Supporting Wind Generation Deployment with Demand Response

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***Abstract*—We investigate how the demand-side of the electricity industry can facilitate the reliable integration of wind generation resources into power system operations. We study how consumers enrolled in demand response (DR) programs provide a valuable demand-side reserve capacity which can help manage the volatility of wind generation. We also study how a levelized load profile can help accommodate wind generation. Our analysis is based on a stochastic unit commitment model that explicitly represents the uncertainty in the day-ahead scheduling decisions using a two-stage stochastic control problem. We extend the standard problem formulation to accommodate the DR outcomes. Simulation results provide a proof of concept that DR-based reserve capacity is an effective mechanism to counter the volatility and uncertainty of wind resources. These results also show how load leveling relaxes the constraints imposed on the unit commitment solution and can thus help accommodate wind generation. Finally, our analysis raises some research- and policy-oriented questions on the best possible ways to implement demand response programs.**

***Index Terms*—demand response, demand-side reserves, electricity markets, load leveling, load shifting, operational planning, reserves, scheduling, uncertainty, unit commitment .**

I. Introduction

Since electricity is considered the backbone of modern society, power systems have been typically planned and operated in a way which ensures that the electricity demands of the consumers are met in a *reliable* and *economic* manner. More recently, with increased awareness of global warming and green house gas emissions, the scope of power system planning and operations has been extended to consider the *environmental* impacts of electricity production. Considerable investments have been made in wind and solar energy resources in the hopes of creating a more sustainable grid [1]. The deployment of renewable resources presents major challenges in system operations due its intermittent, volatile and uncertain nature. There is a need to investigate afresh the supply- and demand-side management approaches so as to temper the adverse impacts of renewable generation. In this paper, we discuss how the flexibility in the demand-side loads with respect to consumption can be effectively harnessed to integrate volatile renewable generation in power system operations.

Wind power is one such volatile resource that has seen an exponential growth in installed capacity over the last decade [2]. While wind generation (WG) is attractive for massive deployment due to rapid installation and low investment/operational/maintenance costs, it comes with its challenges – poor prediction, especially for forecasting horizons greater than a few hours, and very high variability. As of today, operational practices are designed to be robust, to some extent, to the uncertainty and variability in the supply from thermal generators as well as from the electric demand, which exhibit fairly well understood patterns. However, WG patterns are not as well understood — *it is unclear whether there exists any pattern at all*. Therefere, there is a need to redesign operational practices for systems with deep penetration of WG resources.

The approach so far has been to manage the WG volatility and uncertainty through supply-side reserves. The determination of optimal reserve levels in a stochastic power system model can be cast as a variant of the newsboy's problem for optimal inventory modeling [3]–[5]. The economic efficiency of this optimal outcome has been established in [3]–[5] and the references there in. The analysis in [5] concludes that as WG penetration increases, more reserves will be required to ensure system reliability. Similar results have also been observed in unit commitment-based analysis which explicitly consider uncertainty due to wind forecasts [6], [7]. Thus, there is the need for fast responding reserves from both the supply- and the demand-side in systems with significant WG penetration. While the nature and costs of supply-side reserves are well understood, the demand-side options have not been fully explored.

With the Smart Grid implementation well underway, it is envisioned that the demand-side will play a key role in facilitating reliable integration of the WG resources [8]–[13]. In particular, the so-called demand response (DR) programs – which allow consumers to modify their electricity consumption in response to certain signals or operator requests – provide potential means of managing the intermittency of WG. For example, on February 26 2008, the Electric Reliability Council of Texas dispatched nearly $1,150$ MW of reserve capacity provided by large industrial and commercial loads enrolled in their DR program to bring about a balance in supply and demand when there was a sudden loss of WG coupled along with other unanticipated events (see [14] for details).

In this paper, we investigate how the demand-side flexibility can be directed towards ensuring reliability in operations for the wind-integrated power grid of the future. We also study how demand-side actions can bring about a more effective utilization of the available WG. We consider two possible outcomes of DR programs: (1) the availability of DR capacity as reserves through emergency and/or market-based DR programs, and, (2) the leveling of the demand profile due to load-

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shifting triggered by consumer response to dynamic pricing schemes. Specifically, we consider only those dynamic pricing schemes in which prices are known *in advance*, on a day-ahead basis (or longer). For analysis, we cast the operator's day-ahead scheduling process – referred to as the security-constrained unit commitment (SCUC) problem – as a two-stage stochastic optimal control problem, similar to [6], [11] (see [4] for further references). The stochastic SCUC problem represents explicitly the uncertainty faced in unit commitment decisions which are typically taken a day-ahead of real-time operations. Although unit commitment-based analysis of systems with integrated WG and DR resources have been attempted in [9]–[11], none of this prior work investigates, in toto, the interplay between volatile WG and DR – either as fast response reserves, or as levelized load profiles, or both – in a stochastic setting. Therefore, not only can we say that demand response can help integrate wind resources, but we can also study how different demand response mechanisms impact WG deployment.

This paper has four additional sections. In § II, we discuss briefly the characteristics of WG and DR resources. We present, in § III-C, the unit commitment formulation to schedule WG and DR. We investigate the interplay between DR and WG through case studies and present our analysis in § IV. We conclude in § V with insights and open questions for future research.

II. Operating Systems with Wind Generation and Demand Response Resources: An Overview

The reliable integration of WG and DR resources into power system operations requires an understanding of the characteristics of such resources. To that effect, this section provides a brief overview of WG and DR programs.

