Large-Scale Integration of Deferrable Demand and Renewable Energy Sources

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***Abstract*—We present a stochastic unit commitment model for assessing the impacts of the large-scale integration of renewable energy sources and deferrable demand in power systems in terms of reserve requirements. We analyze three demand response paradigms for assessing the benefits of demand flexibility: the centralized co-optimization of generation and demand by the system operator, demand bids and the coupling of renewable resources with deferrable loads. We motivate coupling as an alternative for overcoming the drawbacks of the two alternative demand response options and we present a dynamic programming algorithm for coordinating deferrable demand with renewable supply. We present simulation results for a model of the Western Electricity Coordinating Council.**

***Index Terms*—Wind power generation, load management, power generation scheduling.**

I. Introduction

The key disadvantage of renewable resources relative to conventional dispatchable generation is their high variability, their unpredictable fluctuation and the fact that their output can only be controlled to a limited extent. Demand response can strongly benefit the large-scale integration of these resources. In order to accurately assess the impacts of renewable energy integration and demand response integration on power system operations it is necessary to represent the balancing operations of the remaining grid by using a unit commitment model.

The purpose of this paper is to incorporate a fairly detailed representation of deferrable demand resources in a unit commitment and economic dispatch model, in order to assess the benefits of demand response in reducing reserve requirements and operating costs in scenarios of large-scale renewable energy integration. As we discuss in the literature review below, existing work in this area either does not model the deferrable nature of various demand response resources (e.g. electric vehicle charging, agricultural pumping or certain residential appliances), or does not account for the uncertainty that is introduced by the large-scale integration of renewable resources. Both of these features need to be accounted for simultaneously in a unit commitment and economic dispatch model in order to accurately assess the impact of demand response integration on reserve requirements and operating costs in cases of large-scale renewable energy integration.

One additional contribution of this paper is to explore the direct coupling of deferrable consumers with renewable resources into a virtual resource through a contractual agreement based on a strike price that limits the impact of the coupled system on the rest of the network. The coupling contract that we present attempts to overcome various institutional or technological barriers associated with alternative demand response paradigms.

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A. Literature Review

A major economic barrier in the large-scale integration of renewable resources is the high investment cost of backup reserves that can guarantee the reliable operation of the system. Stochastic unit commitment models can be used for quantifying reserve requirements as well as the impacts of renewable integration on operating costs. For this reason, numerous renewable integration studies based on unit commitment have been performed recently by Ruiz et al. [1], Sioshansi and Short [2], Wang et al. [3], Contantinescu et al. [4], Tuohy et al. [5], Morales et al. [6], Bouffard et al., Papavasiliou et al. [7] and Papavasiliou and Oren [8]. However, these publications focus exclusively on the impact of renewable supply uncertainty on power system operations and do not account for the potential benefits of demand response integration.

The power system economics literature often represents demand response through demand functions. Sioshansi and Short [2] use this approach in the context of a unit commitment model and Borenstein and Holland [9] and Joskow and Tirole [10], [11] also use this approach for analyzing retail pricing. However, many flexible consumption tasks are best characterized as deferrable, in the sense that consumers need a certain amount of energy within a certain time window. As such, deferrable demand behaves much like a hydro or storage resource from the view point of the system operator. Electric vehicle charging, agricultural pumping, pre-cooling, and residential consumption such as laundry fit this characterization.

In a recent publication, Sioshansi [12] considers a unit commitment model where electric vehicles are centrally co-optimized and dispatched by the system operator along with controllable generation resources. This model extends the state of the art by explicitly representing the deferrable nature of electric vehicle energy demand. However, the model is deterministic and does not account for the uncertainty associated with renewable energy supply.

Both demand response paradigms discussed previously are currently limited by institutional barriers. The real-time benefits of demand-side bidding require real-time pricing at the retail level. This possibility was introduced by Schweppe et al. [13] and is discussed by Borenstein et al. [14]. However, there is strong political opposition to this approach as it exposes retail consumers to the volatility of wholesale electricity prices.

In addition, real-time prices often fail to convey the economic value of demand response due to the non-convex costs of system operations. This effect has been reported by Sioshansi [2], who notes that the failure of real-time prices to capture non-convexities induces a dispatch of deferrable resources that results in excessive startup and minimum load costs. The central co-optimization of demand-side resources, renewable supply and generator dispatch discussed by Sioshansi [12] represents the most efficient approach for exploiting demand-side flexibility. However, this paradigm cannot be implemented in practice as the system operator dispatches the system at a bulk scale and cannot control individual retail loads. In addition, the optimization problem is too complex to solve.

An alternative demand response paradigm that is not discussed in this paper has been set forth by Hirst and Kirby [15] and Kirby [16], whereby flexible loads deliver services to the ancillary services market. According to this paradigm, an aggregator bids on behalf of load aggregations for providing ancillary services to the system operator. The aggregator coordinates aggregate consumption by a price-based or direct control method. The technical feasibility of demand-side aggregation for the provision of spinning reserve has been studied in practice by Eto [17]. As ancillary services requirements are expected to increase due to renewable energy integration, this solution could prove lucrative for users who would be willing to respond to the instantaneous needs of power system operators. However, there are concerns about defining market products that correspond to the types of services that loads can actually offer, which raises the need for reform in existing electricity markets.

A stream of literature with a focus on strategic demand-side bidding in unit commitment models has been developed by Lamont and Rajan [18] and Zhang et al. [19]. Such models typically involve a utility owning both generation assets as well as own demand, where the utility strives to optimize market bids while accounting for uncertainty in competitors' bids as well as the impact of its own bids on market prices. A literature review is provided by David and Wen [20]. This literature focuses on strategic interactions among bidders and is therefore not explored further in this paper.

B. Paper Contributions

The methodological contribution of this paper is to present a stochastic unit commitment model that can be used in order to quantify the benefits of deferrable demand in mitigating the increased operating costs and day-ahead reserve requirements resulting from the random fluctuation of renewable energy supply. The use of stochastic planning models for simulating long-term market equilibrium in order to quantify generation investment in the face of long-term uncertainty was recently introduced by Ehrenmann and Smeers [21]. Analogously, the stochastic unit commitment model presented in this paper is used in order to simulate the two-stage operation of day-ahead and real-time electricity markets. The use of a stochastic unit commitment model for the purpose of simulating the operations of a day-ahead market introduces computational challenges that can be addressed by using an appropriate scenario selection technique to discretize the uncertainty space of the problem [22], [23], [24], [5] and exploiting the decomposable structure of the resulting stochastic optimization problem [25], [26], [27], [28], [3], [29]. These computational challenges have been addressed in previous work by the authors [7], [8] and will not be the focus of this paper.

