binary variables) for these units have to be the same across all scenarios (first stage variables). On the other hand, the other variables of the problem, such as the commitment of fast generating units and the generation levels, are allowed to vary depending on which scenario of nature was realized (the decision for them is made with knowledge of the uncertainty), hence their value can be different for every scenario (second stage variables).

Our formulation is that of [23], adapted to explicitly model the flexibility of wind resources. The objective of

the SUC problem is minimizing the expected, over the different scenarios, operational costs (startup, minimum load and fuel costs), as well as the highly penalized load shed variables. Wind generation is not associated with any fuel costs in the objective. The only modification of our formulation, compared to the one in [23], is that wind will be treated as a must-take resource when an additional parameter i_{allin} is set to 1. This is imposed through the (additional) constraints:

$$p_{gts} + p_{WS_{gts}} = P_{W_{gts}}, \forall g \in G_w, \forall t \in T, \forall s \in S, \quad (2a)$$

$$p_{WS_{gts}} \geq 0, \forall g \in G_w, \forall t \in T, \forall s \in S, \quad (2b)$$

$$p_{WS_{gts}} \leq (1 - i_{\text{allin}})P_{W_{gts}}, \forall g \in G_w, \forall t \in T, \forall s \in S, \quad (2c)$$

where the wind spill $p_{WS_{gts}}$ is set to zero if $i_{\text{allin}} = 1$ (forcing the wind generation p_{gts} to equal the available generation $P_{W_{gts}}$), or optimized to a value between zero and the maximum available wind production $P_{W_{gts}}$, if $i_{\text{allin}} = 0$. Note, however, that the policy adopted by the operators when prioritizing wind generation is that they may still impose curtailments of wind generation, if the system feasibility is compromised. This corresponds to introducing constraint (2c) with a big-M penalty in the objective instead (which will lead to positive wind spill only in case enforcing (2c) as a hard constraint would cause infeasibility). The impact of the penalty is in that case subtracted from the objective cost reported, since the big-M has no physical meaning for the problem costs.

3.2.2. Scenario Decomposition Algorithm The optimization problem described previously has the form of a two-stage stochastic program. For concreteness, let \mathbf{x} be the vector of first stage variables, i.e. the slow generator (binary) commitment. Let f_s , for $s \in S$, be the set of (well defined) functions that, given the first stage variables, yield the optimal cost for the second stage. That is, each evaluation of $f_s(\mathbf{x})$ accounts for solving an optimization problem for scenario $s \in S$ and for first stage variable \mathbf{x} . Then, the SUC can be reformulated:

$$\underset{\mathbf{x} \in X}{\text{minimize}} \sum_{s \in S} \pi_s f_s(\mathbf{x}) \quad (3)$$

The binary nature of the first stage decisions in (3) allows the decomposition scheme proposed in [34] and elaborated in [35] to be employed in order to decompose the problem and reduce the computational burden. The form of decomposition utilized in this work is given in Fig. 3. The main body of the algorithm is divided

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Initialization Phase
 $t \leftarrow 0, UB \leftarrow \infty, LB \leftarrow -\infty, w_s^t \leftarrow 0, \forall s \in S, W \leftarrow \emptyset$ 
Main Body
repeat
   $t \leftarrow t + 1,$ 
  Lower Bounding and Lagrangian Update Phase
  Solve scenario subproblems:
  for  $s \in S$  do
     $\mathbf{x}_s^t \in \underset{\mathbf{x} \in X \setminus W}{\text{argmin}} \{f_s(\mathbf{x}) + \mathbf{x}^T \mathbf{w}_s^{t-1}\}$ 
  end for
  Update Lower Bound:
   $LB \leftarrow \sum_{s \in S} \pi_s f_s(\mathbf{x}_s^t)$ 
  Update objective weights:
  for  $s \in S$  do
     $\hat{\mathbf{x}}^t \leftarrow \sum_{s \in S} \pi_s \mathbf{x}_s^t$ 
     $\mathbf{w}_s^t \leftarrow \mathbf{w}_s^{t-1} + \rho_t (\mathbf{x}_s^t - \hat{\mathbf{x}}^t)$ 
  end for
  Upper Bounding and Cut Phase
  Evaluate scenario solutions for Upper Bounds:
  for  $s \in S$  do
     $UB_s \leftarrow \sum_{i \in S} \pi_i f_i(\mathbf{x}_s^t)$ 
  end for
  Update Upper Bound:
   $UB \leftarrow \min\{UB, \{UB_s\}_{s \in S}\}$ 
  Exclude points tested:
  for  $s \in S$  do
     $W \leftarrow W \cup \{\mathbf{x}_s^t\}$ 
  end for
until  $\frac{UB-LB}{UB} \leq \text{eps}$ 