Variability in WG is much more pronounced as compared to the electricity demand, and wind forecast errors are much higher than the 2-3% demand forecast errors that system operators are typically accustomed to (see, for example, data from `www.caiso.com` or `www.bpa.gov`). Under the "use all available wind generation" policy that is typically adopted, the variability and uncertainty of WG is transferred to the net load, resulting in potentially huge deviations – both positive and negative – from the forecast value used for day-ahead scheduling operations. To maintain reliability, the operator has to increase or lower the outputs of controllable generators. Thus, to accommodate wind forecast errors, operators need to commit generators in such a way that they can provide both conventional spinning reserves to be dispatched if WG falls below its forecast, as well as "negative" reserves for situations when the WG is higher than its forecast. We use Fig. 1 to demonstrate the need for negative reserves.

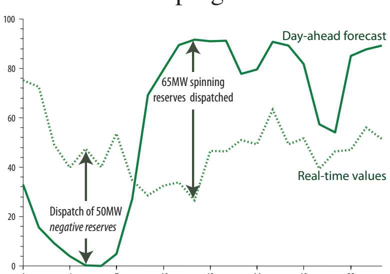

Fig. 1. Day-ahead forecast and real-time observed values of WG for a typical winter day in 2006. (`www.nrel.gov`).

Henceforth, we refer to the conventional spinning reserves as *ramp-up* reserves and the negative reserves as *ramp-down* reserves. We include both types of reserves in our analysis.

The ERCOT incident [14] is a very good example of how DR programs can contribute towards managing the uncertainty in WG. Market and policy developments have led to the implementation of many different DR programs. Depending on how the load changes are induced, these programs can be broadly classified into the following two categories [8]:

- *incentive-based programs*, wherein the system operator requests load reduction from consumers and provides incentives to induce it, and,
- *price-based programs*, wherein consumers are charged time-varying prices which reflect the system conditions and bring about changes in load consumption patterns.

We refer the reader to [15] for an overview of DR programs in the United States.

Emergency DR programs, such as ERCOT's LaaR program, are a type of incentive-based program in which consumers are paid for their reserve capacity which can be dispatched in real-time to avoid system emergencies. Other examples of incentive-based programs include ISO operated DR mechanisms that allow consumers to compete with the supply-side, bidding on load curtailments in the ancillary services market. There are many incentive-based DR programs which provide the system operator with a demand-side reserve capacity (analogous to the reserves of a fast-responding generator) that can be dispatched in real-time to maintain supply-demand balance. Details of such programs can be found in [15].

Unlike the incentive-based programs described above, price-based DR programs, like *time-of-use* (TOU) and other dynamic pricing schemes, impose a price structure on the consumers that is representative of the actual electricity production costs. Such programs typically cause consumers to shift load from the high-priced peak hours to the low-priced off-peak hours [12], [13], [16], thereby, resulting in a levelized demand profile. In addition to lowering the total scheduling costs – due to reduced costs associated with start-up and shut-down of units – a levelized demand profile relaxes, to some extent, the constraints imposed in the unit commitment problem due to variability in demand and, thus, can help accommodate variable WG on the system.

In what follows, we describe the modeling of the scheduling decisions for systems with WG and DR resources.

III. The Stochastic SCUC Problem with WG and DR Resources

From an operational point of view, the physical constraints on the generation units such as ramping limitations and start-up constraints make it impossible to support the "just-in-time" electricity production. The system operator – role played by the ISO in market setting or by utility in a vertically integrated environment – schedules generation one day prior to the actual production and delivery of energy in such a way that the physical constraints are met and the supply-demand balance is maintained. As the supply and demand are not perfectly predictable in the day-ahead decision-making process, the operator typically maintains extra generation capacity online at all times as reserves to ensure that electricity supply is reliable in-spite of uncertainty as well as variability in both demand and supply. The deviations from the promised supply and demand schedules are managed by the deployment of the procured reserves. We describe a stochastic framework which mimics this decision process of the operator for systems with WG and DR.

A. The Unit Commitment Problem: A Recap

A compact formulation of the SCUC problem for a system with I conventional generators and a scheduling period of T time steps is as follows:

$$\left.\begin{array}{llll} & \min_{\underline{\boldsymbol{u}},\underline{\boldsymbol{g}},\underline{\boldsymbol{r}}} \sum_t \sum_i c_i\left(u_{it}, g_{it}, r_{it}\right) & & \\ s.t. & \sum_i g_{it} & = & d_t^{fr} \quad \forall\, t \\ & \sum_i r_{it} & \geq & r_t^{sp} \quad \forall\, t \\ & (\underline{\boldsymbol{u}}_i, \underline{\boldsymbol{g}}_i, \underline{\boldsymbol{r}}_i) & \in & \mathscr{G}_i \quad \forall\, i \\ & (\underline{\boldsymbol{u}}, \underline{\boldsymbol{g}}, \underline{\boldsymbol{r}}) & \in & \mathscr{N} \end{array}\right\} \tag{1}$$

In (1), $u_{it} \in \{0,1\}$ is the commitment status of the generator i at time t; $g_{it} \in \{0\} \cup \left[g_{it}^{min}, g_{it}^{max}\right]$ is the energy output of i with g_i^{min} and g_i^{max} as its capacity limits; and r_{it} is its spinning reserve. We use $\underline{\boldsymbol{u}}_i \triangleq [u_{i1}, \ldots, u_{iT}]'$ to denote the trajectory of commitment statuses of generator i over the scheduling period and let $\underline{\boldsymbol{u}}$ denote $[\underline{\boldsymbol{u}}_1, \ldots, \underline{\boldsymbol{u}}_I]'$. $\underline{\boldsymbol{g}}_i, \underline{\boldsymbol{r}}_i, \underline{\boldsymbol{g}}$ and $\underline{\boldsymbol{r}}$ are defined in an analogous manner. The set $\mathscr{G}_i$ represents the physical constraints – such as the minimum up/down time constraints, ramping limits and capacity limits – on a generator i and set $\mathscr{N}$ represents the power flow constraints imposed by the transmission network. The function $c_i(\cdot)$ denotes the offer function of generator i which we assume implicitly incorporates the fuel charges, start-up/shut-down costs, capacity costs for reserve provision and other operating costs. The *least-cost* day-ahead commitment schedule is obtained from the solution of (1) and is denoted by $(\underline{\boldsymbol{u}}^\star, \underline{\boldsymbol{g}}^\star, \underline{\boldsymbol{r}}^\star)$.