The modeling contribution of this paper is to simultaneously incorporate deferrable demand response resources and stochastic renewable supply resources in the stochastic unit commitment and economic dispatch models. The demand bidding models cited earlier [10], [11], [14], [2] do not account for inter-temporal elasticities, thereby making demand appear independent across time periods. In the present paper we highlight the inadequacy of this approach in representing deferrable demand. On the other hand, the work of Sioshansi [12] does not account for the uncertainty introduced by renewable energy supply and inflexible demand fluctuations. In this paper we extend existing models by simultaneously modeling the inter-temporal dependency of deferrable demand and renewable supply uncertainty.

The third and final contribution of this paper is to present a contractual alternative for coupling the operations of renewable resources with deferrable demand that attempts to overcome the implementation barriers associated with centralized load dispatch and real-time pricing of retail loads, and compare the relative performance of each demand response paradigm in terms of system operating costs. The motivation of directly coupling renewable generation with deferrable demand is to create a net resource or load that appears 'behind the meter' from the point of view of the system operator, thus limiting the risk that the system operator needs to offset by procuring reserves.

The California ISO provides a representative example of the institutional and regulatory difficulties that render coupling a pragmatic approach to the large-scale integration of demand response. The Board of Governors of the California ISO recently appraised the current status of integrating distributed resources, including demand response, in the California ISO energy market [30]. The presentation and executive summary justify, in detail, why the market-based integration of demand response is far from foreseeable, which justifies the coupling approach that the authors present in this paper for overcoming exactly these institutional difficulties. The most that the California ISO can expect currently from distributed resources are rough estimates that can be incorporated into load forecasts but not direct accounting of demand response in the dispatch or unit commitment of the system [30].

The remaining paper is organized as follows. In Section II we provide an overview of the components of our model. In Section III we describe in detail the demand flexibility models that we consider in our analysis. Results from a test case of the Western Electricity Coordinating Council are presented in Section IV. In Section V we discuss the conclusions of our work.

II. Model Overview

In Fig. 1 we present a diagram of a stochastic unit commitment model that accounts both for the fluctuations of

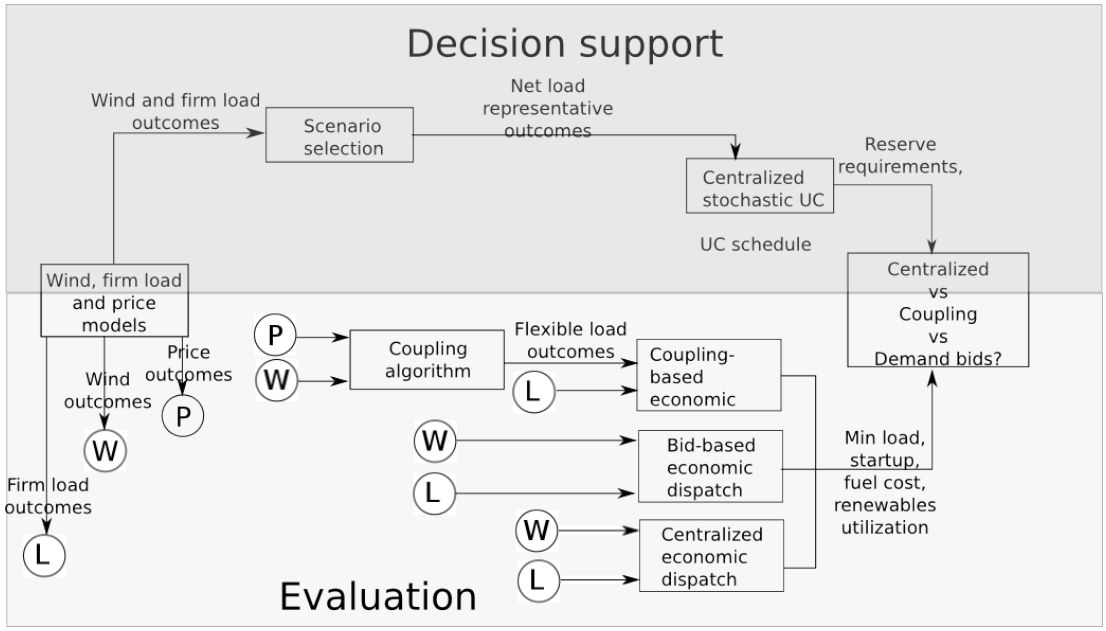

Fig. 1. Overview of the model.

renewable supply as well as the benefits of demand response in absorbing these fluctuations. Uncertainty in the model is driven by renewable supply and demand. Demand resources in the system are categorized as inflexible (firm) consumers with stochastic consumption patterns and deferrable consumers that require a fixed amount of energy within the day and adapt their instantaneous consumption patterns to the prevailing system conditions. The model of Fig. 1 serves two purposes. The decision support module in the upper portion of the figure simulates day-ahead market operations and is used for determining day-ahead reserve requirements when deferrable demand contributes to absorbing the variability of renewable energy supply. The evaluation module in the lower portion of the figure uses the reserves committed by the day-ahead model in order to compare the real-time operating costs of the system under the three demand response paradigms that are discussed in the introduction of the paper. In what follows we describe each component of the model in further detail.

A. Statistical Models

The stochastic unit commitment model presented in Section II-B which is used for determining the optimal amount of reserves in the system accounts for firm demand and renewable supply uncertainty. We use a second order autoregressive model for modeling demand and load. We assume that firm demand and renewable production are independent in the stochastic unit commitment model.