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Figure 3: Decomposition scheme proposed in [34], adapted to solve the SUC problem. The Lower Bounding Phase involves solving smaller optimization problems than the original, since the scenario is fixed, whereas the Upper Bounding Phase involves smaller problems since the first stage and the scenario are fixed. As discussed in subsection 3.2.2, not both phases are necessarily executed at every iteration.

into two phases, the Lower Bounding and Lagrangian Update Phase and the Upper Bounding Phase and Cut Phase. In the Lower Bounding Phase, we fix every scenario $s \in S$ and solve for the optimal first stage decision given that scenario, over a space $X \setminus W$. This yields $|S|$ scenario specific solutions for the first stage variables \mathbf{x}_s^t at iteration t . In the first iteration, the set W is empty and the penalty coefficients \mathbf{w}_s^t are zero, so we are essentially solving $|S|$ scenario subproblems without any interaction, i.e. we are solving the initial problem after relaxing the non anticipativity constraints. Since we are solving a relaxation, at least for the first iteration, we are guaranteed to get a lower bound on the optimal solution to (3). For the next iterations, it is still straightforward [36] to show we get lower bounds for (3) solved in the restrained space of first stage variables $X \setminus W$.

Following that, the objective value penalties w_s for every scenario $s \in S$ are updated. These penalties aim to drive the scenario solutions together. Intuitively this is achieved in the following way: say that \mathbf{x} is just an one dimensional x and for some iteration t we have that the mean of the scenario specific solutions is \hat{x}^t . If for some scenario $s \in S$, the scenario specific solution x_s^t is away from the mean of the scenarios \hat{x}^t (say $x_s^t = 0$ and $\hat{x}^t = 0.9$), we would like to penalize this deviation

in the objective of the scenario subproblem the next time we iterate, at time $t+1$. So, at iteration $t+1$ a term $(x_s^t - \hat{x}^t)x$ will appear in the objective of scenario s , so that the new solution x of the scenario will be driven towards the mean of the scenarios (in the arithmetic example, the penalty in the objective would be $(0 - 0.9)x = -0.9x$ which will drive x to be 1 in the minimization, i.e. closer to the mean of the scenarios at the previous iteration).

In the Upper Bounding Phase of the algorithm, the $|S|$ scenario specific solutions for the first stage variables found during the previous phase are tested into the full problem. If feasible, each one of them yields an upper bound to (3). That way, we can possibly update the upper bound and the first stage solution that yields it. We then add the points $\{x_s^t\}_{s \in S}$ in the set W . Our objective function value has already been calculated for all of these points, so we can exclude them from further consideration, except for the one that has yielded the best upper bound so far. That is, the execution of the Lower Bounding Phase for the next iteration should only consider points not in W . In practice, this is achieved by adding a global cut in the optimization problems solved in the first phase, for every point in W so as to cut off this particular point. More specifically, a “No-Good-Cut” is employed, i.e. a constraint of the form

$$x^T(1 - x_s^t) + (1 - x)^T x_s^t \geq 1, \quad (4)$$

in order to cut off the point x_s^t . The algorithm iterates until the Lower Bound (LB) and Upper Bound (UB) come close enough to satisfy the desired optimality guarantee (eps).

To get some technical intuition for the algorithm, let us note that the Lower Bounding phase is essentially a step in a projected subgradient ascend scheme for the dual of (3) in the reduced space $X \setminus W$, if the non-anticipativity constraints are dualized. For a suitable choice of ρ_t as a function of time, repeated evaluations of that phase would converge to the dual optimum. However, the dual optimum could be quite smaller than the primal optimum, due to the existence of a non zero duality gap, so we may never reach our desired optimality guarantee. This is where the existence of the second phase of the algorithm becomes important: by expanding the set W , the duality gap between the primal in the space $X \setminus W$ and its dual becomes smaller and, due to the finiteness of X , we are guaranteed to eventually reach any predefined optimality guarantee threshold. In practice, the objective penalties of the first phase are more useful at the beginning of the algorithm, since they lead the scenario specific solutions towards the same point x , while the global cuts are more useful after the first iterations, to reduce the optimality gap by cutting out points when the scenario solutions are similar to each

Type	Units	Capacity [MW]
Nuclear	2	4499
Gas	101	21781
Coal / Oil	3 / 1	199 / 121
Dual Fuel	23	4679
Import	5	9931
Biomass	3	502
Geothermal	2	1073
Hydro	6	8613
Wind Low / Medium / High	5	1414 / 2121 / 2828

Table 1: Generator mix for the test system from [31, 39].