The SCUC problem can be extended to accommodate generation from J wind generators by modifying the supply-demand balance in (1) and replacing the spinning reserve requirement r_t^{sp} by a higher value $r_t^{sp\mathrm{w}}$, which represents the greater degree of uncertainty in deployment of WG, with

$$\left.\begin{array}{lll} \sum_i g_{it} + \sum_j w_{jt}^{fr} & = d_t^{fr} & \forall\, t \\ \sum_i r_{it} & \geq r_t^{sp\mathrm{w}} & \forall\, t \end{array}\right\} \tag{2}$$

where w_{jt}^{fr} is the forecast output of wind generator j.

Note that the approach described above does not explicitly model the uncertainty in real-time conditions and may lead to procurement of insufficient or excess reserves. As an alternative, we use a stochastic SCUC formulation for our case studies.

B. Representation of Uncertainty

We consider three main sources of uncertainty with respect to the real-time conditions in the day-ahead scheduling process:

a) Generator i's availability in real-time

b) Error in the forecast value of demand at time t

c) Error in the WG forecast for time t

While the transmission line outages are also subject to unexpected failures, the probability of failure is negligible and can be ignored. Each source of uncertainty is modeled as a random variable (r.v.). All the r.v.s are supported on a probability space $(\Omega, \mathcal{F}, \mathcal{P})$.

a) Generator Availability: A generator's availability indicates if the unit is operating or has incurred a forced outage. We adopt a 2-state representation for the availability of a generator during the entire scheduling period. The r.v. α_i denotes the availability of the i^{th} generator[1], and takes values 1 or 0. The energy output in scenario $\omega \in \Omega$, denoted by $\widetilde{g}_{it}(\omega)$, is zero if generator i is unavailable, else it is equal to the day-ahead energy commitment $\widehat{g}_{it}$. That is,

$$\widetilde{g}_{it}(\omega) \quad = \quad \alpha_i(\omega)\widehat{g}_{it} \quad \forall\, t\ . \tag{3}$$

Similarly, the reserves provided by generator i in scenario ω, denoted by $\widetilde{r}_{it}(\omega)$, will be zero if the generator is unavailable; else $\widetilde{r}_{it}(\omega)$ is bounded by the day-ahead reserve commitment $\widehat{r}_{it}$.

b) Demand forecast error: The forecast error for the demand at time t is modeled as a r.v. $\varepsilon_t^{\mathrm{D}}$. The distribution of $\varepsilon_t^{\mathrm{D}}$ depends on the specific system. The demand in scenario ω is expressed as

$$\widetilde{d}_t(\omega) \quad = \quad d_t^{fr} + \varepsilon_t^{\mathrm{D}}(\omega)\ . \tag{4}$$

c) WG forecast error: The wind forecast error is modeled in a manner analogous to the demand forecast error. We denote by $\varepsilon_{jt}^{\mathrm{W}}$ the forecast error in the output of wind generator j. In scenario ω, the actual output of generator j is expressed as

$$\widetilde{w}_{jt}(\omega) \quad = \quad w_{jt}^{fr} + \varepsilon_{jt}^{\mathrm{W}}(\omega)\ . \tag{5}$$

We use the r.v.s defined above in the stochastic SCUC formulation to explicitly represent the impacts of uncertain real-time conditions on the day-ahead scheduling operations of the system operator.

C. The Stochastic SCUC Formulation

SCUC formulations in a stochastic setting explicitly model the uncertainty in the day-ahead scheduling decisions. A commonly used SCUC formulation minimizes the expected total cost over a representative set of scenarios with physical and operational constraints enforced for all such scenarios. References [6], [7] all use variations of this approach. In this paper, we cast the SCUC problem as a *two-stage stochastic program* with *recourse actions*, which is a special case of the multi-stage stochastic optimal control problem. Such programs are often applied to inventory management problems [17]. The multi-stage decision framework mimics the decision-making process of the system operator described at the start of this section.

In the proposed SCUC formulation, the determination of the day-ahead commitment schedule is modeled as the first stage of the stochastic program. The real-time balancing operations

[1] Historical operating data is often used to construct a distribution of α_i

depend on both the day-ahead commitment schedule as well as the actual real-time conditions. The real-time supply-demand balance is maintained by dispatching reserves and/or shedding load[2] subject to the constraints on both the reserves dispatched and the load shed. We model the system operator's real-time decision-making process as a recourse action – the second stage of the stochastic program.

The first stage decision variables in the stochastic SCUC problem are the commitment status, energy outputs, ramp-up reserves and ramp-down reserves of the generators, denoted by $\widehat{\underline{\boldsymbol{u}}}, \widehat{\underline{\boldsymbol{g}}}, \widehat{\underline{\boldsymbol{r}}}^{up}$ and $\widehat{\underline{\boldsymbol{r}}}^{dn}$ respectively. Note that $\widehat{\underline{\boldsymbol{u}}}$ and $\widehat{\underline{\boldsymbol{g}}}$ are defined analogous to the variables $\underline{\boldsymbol{u}}$ and $\underline{\boldsymbol{g}}$ of (1) while $\widehat{\underline{\boldsymbol{r}}}^{up}$ and $\widehat{\underline{\boldsymbol{r}}}^{dn}$ are defined analogous to the variable $\underline{\boldsymbol{r}}$ of (1). We use $\widehat{\underline{\boldsymbol{r}}}$ to denote the pair $\left(\widehat{\underline{\boldsymbol{r}}}^{up}, \widehat{\underline{\boldsymbol{r}}}^{dn}\right)$.