Our analysis in this paper focuses on wind power resources. Due to the nonlinear relation of wind speed to wind power, we develop a stochastic model of wind speed and use an appropriately calibrated static power curve to determine the corresponding wind power production. We employ a data set published by the National Renewable Energy Resources Laboratory (NREL) which provides hourly time series of wind speed at various geographic locations over a year. In order to calibrate our wind speed model to the available data, we first remove seasonal and diurnal patterns, and subsequently transform the data set in order to obtain a strictly stationary Gaussian data set. The autoregressive parameters of the strictly stationary data set are estimated using the Yule-Walker equations. Our methodology follows Brown et al. [31], Torres et al. [32] and Callaway [33]. The calibration and simulation procedure and the fit of the model to the available data set is presented in Papavasiliou and Oren [34]. The calibration of firm demand follows as a special case, since the strictly stationary data set that is obtained after removing seasonal and diurnal patterns is already approximately Gaussian. The fit of the stochastic demand model to the data is shown in Fig. 2.

In the present analysis we use a single-area wind model and ignore transmission constraints in order to focus on the impact of demand response. The effect of transmission constraints in a system with multi-area renewable supply and demand response will be addressed in future work. The problem of balancing the schedules of coupled resources with the rest of the system while respecting transmission constraints would be addressed by the system operator and would be reflected in locational marginal prices from the point of view of aggregators. In the framework of a nodal market any transaction is exposed to congestion charges that the aggregator can hedge by buying financial transmission rights (FTRs) [35].

B. Stochastic Unit Commitment

In order to determine the day-ahead reserves that are committed by the system operator in order to accommodate the simultaneous integration of renewable supply and deferrable demand, we formulate a unit commitment model which assumes that the system operator co-optimizes the dispatch

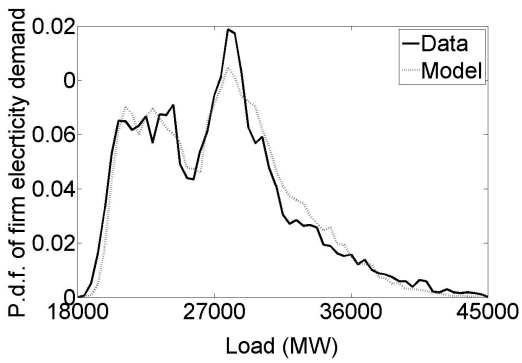

Fig. 2. Probability distribution function of inflexible demand.

of flexible loads and generation resources. The uncertainty stemming from renewable supply and load fluctuations is represented in terms of a discrete set of scenarios S. The stochastic unit commitment model is formulated as a two-stage decision model where the first stage represents day-ahead unit commitment and the second stage represents real-time economic dispatch in the hour-ahead market, in hourly intervals, subsequent to the realization of uncertainty. As we illustrate in Fig. 1, we use this model to determine the day-ahead schedule of slow reserves assuming that the system operator can co-optimize the dispatch of generators and deferrable loads.

$$(SUC):$$
$$\min \sum_{g\in G}\sum_{s\in S}\sum_{t\in T}\pi_s(K_g u_{gst} + S_g v_{gst} + C_g p_{gst}) \quad (1)$$
s.t.
$$\sum_{g\in G} p_{gst} = D_{st} + e_{st}, s\in S, t\in T \quad (2)$$

$$\sum_{t\in T} e_{st} = R, s\in S \quad (3)$$
$$0 \le e_{st} \le C, s\in S, t\in T \quad (4)$$
$$u_{gst} = w_{gt}, v_{gst} = z_{gt}, g\in G_s, s\in S, t\in T \quad (5)$$
$$(\mathbf{p},\mathbf{e},\mathbf{u},\mathbf{v},\mathbf{w},\mathbf{z}) \in \mathcal{D}. \quad (6)$$

The set of generators G in the system is partitioned into a set of slow generators G_s for which commitment decisions are fixed in the day-ahead time frame, and fast generators that can adjust their commitment schedule in the second stage. This approach is inspired by the work of Ruiz et al. [1], and adopted by Papavasiliou et al. [7]. First-stage decisions w_{gt}, z_{gt} represent the binary unit commitment and startup decisions for slow generators. The second-stage decisions include the unit commitment, startup and power output of all generators, denoted respectively as u_{gst}, v_{gst} and p_{gst}. The dispatch of deferrable loads is also a second-stage decision variable denoted as e_{st}. The objective function of Eq. (1) minimizes operating costs. Startup costs, minimum load costs and constant fuel costs for each generator g are denoted respectively as S_g, K_g and C_g. The model is solved for a 24-hour horizon with hourly time steps. Power balance is enforced in Eq. (2). The net demand D_{st}, which is the net of firm demand minus renewable power supply, represents the source of uncertainty. The constraint of Eq. (3) requires that deferrable loads be supplied an amount of energy R within a given time window and Eq. (4) enforces a limit of C on the consumption (e.g. charge) rate of deferrable loads. The non-anticipativity constraints on first-stage decisions is enforced in Eq. (5). Note that all generators, including slow units, can adjust their production level in the second stage. The set $\mathcal{D}$ includes generator capacity constraints, ramping constraints, and minimum up and down times, where bold fonts indicate vectors. The notation of the stochastic unit commitment model and the economic dispatch models that are presented subsequently is summarized in the appendix. The solution of the stochastic unit commitment model is described in detail by Papavasiliou [36].

The scenario selection algorithm used in the stochastic unit commitment model of this paper is inspired by importance sampling, whereby scenarios are selected according to their effect on expected cost and weighed such that their selection does not bias the objective function of the stochastic unit commitment formulation. The decomposition algorithm which is employed relies on a Lagrangian relaxation scheme for scenario decomposition. Both the scenario selection algorithm and decomposition algorithm developed by the authors account for transmission constraints, load uncertainty and renewable supply uncertainty as well as generator and transmission line outages [7], [8]. However, transmission constraints and element outages are not accounted for in this paper in order to isolate the effect of demand response on absorbing the uncertainty of renewable energy supply.

The centralized stochastic unit commitment model presented in this section presumes the ability of the system operator to centrally monitor and control individual loads. This is unrealistic in practice due to technological and institutional reasons. Nevertheless, such a centralized model provides a useful benchmark for estimating the maximal potential benefits of demand response, and the efficiency losses of decentralizing demand response through load aggregators. For this reason, such a centralized demand response model has been previously employed in the literature [12].

The aggregate load represented in Eqs. (2) - (4) can be perceived as a collection of a large number of identical deferrable loads that place identical requests for energy demand, are characterized by the same power rating and share power consumption equally across the entire population. In future research the authors intend to exploit high performance computing in order to incorporate a more detailed representation of deferrable loads according to their energy demand, capacity rating, and availability for charge.