Wind Integration Level	Cost with/without load shed [\$/M]		Wind Integration [%]	
	Must Take	Wind Spill	Must Take	Wind Spill
Low	8.23/8.23	8.23/8.23	13.2	13.0
Medium	6.98/6.98	6.95/6.95	19.8	18.9
High	16.09/7.27	6.11/6.11	26.3	23.4

Table 2: SUC solution evaluated on the test set: Mean cost of operation (without accounting for load shed) and wind penetration (percentage of mean, over the scenarios, wind energy over mean total generated energy).

other and the Lagrangian penalties do not offer significant improvements any more. So, the first phase of the algorithm is executed multiple times until a convergence indication is obtained. Following that, the second phase is executed and this process is repeated a few times.

4. Simulation Results

We consider a reduced model of the Western Electricity Coordinating Council (WECC) system [37] with 225 buses, 371 lines and 130 conventional generators. The same model is used in [39] and [31]. A typical winter weekday is simulated for three different integration cases: high, medium and low. High integration corresponds to 26% wind energy penetration, the medium integration corresponds to 19% penetration and the low integration to 13%. The average load is 28056MW, with a minimum of 21438MW and a maximum of 32300MW. The capacity of thermal generation is 31281MW and the total generating capacity, not including wind resources, is 51402MW. The cost of load shedding is assumed \$5000/MW-h and twice this value is assigned to the big-M relaxation of (2c). The generation mix is shown in

Wind Integration Level	Wind Spill [%]		Load Shed [%]	
	Must Take	Wind Spill	Must Take	Wind Spill
Low	0	1.06	0	0
Medium	0	4.48	0	0
High	0.3	11.1	0.26	0

Table 3: SUC solution evaluated on the test set: Percentage of mean (over scenarios) wind spill over mean available generation and percentage of mean loadshed over the total load.

Table 1.

The uncertainty model is trained based on data taken from [23]. These correspond to yearly time series of wind speeds and wind power generations with hourly resolution for five aggregate wind sites. The initial source was 2006 wind production data from the National Renewable Energy Laboratory database. A discrete distribution is assumed for the reliability model, as in [39]. More specifically, a probability of generator failure of 1% and a probability of transmission line failure of 0.1% is assumed, independently.

All the simulations are performed on the Cab cluster of the Lawrence Livermore National Laboratory. For the simulations, Mosel 4.0.4 was used with Xpress [42]. Each execution was parallelized in 10 nodes of the Cab cluster by utilizing the dedicated features of Mosel [43], allowing 4 threads per job and 4 jobs per node. The typical values used for ρ_t for the decomposition algorithm were $\rho_t \in [0.001, 0.01]$, where the objective costs were normalized in \$M. A 2% optimality guarantee was set as a stopping criterion for the algorithm.

A total of 160 scenarios was generated and used as an input to the SUC problem. These scenarios represent the model available to the operator in the day ahead, based on which the optimization problem that defines the first stage variables is solved. A new set of 160 scenarios is generated, representing the actual realization of the uncertainty the day ahead. We explore two alternative policies; one that allows for wind spill and one that assumes wind is a must-take resource, for the three integration cases. The evaluation of the two policies, each one yielding a different first stage solution, is based on how they perform with the unseen scenarios.

The typical computational performance of the algorithm was as follows. The Lower Bounding phase would be executed until the LB would not improve more than 0.05% for two iterations. Note that, since the dual function is non-differentiable, there is no guarantee that the subgradient will yield a descent direction, so this stopping criterion is merely a heuristic. Typically, the lower bounding phase would terminate within at most 10-15 iterations. After that, the upper bounding phase would start by evaluating the function for the points that correspond to the best LB obtained. This process would be repeated typically 2 – 3 times to obtain the desired optimality guarantee. It is important to note that, while the algorithm offers guaranteed convergence to any required precision (as opposed to subgradient optimization schemes), it has a significant disadvantage for applications that prioritize speed instead of accuracy. The Lower Bounding phase essentially has to solve multiple subgradient optimization problems and the Upper Bounding phase needs to evaluate the objective for

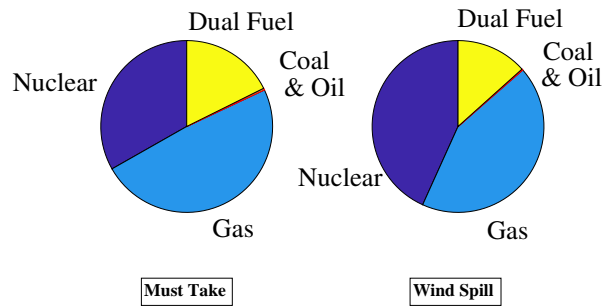


Figure 4: Breakdown of total energy generation from conventional sources for the two policies examined in the high integration case. Note that the increased flexibility introduced by the wind allows for a higher utilization of the cheap generation from nuclear power plants.