Suppose the real-time conditions are characterized by scenario $\omega \in \Omega$. Then the recourse action taken by system operator depends on $\alpha_i(\omega)$, $\varepsilon^{\mathrm{D}}_t(\omega)$ and $\varepsilon^{\mathrm{W}}_{jt}(\omega)$ as well as the first stage decision variables describing the operations of all the generators at time t, i.e. variables $\widehat{u}_{it}$, $\widehat{g}_{it}$ and $\widehat{r}_{it} := \left(\widehat{r}^{up}_{it}, \widehat{r}^{dn}_{it}\right)$ for all i. We use shorthand notation $\widehat{\underline{\boldsymbol{x}}}_t$ to denote the vector consisting of $\widehat{u}_{it}$, $\widehat{g}_{it}$ and $\widehat{r}_{it}$ for all i.

The second stage decision variables are the quantities of ramp-up and ramp-down reserves to be dispatched as well as the amount of load to be shed. In scenario ω, the decision variables take the forms $\widetilde{r}^{up}_{it}(\omega)$, $\widetilde{r}^{dn}_{it}(\omega)$, and $\widetilde{\ell}_t(\omega)$, respectively. The second stage decision problem for scenario ω is as follows:

$$\min_{\widetilde{\underline{\boldsymbol{y}}}_t(\omega)} \sum_i \phi_i\left(\widetilde{r}^{up}_{it}(\omega), \widetilde{r}^{dn}_{it}(\omega), b_{it}(\omega)\right) + \upsilon \cdot \widetilde{\ell}_t(\omega) \tag{6a}$$

$$\begin{aligned} s.t. \; & \sum_i [\, \alpha_i(\omega) \cdot \widehat{g}_{it} + \widetilde{r}^{up}_{it}(\omega) - \widetilde{r}^{dn}_{it}(\omega) \,] + \\ & \sum_j [w^{fr}_{jt} + \varepsilon^{\mathrm{W}}_{jt}(\omega)] = [d^{fr}_t + \varepsilon^{\mathrm{D}}_t(\omega)] - \widetilde{\ell}_t(\omega) \end{aligned} \tag{6b}$$

$$0 \le \widetilde{r}^{up}_{it}(\omega) \le \alpha_i(\omega) \cdot b_{it}(\omega) \cdot \widehat{r}^{up}_{it} \quad \forall\, i \tag{6c}$$

$$0 \le \widetilde{r}^{dn}_{it}(\omega) \le \alpha_i(\omega) \cdot (1 - b_{it}(\omega)) \cdot \widehat{r}^{dn}_{it} \quad \forall\, i \tag{6d}$$

$$b_{it}(\omega) \in \{0, 1\} \quad \forall\, i \tag{6e}$$

$$0 \le \widetilde{\ell}_t(\omega) \le \ell^{max}_t \tag{6f}$$

$$\widetilde{\underline{\boldsymbol{y}}}_t \in \mathscr{N}|_{(\widehat{\underline{\boldsymbol{x}}}_t, \omega)} \tag{6g}$$

In (6), $\widetilde{\underline{\boldsymbol{y}}}_t(\omega)$ is the shorthand notation for the second-stage decision variables at time t. $\phi_i(\cdot)$ is the cost of dispatching the ramp-up or ramp-down reserves in real-time and υ is the *value of lost load* (VOLL). Equation (6b) represents the real-time supply-demand balance. We introduce the binary variable $b_{it}(\omega)$ in (6c) and (6d) to represent the condition that the system operator can either dispatch the ramp-up reserves or ramp-down reserves of a generator i; not both. Both equations also incorporate generator i's availability $\alpha_i(\omega)$ in scenario ω. In (6f), ℓ^{max}_t represents the upper bound on the amount of load that can be shed at time t. Equation (6g) implies that the second stage decisions satisfy the network constraints for first stage decision $\widehat{\underline{\boldsymbol{x}}}_t$ and scenario ω.

[2]Such load shedding induced by the operator is not the same as the voluntary load curtailments by the consumers enrolled in DR programs. It is typically invoked only under extreme conditions.

Let $\varphi^\star(\widehat{\underline{\boldsymbol{x}}}_t, \omega)$ denote the optimal value of the second stage problem (6) for scenario ω and first stage variable $\widehat{\underline{\boldsymbol{x}}}_t$. For each $\widehat{\underline{\boldsymbol{x}}}_t$, $\varphi^\star(\widehat{\underline{\boldsymbol{x}}}_t, \cdot)$ is a r.v. on the probability space $(\Omega, \mathcal{F}, \mathcal{P})$; it represents the optimal recourse cost for the second stage problem. Since a first stage decision $\left(\widehat{\underline{\boldsymbol{u}}}, \widehat{\underline{\boldsymbol{g}}}, \widehat{\underline{\boldsymbol{r}}}\right)$ impacts the r.v.s $\varphi^\star(\widehat{\underline{\boldsymbol{x}}}_t, \cdot)$, $t = 1, \ldots, T$; the expected value of the optimal recourse costs is included in the total cost function for the first stage. The first stage decision problem is as follows:

$$\min_{\widehat{\underline{\boldsymbol{u}}}, \widehat{\underline{\boldsymbol{g}}}, \widehat{\underline{\boldsymbol{r}}}} \sum_t \left[\sum_i c_i\left(\widehat{u}_{it}, \widehat{g}_{it}, \widehat{r}_{it}\right) + \mathsf{E}[\varphi^\star(\widehat{\underline{\boldsymbol{x}}}_t, \omega)] \right] \tag{7a}$$