In order to draw a comparison between the operating cost impact of the three demand response policies discussed in this paper, we use a single stochastic unit commitment model in order to model day-ahead market interactions. As a result, there is a misrepresentation of recourse as far as the alternative demand response models are concerned. In effect, the first stage reserve commitment decisions are somewhat overoptimistic, in assuming that the system operator can centrally

coordinate generation and demand response resources. The price of this simplification is that we are obtaining a lower bound on the performance of demand response, a pessimistic assessment of how different demand response strategies will perform. As a result, we are able to isolate the effect of demand response on operating costs and draw a consistent comparison among different demand response paradigms.

III. Demand Flexibility

In this section we describe each of the three demand response paradigms that were discussed in the introduction and how these are integrated in the economic dispatch model of real-time operations. The optimal unit commitment and startup schedules $w^\star_{gt}, z^\star_{gt}$ determined by the optimal solution of the stochastic unit commitment model in the day-ahead phase are used as input to an economic dispatch model for each realization of uncertainty ω. As in the case of the stochastic unit commitment model, the horizon T of the problem is 24 hours in hourly time steps.

A. Centralized Load Control

In the centralized load control approach we assume that the system operator co-optimizes the dispatch of flexible loads and generation resources:

$$(ED_\omega) : \min \sum_{g\in G}\sum_{t\in T}(K_g u_{gt} + S_g v_{gt} + C_g p_{gt}) \tag{7}$$

s.t.

$$\sum_{g\in G} p_{gt} = D_{\omega t} + e_t, t \in T \tag{8}$$

$$\sum_{t\in T} e_t = R \tag{9}$$

$$0 \le e_t \le C, t \in T \tag{10}$$

$$u_{gt} = w^\star_{gt}, v_{gt} = z^\star_{gt}, g \in G_s, t \in T \tag{11}$$

$$(\mathbf{p}, \mathbf{e}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}. \tag{12}$$

Despite the fact that the centralized model is not realistic in practice, it is useful for providing a benchmark for the potential benefits of demand flexibility. In this formulation, $D_{\omega t}$ represents the net of firm demand minus renewable supply.

B. Demand Bids

The demand model that we present in this section is based on Borenstein and Holland [9] and Joskow and Tirole [10], [11]. We assume a linear demand function that consists of a fraction α of inflexible consumers who face a fixed retail price λ^R, and a fraction $1-\alpha$ of price-responsive consumers who face the real-time price of electricity λ_t. The demand function $Q_t(\cdot)$ for each period can therefore be expressed as:

$$Q_t(\lambda_t;\omega) = a_t(\omega) - \alpha b\lambda^R - (1-\alpha)b\lambda_t, \tag{13}$$

where $a_t(\omega)$ is the intercept and b is the slope of the demand function. Note that we assume a common slope for all time periods and a time-varying stochastic intercept that depends on the realization of inflexible demand.

In order for the demand function model to be consistent with the two alternative demand response models, we calibrate the demand function parameters so that they satisfy the following two conditions: the demand functions have to yield a total daily demand of R subject to the charging rate constraint C, and the demand functions have to be consistent with the observed inflexible demand in the system. The calibration process is summarized in the following steps:

Step (a). Select the fraction of inflexible demand α such that R represents a fraction $1-\alpha$ of total daily demand. In particular, given R, the fraction α for each day type is determined as $1-\alpha = \frac{R}{R+\bar{D}}$, where $\bar{D}$ is the average daily firm demand for each day type, as estimated from the available data.

Step (b). Set the slope b such that the supply to price-responsive consumers equals R in the economic dispatch model with slow generator schedules fixed according to the optimal solution $w^\star_{gt}, z^\star_{gt}$ of (SUC). In particular, we proceed by fixing the demand functions at the point $(\lambda^R, \frac{\bar{D}_t}{\alpha})$ and calibrating the demand function slope b until the deterministic unit commitment model corresponding to an average wind power supply profile results in a total demand $\frac{\bar{D}}{\alpha}$. Here $\bar{D}_t$ corresponds to the average hourly firm demand for each day type as estimated from the available data, and $\bar{D} = \sum_{t\in T}\bar{D}_t$.

Step (c). For each realization ω resulting in inflexible demand $\alpha Q_t(\lambda^R;\omega)$, set $a_t(\omega) = Q_t(\lambda^R;\omega) + b\lambda^R$ in order to be consistent with the observed inflexible demand.

Step (d). The inverse demand function for deferrable demand is given by $B_t(q_t;\omega) = \frac{1}{b}(a_t(\omega) - \frac{q_t}{1-\alpha}), q_t \le C$. We can then discretize the inverse demand function to obtain valuations B_{lt} for the set of price-responsive loads L and include these valuations in a welfare maximization formulation of the economic dispatch model:

$$(ED_\omega) : \max \sum_{l\in L}\sum_{t\in T} B_{lt} d_{lt} - \sum_{g\in G}\sum_{t\in T}(K_g u_{gt} + S_g v_{gt} + C_g p_{gt}) \tag{14}$$

s.t.

$$\sum_{g\in G} p_{gt} = D_{\omega t} + \sum_{l\in L} d_{lt}, t \in T \tag{15}$$

$$0 \le \sum_{l\in L} d_{lt} \le C, t \in T \tag{16}$$

$$u_{gt} = w^\star_{gt}, v_{gt} = z^\star_{gt}, g \in G_s, t \in T \tag{17}$$

$$(\mathbf{p}, \mathbf{e}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}, \tag{18}$$

where d_{lt} represents the power draw of load segment l in period t. As in the case of the centralized demand response model in Section III-A, $D_{\omega t}$ represents the net of firm demand minus renewable supply.

C. Coupling

Here we consider a contractual arrangement for coupling renewable suppliers with deferrable loads. According to such

a contract, an aggregator is entitled to any amount of output from a large group of renewable generation assets up to its loading capability. The aggregator then enters into a contractual agreement to supply deferrable loads. Loads are characterized by a fixed amount of energy demand within a fixed time window. The aggregator controls the loads directly and uses renewable resources as the primary energy source for satisfying deferrable demand. In the case of renewable supply shortage, the aggregator resorts (to a limited extent) to the real-time wholesale market for procuring power at the prevailing price. The aggregator compensates deferrable loads at a rate ρ for each unit of unserved energy. The setup is similar to dynamic scheduling [15], whereby demand and supply resources from different control areas pair their schedules in order to produce a zero net output to the remaining system. Such scheduling is currently implemented in the ERCOT market.