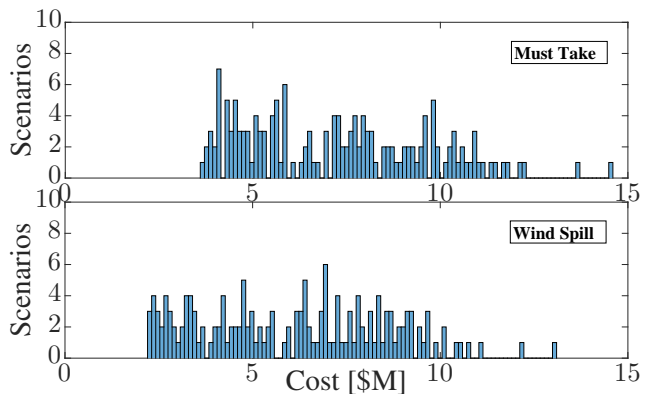


Figure 5: Histogram for the scenarios of stochastic unit commitment for the two policies in the high integration case. The variance of the scenario costs remains approximately the same (approximately equal to 6) for both policies, but the scenarios are spread around a lower mean for the wind spill case.

$|S|$ points (which can be decomposed to solving $|S|^2$ smaller mixed integer programs). The typical execution time was in the order of 1 – 2 hours, which is above the state-of-the-art times reported in literature [32].

Tables 2 and 3 show the policy testing results. The fuel cost without load shedding is also provided. We observe that in the case of low and medium wind integration, wind spilling does not result in a significant benefit. However, for high wind integration, the cost of operation is significantly lower when wind spill is allowed and load shed does not happen, whereas demanding the wind energy to be fully integrated leads to both an inefficient dispatch (high fuel costs) and an increased load shedding.

In Fig. 4, the reason of the more economical dispatch can be seen: the extra flexibility enabled by optimizing the wind output allows for a higher utilization of the cheap nuclear plants. Fig. 5 shows the empiri-

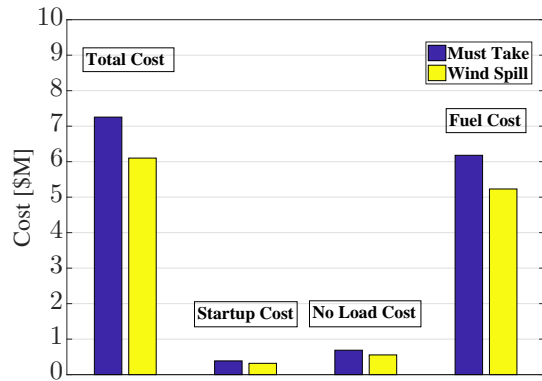


Figure 6: Comparison of the total cost, startup cost, no load cost and fuel cost for the two policies in the high integration case. Note that the bulk savings are obtained from the lower fuel costs due to the higher nuclear utilization.

cal distribution of the costs for the different scenarios of the stochastic unit commitment in the high integration case for the two policies. Finally, Fig. 6 shows the cost breakdown in the high integration case.

5. Conclusions and Discussion

The main objective of this work is to convey that wind resources, and renewables in general, should be treated, to the extent possible, as any other resource for the unit commitment problem. Renewable integration is vital to achieve environmental goals, but it often competes with ensuring the secure and reliable operation of the grid due to the variability and stochasticity of the available wind power. However, current wind turbines are capable to control their output power setpoint within the limits allowed by wind availability. By exploiting this capability a safer and more economic grid operation can be ensured.

Regarding policy implications of adopting the proposed strategy, active wind spilling based on market operations can allow for a more efficient allocation (increased total welfare for the society), which could translate to benefits for the customers (in the form of reduced bills). The conventional generators will also be benefited, since they won't have to fully carry the burden of grid security and reserve. Finally, even though adopting this policy would mean an initial decrease in wind integration levels (since wind energy would be spilled), this strategy would enable a long term increase of renewable integration, since part of the renewable intermittency problems would be resolved.

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