$$s.t. \quad \sum_i \widehat{g}_{it} + \sum_j w^{fr}_{jt} = d^{fr}_t \quad \forall\, t \tag{7b}$$

$$\left(\widehat{\underline{\boldsymbol{r}}}^{up}, \widehat{\underline{\boldsymbol{r}}}^{dn}\right) \in \mathscr{R} \tag{7c}$$

$$\left(\widehat{\underline{\boldsymbol{u}}}_i, \widehat{\underline{\boldsymbol{g}}}_i, \widehat{\underline{\boldsymbol{r}}}_i\right) \in \mathscr{G}_i \quad \forall\, i \tag{7d}$$

$$\left(\widehat{\underline{\boldsymbol{u}}}, \widehat{\underline{\boldsymbol{g}}}, \widehat{\underline{\boldsymbol{r}}}\right) \in \mathscr{N} \tag{7e}$$

In (7a), $\mathsf{E}[\cdot]$ is the expectation operator and the term $\mathsf{E}[\varphi^\star(\widehat{\underline{\boldsymbol{x}}}_t, \omega)]$ is the expected cost of real-time balancing operations. The constraint set $\mathscr{R}$ in (7c) includes constraints on the ramp-up and ramp-down reserves, such as total reserves required on the system and upper bounds on the reserves due to ramping constraints.

The stochastic SCUC problem is defined by the first stage problem in (7) and the second stage problem in (6). Equations (6c) and (6d) explicitly represent the coupling between the first and second stage decision variables. The solution of (6)-(7), denoted by $(\widehat{\underline{\boldsymbol{u}}}^\star, \widehat{\underline{\boldsymbol{g}}}^\star, \widehat{\underline{\boldsymbol{r}}}^\star)$, is the least-cost day-ahead commitment schedule which meets the demand and reserve requirements, satisfies the physical constraints, and minimizes the expected cost of real-time balancing operations.

Next, we discuss how the SCUC formulation can be extended to accommodate the outcomes the DR programs.

D. Representation of DR in Stochastic SCUC problem

To incorporate DR in the stochastic SCUC problem, we consider the following scenarios:

a) The availability of DR capacity as reserves from the implementation of emergency DR programs and ancillary services market programs, and,

b) The leveling of the demand profile brought about by the consumer response to a TOU pricing scheme implemented in the system.

In what follows, we discuss the modeling of these two scenarios and their incorporation in the stochastic SCUC formulation.

We model the consumer loads providing DR reserve capacity analogous to very reliable, fast-start generators, who only contribute towards system reserves. The amount of reserves that such consumers can provide is constrained by the amount of load they are consuming – they can only reduce as much load as they consume. Next, we model the response of the consumers enrolled in the TOU pricing scheme by modifications on the demand profile which result in load leveling. The stochastic SCUC problem of § III-C can be easily augmented to incorporate DR outcomes modeled in this manner.

We assume that there are a total of K consumers that contribute their load curtailment capacities towards system reserves. We denote by q_{kt}^{max} the maximum load curtailment offered by consumer k at time step t in the scheduling period. For the day-ahead scheduling problem, we use $\widehat{v}_{kt} \in \{0,1\}$ to represent the commitment status of consumer k indicating whether it is selected to provide reserve at time t or not. $h_k(\widehat{v}_{kt}, \widehat{q}_{kt})$ represents the offer function consumer k; it accounts for the cost of DR reserves. The costs are computed based on the specific incentive mechanism of the DR program in which consumer j is enrolled, and it impacts the day-ahead scheduling costs. We use $\underline{\widehat{\boldsymbol{v}}}_i \triangleq [\widehat{v}_{k1}, \ldots, \widehat{v}_{kT}]'$ to denote the trajectory of commitment statuses of consumer k over the scheduling period and let $\underline{\widehat{\boldsymbol{v}}}$ denote $[\underline{\widehat{\boldsymbol{v}}}_1, \ldots, \underline{\widehat{\boldsymbol{v}}}_K]'$. In an analogous manner, we can define $\underline{\widehat{\boldsymbol{q}}}_k$ and $\underline{\widehat{\boldsymbol{q}}}$. The variables $\underline{\widehat{\boldsymbol{v}}}$ and $\underline{\widehat{\boldsymbol{q}}}$ are decision variables in the day-ahead scheduling process.

We assume that if a consumer k has been committed in the day-ahead to provide a reserve capacity of $\widehat{q}_{kt}$ at time t, that reserve capacity will indeed be available in real-time at t. Suppose the real-time conditions at time t correspond to scenario $\omega \in \Omega$. We use $\widetilde{q}_{kt}(\omega)$ to denote the actual reserves of consumer k that are dispatched at time t. Let $\theta_k(\widetilde{q}_{kt})$ denote the cost of dispatching $\widetilde{q}_{kt}$ units of DR reserves of consumer k at real time. Clearly, $\theta_k(\cdot)$ impacts the second stage cost of the SCUC formulation.

The scheduling problem for systems with DR reserve capacity consists of two types of decision variables: those for the generators (same as in § III-C), and, those for the consumers with DR reserve capacity. The variables for the first stage – day-ahead – decisions are $\widehat{u}_{it}$,$\widehat{g}_{it}$ and $\widehat{r}_{it}$ for I generators, and, $\widehat{v}_{kt}$ and $\widehat{q}_{kt}$ for K consumers for each time step t in the scheduling period. The second stage variables for balancing operations at time t depend on the specific scenario $\omega \in \Omega$ that is realized in real-time and, hence, are r.v.s. The second stage variables in scenario ω are $\widetilde{r}_{it}^{up}(\omega)$ and $\widetilde{r}_{it}^{dn}(\omega)$ for I generators, $\widetilde{q}_{kt}(\omega)$ for K consumers and $\widetilde{\ell}_t(\omega)$ quantifying the load shed which is different from the voluntary curtailments of the K consumers.