For practical purposes we do not envision the load aggregator as becoming a trader of renewable power. We therefore assume that the aggregator has the option to consume renewable energy but not ownership over the renewable energy output. The aggregator can then schedule as much load as it has against the renewable supply but has no title against the residual. Effectively, the aggregator is holding a "use it or lose it" contract for the renewable supply output.

1) Implementation: As Schweppe et al. [13] discuss, the operating cost benefits of incorporating demand flexibility in power systems are expected to be outweighed by the savings in capital investment on balancing generation capacity. Such savings can be ensured, in the context of coupling contracts, by limiting the participation of aggregators in the real-time wholesale market. It is therefore necessary to provide financial incentives to deferrable loads for limiting their consumption to an efficient level that ensures the satisfaction of their demand while not imposing excessive capacity requirements on the system. Priority pricing introduced by Chao, Wilson, Oren and Smith [37], [38] and the derivative idea of callable forward contracts introduced by Gedra and Varaiya [39], and extended by Oren [40] can be used for limiting the participation of deferrable loads in the real-time market, while compensating loads for the capacity savings they enable. Callable forward contracts bundle a forward contract on power supply with a call option that can be exercised by the system operator in real time in order to limit the consumption of deferrable loads whenever real-time price exceeds a strike price k. Callable forward contracts therefore enable flexible consumers to enter the merit order stack of the system operator at the price k, which translates to capacity savings for the system operator.

It is important to ensure that callable forward contracts, or other mechanisms for inducing deferrable loads to limit the degree of their participation in real-time markets, induce loads to self-select the degree of their participation in the real-time market efficiently. In particular, it is desirable to provide strong financial incentives for loads to limit their participation in the real-time market to the greatest possible extent, without however making these financial incentives so strong as to distort allocative efficiency. In the context of callable forward contracts, this translates to inducing loads to self-select the lowest strike price k that still provides sufficient flexibility for deferrable loads to participate in the real-time market in order to satisfy their entire demand.

2) Problem Formulation: The coupling contract that we described in the previous section can be formulated as a stochastic optimal control problem. The aggregator solves the following:

$$\min_{\mu_t(x_t)} \mathbb{E}[\sum_{t\in T} \lambda_t(\mu_t(x_t) - w_t)^+ \Delta t + \rho r_N], \quad \text{s.t.} \tag{19}$$

$$r_1 = R \tag{20}$$

$$\mu_t(x_t) - w_t \leq M_t \tag{21}$$

$$0 \leq \mu_t(x_t) \leq C \tag{22}$$

where $\mu_t(x_t)$ represents the rate at which power is supplied to deferrable loads. The state vector $x_t = (\lambda_t, w_t, r_t)$ consists of the real-time price λ_t, the available renewable power supply w_t and the remaining energy demand of the deferrable consumers r_t. The initial condition for the residual demand is $r_1 = R$, where R is the amount of energy demand to be satisfied. The control $\mu_t(x_t)$ is constrained by the rate of supply C and by the amount of energy that can be procured in the real-time electricity market M_t, which is a random variable. The rate of supply C is the same as the rate of deferrable loads that appears in Eq. (4). Hence, we obtain the constraints of Eqs. (21), (22). Unsatisfied energy incurs a penalty ρ. As we explain in the appendix, the limit on real-time market participation M_t depends on the choice of strike price. The optimal control problem stated above is solved by backward dynamic programming, with a lattice representing the state space of the stochastic processes. The lattice model of renewable power supply and real-time prices is presented in Section III-C3.

3) Lattice Models: Recombinant lattices are used for controlling the rate of growth of the dynamic programming lattice. Due to the fact that the state space of the optimal control problem of Eq. (19) includes residual energy demand, we need to limit the size of the state space for the stochastic state variables, in order to solve the problem using the dynamic programming algorithm. Therefore, although it is well known that wind power production and load (and therefore real-time prices) exhibit significant autocorrelation [31], [32], [41], [33], we will simplify the stochastic models of wind power and real-time prices by representing them as first-order autoregressive processes in order to control the size of the state space. Specifically, we assume that wind speed and real-time prices are driven by two correlated mean-reverting processes:

$$X_{t+1} = X_t + \kappa_\lambda(\theta_\lambda - X_t)\Delta t + \sigma_\lambda\sqrt{\Delta t}\omega_1 \tag{23}$$

$$Y_{t+1} = Y_t + \kappa_w(\theta_w - Y_t)\Delta t + \sigma_{\lambda w}\sigma_w\sqrt{\Delta t}\omega_1 + \sqrt{(1-\sigma_{\lambda w}^2)}\sigma_w\sqrt{\Delta t}\omega_2, \tag{24}$$

where X_t and Y_t are the noise terms of the price and wind models respectively, ω_1 and ω_2 are independent standard normal random variables, θ_λ and θ_w represent the average

trends of the price and wind noise respectively, the variance terms σ_λ and σ_w capture the effect of random shocks, κ_λ and κ_w model the rate at which the processes return to their mean value and $\sigma_{\lambda w}$ is a correlation coefficient that couples the evolution of the two processes.

In our study we employ a discrete model that approximates the model of Equations (23), (24). The model is presented in Deng and Oren [42]. The dynamics of the process are given by:

$$
\begin{aligned}
X_{t+1}^j &= \begin{cases} X_t + \sigma_\lambda \sqrt{\frac{3}{2}}\sqrt{\Delta t}, & j=1 \\ X_t, & j=2 \\ X_t - \sigma_\lambda \sqrt{\frac{3}{2}}\sqrt{\Delta t}, & j=3 \end{cases} \\
Y_{t+1}^j &= \begin{cases} Y_t + (\sqrt{3}\sigma_{\lambda w} + \sqrt{1-\sigma_{\lambda w}^2})\sigma_w \sqrt{\frac{\Delta t}{2}}, & j=1 \\ Y_t - \sigma_w \sqrt{1-\sigma_{\lambda w}^2}\frac{2}{\sqrt{2}}\sqrt{\Delta t}, & j=2 \\ Y_t - (\sqrt{3}\sigma_{\lambda w} - \sqrt{1-\sigma_{\lambda w}^2})\sigma_w \sqrt{\frac{\Delta t}{2}}, & j=3. \end{cases}
\end{aligned} \tag{25}
$$

where X_t^j and Y_t^j are the noise terms of the discrete price and wind models respectively and Δt is the discretization interval. Each state j is visited with a probability p_j that depends on the current state. The transition probabilities are defined in [42]. The lattice grows as $\mathcal{O}(n^2)$, which enables us to control the growth rate and therefore the running time of the dynamic programming algorithm.