We use shorthand notation $\underline{\widehat{\boldsymbol{m}}}_t$ to denote the vector consisting of day-ahead variables for time t, i.e. $\underline{\widehat{\boldsymbol{m}}}_t$ consists of $\underline{\widehat{\boldsymbol{x}}}_t$ defined for problem (7), as well as $\widehat{v}_{kt}$ and $\widehat{q}_{kt}$ for all k. Similarly, we use $\underline{\widetilde{\boldsymbol{n}}}_t(\omega)$ to denote all the real-time decision variables in scenario ω at time t; $\underline{\widetilde{\boldsymbol{n}}}_t(\omega)$ consists of $\underline{\widetilde{\boldsymbol{y}}}_t(\omega)$ from problem (6) and $\widetilde{q}_{kt}(\omega)$ for all k. A compact form of the second stage decision problem for scenario ω is as follows:

$$\min_{\underline{\widetilde{\boldsymbol{n}}}_t(\omega)} \sum_i \phi_i\left(\widetilde{r}_{it}^{up}(\omega), \widetilde{r}_{it}^{dn}(\omega), b_{it}(\omega)\right) + \sum_k \theta_k\left(\widetilde{q}_{kt}(\omega)\right) + \upsilon \cdot \widetilde{\ell}_t(\omega) \tag{8a}$$

$$s.t. \sum_i \left[\alpha_i(\omega) \cdot \widehat{g}_{it} + \widetilde{r}_{it}^{up}(\omega) - \widetilde{r}_{it}^{dn}(\omega)\right] + \sum_j \left[w_{jt}^{fr} + \varepsilon_{jt}^{\mathrm{W}}(\omega) \right] = \left[d_t^{fr} + \varepsilon_t^{\mathrm{D}}(\omega) \right] - \sum_k \widetilde{q}_{kt}(\omega) - \widetilde{\ell}_t(\omega) \tag{8b}$$

$$\text{Constraints (6c)–(6g)} \tag{8c}$$

$$0 \leq \widetilde{q}_{kt}(\omega) \leq \widehat{q}_{kt} \qquad \forall\, k \tag{8d}$$

The constraint (8b) represents the real-time supply-demand balance when DR reserve capacity is dispatched; and (8d) represents the coupling between the first and second stage DR reserve capacity decision variables.

We use $\psi^\star(\underline{\widehat{\boldsymbol{m}}}_t, \omega)$ to denote the optimal value of the second stage problem (8) for scenario ω and first stage time t variable $\underline{\widehat{\boldsymbol{m}}}_t$. The function $\psi^\star(\underline{\widehat{\boldsymbol{m}}}_t, \cdot)$ represents the optimal recourse cost at time t associated with first stage decision $\underline{\widehat{\boldsymbol{m}}}_t$. As before, $\psi^\star(\underline{\widehat{\boldsymbol{m}}}_t, \cdot)$ is a r.v. and we include its expected value in the total cost function of the first stage.

Note that the DR reserve capacity does not impact the day-ahead supply-demand balance constraints stated in (7b) or the (7d) and (7e) constraints representing the physical limitations of the generators and the transmission network. Thus, a compact formulation of the first stage decision problem is as follows:

$$\min_{\underline{\widehat{\boldsymbol{u}}}, \underline{\widehat{\boldsymbol{g}}}, \underline{\widehat{\boldsymbol{r}}}, \underline{\widehat{\boldsymbol{v}}}, \underline{\widehat{\boldsymbol{q}}}} \sum_t \left[\sum_i c_i\left(\widehat{u}_{it}, \widehat{g}_{it}, \widehat{r}_{it}\right) + \sum_k h_k\left(\widehat{v}_{kt}, \widehat{q}_{kt}\right) + \mathsf{E}[\psi^\star(\underline{\widehat{\boldsymbol{m}}}_t, \omega)] \right] \tag{9a}$$

$$s.t. \qquad \text{Constraints (7b), (7c) and (7e)} \tag{9b}$$

$$(\underline{\widehat{\boldsymbol{r}}}^{up}, \underline{\widehat{\boldsymbol{r}}}^{dn}, \underline{\widehat{\boldsymbol{q}}}) \in \mathscr{R} \tag{9c}$$

We assume that the set $\mathscr{R}$ in (9c) also includes the capacity constraints q_{kt}^{max} for the reserves offered by each consumer k at time t in the scheduling period. The stochastic SCUC problem for systems with DR capacity available as reserves is, thus, defined by the first stage problem (9) and the second stage problem (8). The solution of (8)-(9), denoted by $(\underline{\widehat{\boldsymbol{u}}}^\star, \underline{\widehat{\boldsymbol{g}}}^\star, \underline{\widehat{\boldsymbol{r}}}^\star, \underline{\widehat{\boldsymbol{v}}}^\star, \underline{\widehat{\boldsymbol{q}}}^\star)$, is the least-cost day-ahead commitment schedule for the system which satisfies all constraints typically considered in a scheduling problem and minimizes the expected cost of real-time balancing operations.

Next, we discuss the representation of the TOU pricing scheme. We want to emphasize that while the TOU scheme does implement time-varying prices, it is very different from real-time pricing; the TOU prices are known *in advance* unlike the real-time pricing scheme. The TOU price structure is merely representative of time-varying electricity production costs; it does not directly depend on the actual operating conditions. Thus, the consumers enrolled in TOU pricing-based DR program adjust their electricity consumption to prices that are published well-ahead of real time.

To accommodate the impacts of the TOU pricing scheme, we adopt a set of assumptions which simplify the discussion. We assume that the TOU pricing structure induce responses in the consumption patterns of the enrolled consumers that are perfectly predictable in the day-ahead. Next, we assume that the day-ahead demand forecast $\{d_t^{fr} \ : \ t = 1, \ldots, T\}$ reflects the consumers' responses to the TOU pricing structure. Finally, we assume that the demand forecast error $\varepsilon_t^{\mathrm{D}}$ at time is unaffected by the number of consumers enrolled in the TOU pricing scheme[3].

[3]While we recognize that such an assumption would most likely not hold for the real world, the analysis without this assumption would be complicated by the representation of rationality in consumer behavior which is far beyond the scope of this paper.

In the light of the above assumptions, analysis of impacts of TOU pricing scheme reduces to analysis of various demand forecast profiles. We use the *peak-to-average* ratio (PtAR) as a parameter characterizing the effectiveness of the TOU pricing scheme in leveling the load demand profile of the system. For a more in-depth discussion on the development of load profiles under various pricing schemes, we refer the reader to recent articles [12] and [13].

We use the approach presented in this section to investigate how adverse impacts of WG forecast errors and generation patterns can be offset by the effective utilization of DR programs.

IV. An Illustrative Example

The stochastic SCUC framework proposed in § III-C and III-D provides a means of testing the effectiveness of DR programs in supporting volatile WG. We first discuss briefly the scope and the nature of our studies and then provide illustrative examples.

A. Scope and nature of simulations

The central theme of this paper is the interplay between WG and DR. Therefore, our studies primarily focus on how DR can bring about a reliable integration of WG into power system operations.

We use the stochastic SCUC problem to simulate the day-ahead decision process of the ISO. As such, the integrality constraints and stochastic nature of the problem impose a huge burden on the computing resources. Therefore, we make allowances in the simulations studies to make the problem more tractable. In particular,

- we ignore transmission constraints
- we assume the generators are 100% available; i.e., they are not subject to forced outages,
- we approximate the expectation term in (7a) and (9a) by a sample average, where the samples are obtained through Latin hypercube sampling.

Since the focus of this paper is to investigate how DR can help manage uncertainty and volatility of WG, the assumptions imposed above are not altogether unreasonable.

We use the 6 bus system with 3 generators [18] for our studies. Although the test system is small, analysis of WG and DR in such a setting provides us with insights which would be obfuscated by the simulation of a large system. Analysis of larger systems is underway and will be reported in future publications.

B. Test System Data

We modify the 6 bus system with 3 generators of [18] to be suitable for our analysis.

We consider a scheduling horizon of 8 hours and appropriately scale the load data from New England ISO to generate the system demand forecast. The demand forecast is the simple "peak-valley" load pattern shown in Fig. 2.

The cost structure in our simulations is slightly modified from [18]. In [18], the fuel costs of a unit are computed as

$$f(g_{it}) = a_i + b_i g_{it} + c g_{it}^2 \ . \qquad (10)$$

We approximate (10) with a piecewise linear curve that is more representative of the block offer formats of ISOs. We assume that each generator submits offer in 3 blocks. The maximum capacity limits for each block are given by $\bar{g}_i^{(m)}$. Except for the first block of each unit, the minimum capacity limits for the energy blocks are 0; for block 1, it is equal to g_i^{min}. Furthermore, we ignore cold start costs as well as shut down costs.

To study the impacts of WG, we introduce a wind farm with rated capacity 120 *MW* in the system. We use wind forecast data from NREL [19, site 63] to generate WG patterns for the system. We simulate operations for two distinct profiles for WG forecast:

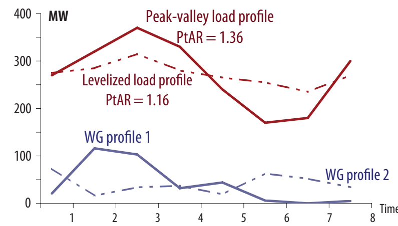

Fig. 2. Wind and Demand profiles for the test system

- WG profile 1, with WG available during the day, and
- WG profile 2, with WG available during the night.

The demand and wind forecast errors, ε_t^{D} and ε_t^{W}, are modeled as a zero-mean normally distributed r.v.s with standard deviation σ_t^{D} and σ_t^{W} respectively. A *minimum* reserve requirement is imposed on the SCUC problem to account of uncertainties that may not have been taken into account. The specific parameters used in our study are listed in Table I.

TABLE I
Simulation parameters

parameter	value
standard deviation σ_t^{D}	3 % of d_t^{fr}
standard deviation σ_t^{W}	10 % of w_t^{fr}
value of lost load υ	1000 \$ / MW
min reserve requirement r_t^{sp}	20% of peak
max load curtailment ℓ_t^{max}	50% of d_t^{fr}

To study impacts of DR on operating decisions, we consider three DR cases:

a) case A with DR reserve capacity available from an incentive-based DR program,
b) case B with levelized load profile due to TOU scheme implemented in a price-based DR program, and,
c) case C in which both incentive- and price-based DR programs are operated side by side.

The specific details for each case are listed in Table II.

TABLE II
Simulation details for DR cases

case	simulation remarks	cost structure
A	$q_t^{max} = 0.25 \cdot d_t^{fr}$	$h(\hat{q}) = 6 \cdot \hat{q}$, $\theta(\tilde{q}) = 12 \cdot \tilde{q}$
B	levalized load profile of Fig. 2	not applicable
C	combination of A and B	same as case A

C. Operational Impacts

To investigate the operational impacts of WG and DR, we present in Fig. 3 the number of hours units 2 and 3 are committed when SCUC is solved for wind forecast given by WG profile 1. We exclude unit 1 from the plot because it is a base-load unit and is committed for all hours in all case scenarios. We notice that with a levelized load profile, the operator can do away with committing unit 2, the most expensive unit in the system. This has significant impact on the costs (discussed later) because in case scenarios with WG, unit 2 is kept ON only to provide reserves.