The real-time price and wind speed values that are used in the stochastic optimal control problem of Eq. 19 can be recovered by using the underlying noise and the systematic patterns of the underlying data, as explained in [36]:

$$\lambda_t = \hat{\mu}_t^\lambda + \hat{\sigma}_t^\lambda \hat{F}_\lambda^{-1}(N(X_t^j)), \tag{26}$$

$$w_t = \hat{\mu}_t^w + \hat{\sigma}_t^w \hat{F}_w^{-1}(N(Y_t^j)). \tag{27}$$

Here $\hat{\mu}_t^\lambda$ and $\hat{\sigma}_t^\lambda$ represent the hourly mean and standard deviation of real-time prices for each day type respectively, as estimated from the available data. The inverse of the non-parametric distribution of the original data set is denoted as $\hat{F}_\lambda^{-1}$ and $N(\cdot)$ indicates the cumulative distribution function of the standard normal distribution. The notation is analogous for the wind speed production process. Wind power is converted is converted to wind speed through a static aggregate power curve, as the authors describe in detail in [34]. The fit of the model to the data is presented in Fig. 3.

4) Incorporating the Coupling Model in Economic Dispatch: For any given realization of uncertainty ω, the solution of the optimal control problem of Section III-C2 induces a net demand profile $\mu_t(x_t) - w_t$ for deferrable loads coupled with renewable resources. The total demand $D_{\omega t}$ in the system is the sum of this net demand profile and the inflexible demand, as in Fig. 1. The resulting total demand is satisfied by the system operator in the economic dispatch phase:

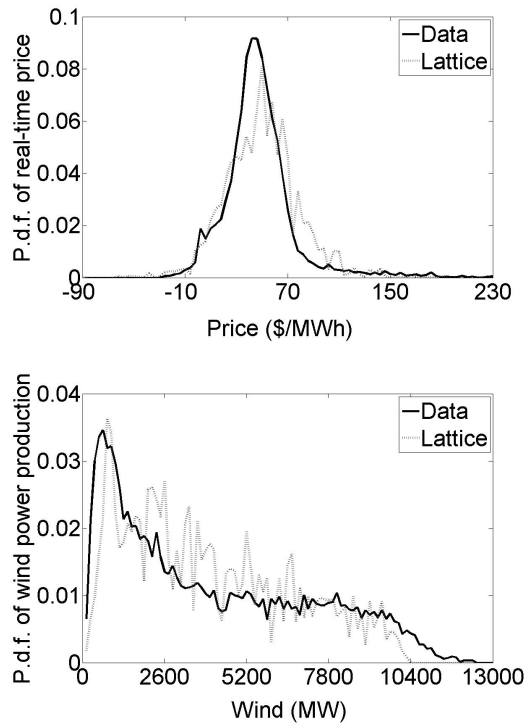

Fig. 3. Probability distribution function of real-time electricity prices (up) and wind power production (down).

$$(ED_\omega) : \min \sum_{g\in G}\sum_{t\in T}(K_g u_{gt} + S_g v_{gt} + C_g p_{gt}) \tag{28}$$

s.t.

$$\sum_{g\in G} p_{gt} = D_{\omega t}, t \in T \tag{29}$$

$$u_{gt} = w_{gt}^\star, v_{gt} = z_{gt}^\star, g \in G_s, t \in T \tag{30}$$

$$(\mathbf{p}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}. \tag{31}$$

IV. Results

We present results for a case study based on a reduced model of the Western Electricity Coordinating Council (WECC), also used in other studies [43], [7], [8]. The model consists of 124 generators. The average load in the system is 27298 MW, with a minimum of 18412 MW and a peak of 45562 MW. The net load profile that needs to be served by thermal generators and wind power, the generation mix of the system and a schematic of the WECC model are presented in Papavasiliou and Oren [8]. The entire thermal generation capacity of the system is 28381.5 MW. Thermal units with a capacity greater than 300 MW are classified as slow generators. There are 82 fast thermal generators with a total capacity of 9156.1 MW and 42 slow thermal generators with a total capacity of 19225.4 MW. The value of lost load is set to 5000 $/MWh.

We use import, hydroelectric, geothermal and biomass production data from Yu et al. [43] that correspond to 2004. Since we are using 2004 import data, we also use load data from the same year, which is publicly available at the California

TABLE I
PARAMETERS OF THE DEMAND RESPONSE CASE STUDY.

	No Wind	Moderate	Deep
Wind capacity (MW)	0	6688	14143
DR Capacity C (MW)	0	5000	10000
Daily wind energy (MWh)	0	46485	95414
Daily DR energy R (MWh)	0	40000	80000
Flexible/firm demand (%)	0	6.1	12.2

ISO Oasis database. We use a retail price of $\lambda^R = 130$ \$/MWh for the calibration of the demand function model, according to data provided by the U.S. Energy Information Administration [44]. The three wind integration cases that we consider are summarized in Table I. The load represented in Table I appears as additional flexible load in the system, as opposed to replacing existing load. For each level of wind integration, we assume a demand response integration level that is approximately one-for-one in terms of energy demand and capacity. We assume that deferrable requests span 24 hours, from midnight to midnight. This implies that the optimal control problem of Eq. (19) is solved for a 24-hour horizon from midnight to midnight. Analogously, the time horizon of the constraints in Eqs. (3), (9), span 24 hours, from midnight to midnight. We consider 6 levels of power supply for the control problem. The penalty of unserved energy is $\rho = 5000$ \$/MWh. We use 12 scenarios for the formulation of the stochastic unit commitment model. The wind data that is used for the calibration of the statistical models is based on the National Renewable Energy Laboratory (NREL) 2006 Western Wind and Solar Integration Study [45]. The moderate and deep wind integration studies correspond to the 2012 and 2020 wind integration targets of California. We consider one day type for each season and in addition we differentiate between weekdays and weekends.

A. Costs, Load Loss, Capacity Requirements and Spillage

As we discuss in Section III-C1, deferrable demand can produce great economic value by limiting the requirements for balancing capacity. Callable forward contracts can be used for limiting the extent to which deferrable loads participate in the real-time market. The strike price of the callable forward contracts determines the extent to which loads can participate in the market. As the strike price of the contracts decreases, the participation of loads in the real-time market is increasingly limited. The strike price that mobilizes deferrable demand to the greatest possible extent is presented in Table II for each of the day types for each integration study. In order to obtain these strike price thresholds, we have gradually decreased the strike price of the stochastic optimal control of Eq. (19). As we explain in the appendix, as the strike price decreases the procurement margin and the ability of the aggregator to serve deferrable demand decreases as well. Below a certain strike price threshold, the aggregator cannot serve the entire amount of deferrable demand under all possible realizations of uncertainty. This is the threshold reported in Table II. In order to simplify the analysis, we assume a common strike price for each hour of the day.

TABLE II
STRIKE PRICE THRESHOLD FOR DEFERRABLE LOAD CALLABLE FORWARD CONTRACTS (\$/MWH).

	Moderate	Deep
WinterWD	45	47
SpringWD	45	49
SummerWD	49	53
FallWD	49	54
WinterWE	45	45
SpringWE	45	47
SummerWE	48	51
FallWE	49	52

TABLE III
DAILY COST OF OPERATIONS AND LOAD SHEDDING FOR EACH DAY TYPE - NO WIND.

	Daily Cost (\$)	Shed (MWh)
WinterWD	7,390,206	0.001
SpringWD	7,145,737	4.317
SummerWD	13,684,880	30.869
FallWD	9,589,506	0
WinterWE	6,079,003	0.001
SpringWE	5,855,883	0
SummerWE	11,839,573	0
FallWE	7,868,146	154.285
Total	9,012,031	17.301

TABLE IV
DAILY COST OF OPERATIONS FOR EACH DAY TYPE - MODERATE INTEGRATION.

	Cost (\$) Centralized	Δ Cost (\$) Coupled	Δ Cost (\$) Bids
WinterWD	**7,320,620**	256,740	300,051
SpringWD	**6,408,355**	172,006	139,589
SummerWD	**13,625,136**	155,096	219,124
FallWD	**9,640,017**	316,089	157,159
WinterWE	**5,890,755**	300,701	246,408
SpringWE	**3,637,240**	707,223	244,353
SummerWE	**11,739,177**	176,230	234,101
FallWE	**7,735,502**	277,817	189,465
Total	**8,677,857**	265,128	211,010
relative (%)		3.06	2.43

In table III we present the operating costs and daily load losses for the case with no wind and no demand response in the system. These costs consist of minimum load, startup and fuel costs, namely $\sum_{g\in G, t\in T}(K_g u_{gt} + S_g v_{gt} + C_g p_{gt})$. The operating costs do not include the cost of lost load.

In Tables IV, VI we present the daily operating cost of each policy for the moderate and deep integration cases respectively. As in the case of Table III, these costs consist of minimum load, startup and fuel costs. The column with bold figures, that corresponds to centralized load dispatch by the system operator, represents absolute cost values. Cost figures corresponding to the other policies are relative to the centralized operating costs. The row with total costs weighs the cost of each day type with its relative frequency in the year in order to yield annual results. The last row shows the relative performance of centralized control with respect to the other policies, normalized by the cost of centralized control. Note that the operating costs of demand-side bidding outperform those of the coupling mechanism. This can be attributed to the diversification benefits of including flexible demand in the market.

TABLE V
DAILY LOAD LOSS FOR EACH DAY TYPE - MODERATE INTEGRATION.

	Shed (MWh) Centralized	Shed (MWh) Coupled	Shed (MWh) Bids
WinterWD	0	0	177.257
SpringWD	1.532	1.869	701.828
SummerWD	3.617	4.346	821.719
FallWD	1.661	1.661	799.323
WinterWE	0	0	642.105
SpringWE	0	0.249	453.791
SummerWE	0.059	1.100	215.816
FallWE	6.792	10.005	976.766
Total	1.705	2.217	609.914

TABLE VI
DAILY COST OF OPERATIONS FOR EACH DAY TYPE FOR THE DEMAND RESPONSE STUDY - DEEP INTEGRATION.

	Cost ($) Centralized	Δ Cost ($) Coupled	Δ Cost ($) Bids
WinterWD	**6,656,665**	633,164	556,775
SpringWD	**5,692,860**	978,182	572,465
SummerWD	**13,661,862**	505,869	835,609
FallWD	**9,321,281**	772,659	404,523
WinterWE	**5,220,109**	711,882	616,931
SpringWE	**4,251,600**	910,253	576,010
SummerWE	**12,136,223**	329,929	472,930
FallWE	**7,930,823**	700,205	515,431
Total	**8,419,322**	705,497	578,909
relative (%)		8.38	6.88

TABLE VII
DAILY LOAD LOSS FOR EACH DAY TYPE FOR THE DEMAND RESPONSE STUDY - DEEP INTEGRATION.

	Shed (MWh) Centralized	Shed (MWh) Coupled	Shed (MWh) Bids
WinterWD	0.001	8.290	552.769
SpringWD	0	351.782	1382.459
SummerWD	0.001	36.643	1952.332
FallWD	33.660	143.629	1210.443
WinterWE	0	0	929.960
SpringWE	0	32.601	1008.222
SummerWE	2.081	58.725	1157.565
FallWE	57.005	132.134	1260.137
Total	10.231	112.452	1221.492

The 'cost of anarchy' that results from using price signals in order to control load response, rather than centralized control, ranges from 2.43% - 6.88% for the case of demand-side bidding and 3.06% - 8.38% in the case of coupling. Although demand bids result in lower operating costs, demand-side bidding results in excessive load shedding. This is due to the failure of demand bids to capture the inter-temporal dependencies of deferrable demand. Instead, the centralized dispatch model accounts for such inter-temporal dependencies in Eq. (9), while the deferrable demand model accounts for such dependencies through the initial conditions of the system expressed in Eq. (20). Note that the lost load presented in Table V accounts for the shortfall of power supply to deferrable loads throughout the entire day from the daily target demand R.

In Table VIII we present a breakdown of operating costs by type for each of the demand response policies that we consider for each integration level. We note that the demand-side bidding and coupling models result in cost increases in all cost categories.