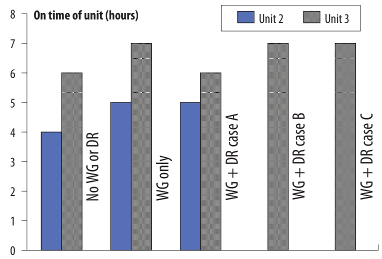

Fig. 3. Operation of units 2 and 3 under different case scenarios with WG profile 1.

When the SCUC is solved for WG profile 2 – recall it simulates WG at night – the scheduling problem becomes infeasible. The "use all WG" – even if it is available at night – policy creates low load conditions at night that violate the physical constraints of the units. Even when DR reserves are available, the problem continues to be infeasible. However feasibility can be induced if consumers – enrolled in the price-based demand response programs – shift their loads at night thereby increasing the base load on the system. Indeed, when the system is simulated with levelized load profile of DR case B, a feasible solution is obtained for WG profile 2. There are multiple reasons for this. The nearly flat load demand of the levelized load profile relaxes the constraints otherwise imposed on the generators by demand variability such as that of the peak-valley load profile. Furthermore, the increased base load due to load shifting alleviates the low load conditions on the net load thus leading to feasibility.

D. Economic Impacts

We now discuss the impacts of WG and DR on the costs. We use the following metrics: cost of generation based on day-ahead commitment, start-up costs, capacity costs for generation reserves, capacity costs for DR reserves and finally, the cost of reliability (it is the expected optimal recourse costs for the scheduling period).

In Fig. 4, we present the cost metrics for the system when forecast WG is given by WG profile 1. With the deployment of zero-fuel-cost WG, the cost of generation reduces, but in case scenarios without DR, we see that such costs are offset by the increase in capacity costs for procuring reserve. Furthermore, injection of all available WG also imparts variability to the net load and causes increase in start-up costs.

In general, we see higher costs of reliability when WG is introduced. But, when WG is combined with DR – either as reserves or as levelized load profile – we see a decrease in reliability costs compared to the WG-only case scenario and the total costs compared to the base case scenario. Our results indicate that a combination of active and passive DR is the most economical solution for the system with WG. Furthermore, we see that although the capacity costs paid to DR reserves are negligible, the availability of DR reserves significantly lowers the overall costs.

E. Insights

In addition to the results reported above, extensive simulations of the 3-generator system provide some interesting insights regarding the unit commitment under uncertainty and the role that WG and DR play in it. We summarize these insights below.

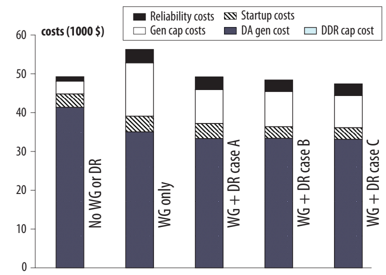

Fig. 4. Cost metrics for different case scenarios under WG profile 1.

Although the stochastic UC problem allows us to implement "loss of load" in real time so as to maintain supply demand balance, simulation results indicate that as long as the VOLL is higher than 500 $/MW, the operator would be better off purchasing reserves in the day-ahead at some capacity cost for it and dispatching them in real-time should the need arise (thereby incurring an additional dispatch cost) than to attempt a loss of load action and incur heavy blackout costs. Only if the VOLL is lower than approximately 200 $/ MW, would load shedding be more economical than purchasing reserves. From this exercise, we can make a case for flexible loads to be used as reserves because for such loads, a temporary loss in supply is not detrimental and hence the VOLL for such loads may be viewed as being less than 500 $/MW.

In a WG-only case scenario, there is a threshold on how much deviation the UC scheduling problem will tolerate between the day-ahead forecast and the real-time WG. As the deviation goes beyond this threshold, the UC problem may become infeasible with respect to the commitment variables (0/1 decisions) because of the physical constraints associated with the generation. In a small power system with less than 5-6 generators, this threshold is especially more pronounced. If a large fleet of generators is available or sufficient DR capability exists on the demand-side, the system may be able to accommodate more WG.

V. CONCLUDING REMARKS

This paper has considered an important emerging problem in the operations of modern power systems – that of reliably integrating wind generation. While traditional methods of power system operation are capable of handling the uncertainties of demand, they are inadequate to accommodate the volatility and high unpredictability of wind generation. We investigated the use of demand response resources as a substitute for fast responding reserves to counter this uncertainty. We proposed an extension of the stochastic unit commitment problem to incorporate demand response resources. Simulation studies described in the paper show that DR-based reserve capacity can serve as an effective mechanism to counter volatility and uncertainty. Results also indicate that load leveling can prove beneficial for systems with wind generation. We emphasize here that our analysis *does not* extend to the complex feedback loop found in a system in which prices to consumers vary according to the current environment, as in many DR programs such as real-time pricing schemes.

This work invites many open questions. For example, a big assumption used in our analysis is that a consumer committed to provide DR reserve in the day-ahead will indeed curtail load when asked to do so. Appropriate models which capture such behavioral considerations may be necessary to obtain a more complete understanding of the value of DR reserves, and how to improve the reliability of systems incorporating DR. Similarly, the quantity of flexible load may not be known accurately in advance. The amount of reserves available through DR depends on the value of power to the consumers, which in turn depends on factors such as weather or the state of the economy; as well as the incentives available to consumers for providing the reserves. With increasing DR penetration, there is a lot of debate on how to incentivize the services provided by DR. A important step towards the resolution of this debate is the derivation of economically efficient prices for reserves. These behavior- and economics-oriented questions are among many fascinating topics for future research.

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