In Table IX we present the amount of capacity that is committed by each policy as well as the amount of renewable supply spillage. Capacity requirements do not change significantly for each integration study, which suggests that the additional deferrable demand can be fully absorbed by the installed renewable capacity. Wind spillage is negligible across all cases.

TABLE VIII
BREAKDOWN OF DAILY OPERATING COSTS FOR EACH DEMAND RESPONSE POLICY FOR EACH INTEGRATION LEVEL ($).

	Min load	Fuel	Startup	Total
No wind	1,382,156	7,549,491	80,384	9,098,537
Centralized Moderate	1,246,552	7,364,815	66,489	8,677,857
Bids Moderate	1,317,383	7,471,363	100,123	8,888,866
Coupled Moderate	1,330,130	7,532,898	79,958	8,942,958
Centralized Deep	1,194,606	7,174,611	50,105	8,419,322
Bids Deep	1,360,543	7,494,472	143,217	8,998,232
Coupled Deep	1,432,948	7,592,595	99,276	9,124,819

TABLE IX
CAPACITY REQUIREMENTS AND WIND POWER SPILLAGE FOR EACH DEMAND RESPONSE POLICY.

	Capacity (MW)	Spillage (MWh)
No wind	26,123	N/A
Moderate	26,254	0
Deep	26,789	2

B. Computational Details

The stochastic unit commitment algorithm was implemented in AMPL. The mixed integer programs were solved with CPLEX 11.0.0 on a DELL Poweredge 1850 server (Intel Xeon 3.4 GHz, 1GB RAM). The Lagrangian relaxation algorithm that was used for solving the problem, which is presented in detail by Papavasiliou et al. [7], was run for 80 iterations, where the first 40 iterations were run without seeking for a feasible solution and the latter 40 iterations were run with feasibility recovery. The average elapsed time for this entire process was 7,047 seconds. The average duality gap $\frac{UB-LB}{LB}$ was 0.8%. Note that if a MIP gap ϵ is used for the computation of the lower bound, then this gap should also be accounted for. In our case study we used a MIP gap of $\epsilon = 1\%$. The average bound on the optimality gap, when also accounting for the MIP gap, is then computed as $\frac{UB-(1-\epsilon)LB}{(1-\epsilon)LB} = 1.81\%$.

V. CONCLUSIONS

In this paper we present a stochastic unit commitment model that accounts for the large-scale integration of renewable energy sources and demand response resources. We consider three types of load response in our analysis, centralized load dispatch, demand-side bidding and coupling. We analyze the case of no wind in the network, as well as cases of wind integration that correspond to the 2012 and 2020 wind integration targets of California, with a corresponding one-for-one increase in flexible demand. Our analysis is performed on a model of the Western Electricity Coordinating Council that consists of 124 generators. We find that the 'cost of anarchy' incurred by decentralizing demand response ranges between 3.06% - 8.38% for the case of coupling. Demand-side bidding outperforms coupling with respect to operating

costs, resulting in a cost increase ranging between 2.43% - 6.88% of the cost corresponding to centralized load dispatch. However, demand-side bidding fails to capture the cross-elasticity of demand across time periods, resulting in excessive load losses. Arguably, if we assume that customers may adjust their response to avoid unserved load the price response functions should have been calibrated to reflect such behavior rather than matching expected energy served. In that case one would expect that cost would rise and unserved load decline, making the coupling strategy more competitive from a cost perspective. The 'cost of anarchy' imposed by coupling renewable resources with deferrable demand is the price for overcoming the institutional and regulatory barriers associated with the large-scale integration of demand response [30] that can in turn facilitate the large-scale integration of renewable resources. For the case studies that we consider, the additional integration of deferrable demand imposes no additional capacity requirements to the system. Renewable supply capacity is adequate for satisfying the added demand, which represents 6.1% - 12.2% of firm power demand for the 2012 and 2020 renewable integration targets respectively. The waste of available renewable power supply is negligible for the demand response integration study.

APPENDIX

A. Notation for the Stochastic Unit Commitment and Economic Dispatch Problems

In this section we introduce the notation that is used in the unit commitment and economic dispatch models.

Sets

G: set of all generators, G_s: subset of slow generators

L: set of load segments

S: set of scenarios

T: set of time periods

Decision variables

u_{gst}: commitment, v_{gst}: startup, p_{gst}: production of generator g in scenario s, period t

w_{gt}: commitment, z_{gt}: startup of slow generator g in period t

e_{st}: supply to deferrable loads in scenario s, period t

d_{lt}: power draw of load segment l in period t

Parameters

π_s: probability of scenario s

K_g: minimum load cost, S_g: startup cost, C_g: marginal cost of generator g

R: total energy energy demand, C: power rating of deferrable loads

D_{st}: demand in scenario s, period t

B_{lt}: benefit of load segment l in period t

B. Procurement Margin in the Aggregator Optimal Control Problem

The computation of the margin M_t of Eq. (21) is explained in Fig. 4. The figure displays the merit order curve of the system. Given a strike price k, the megawatt capacity that corresponds to the given strike price is computed by inverting the merit order curve of the system. The resulting capacity

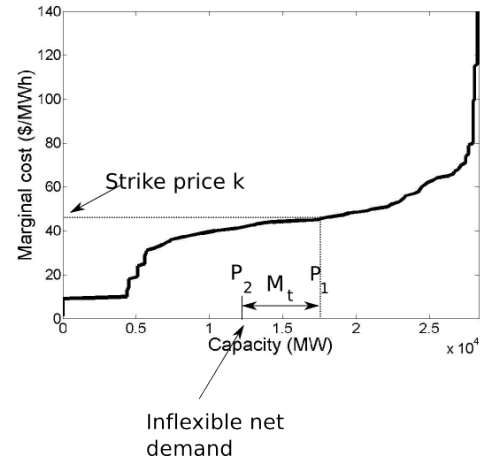

Fig. 4. The computation of the procurement margin M_t for Eq. 21 of the aggregator stochastic optimal control problem.

P_1 represents the conventional capacity that is available up to marginal cost k. Total system load consists of net inflexible demand P_2 (which is equal to inflexible demand minus imports minus non-wind renewable resources) plus deferrable demand. Therefore, the procurement margin of the aggregator is computed as $M_t = P_1 - P_2$.

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