A Market Based Scheme to Integrate Distributed Wind Energy

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***Abstract*—Efficiently integrating wind energy into the smart grid is gaining momentum under renewable portfolio standard (RPS) with deep wind penetration. Due to the randomness of wind energy production, ancillary service (AS) is needed in large amount to regulate wind power for system stability and reliability. As a result, the cost of wind power depends on the AS market and may be, quite higher than that of conventional power. Therefore, it is challenging to economically integrate wind energy with current power system to satisfy RPS. With the communication, sensing and advanced control features incorporated into the smart grid, the interactions among the grid components will facilitate solving this problem. In this paper, we consider the wind energy integration of small-scale utilities installed with wind turbines and acted as distributed energy resources (DERs). Since wind energy can be integrated to serve customer load or enter a separate green energy market, we propose a theoretical framework to dynamically determine the role of wind energy and provide long-term RPS guarantee. This approach results in a simple dynamic threshold control policy which maximizes the expectation of the profit for a green utility and is easily implemented online.**

***Index Terms*—Ancillary service, distributed energy resource, electricity markets, renewable portfolio standard, the smart grid, wind energy integration.**

I. Introduction

CLEAN, GREEN, and renewable energy is one of the biggest drivers of the smart grid. Among these renewable resources, wind energy is growing rapidly and promising to be integrated into the smart grid. In 2009, wind power systems have provided over 38 GW and been ranked first among all sources for new electricity production capacity [1].

Although wind energy is available in large areas and can be potentially used as a clean renewable resource, how to efficiently and economically integrate it into the current power system is challenging due to random fluctuations and intermittence of wind power. Taking California as an example, the real-time wind power generation can be found in [2], which fluctuates considerably in different time scales. In electric power grids, the demand and supply should be balanced in real-time [3]. Since wind power is usually non-dispatchable, shortfalls of power increase the possibility of blackout while sudden increases of wind power generation results in a large amount of spillage or even damage to electric power grids. As a result, ancillary services (ASs) in different time scales are required for system stability and reliability. With deep wind penetration, reserved capacity could face unforeseen challenges, and AS prices could be even higher. Taking this into account, the cost of using wind energy may be quite high although wind energy appears to be a windfall.

Integrating wind energy into an electric power grid has been an important research subject for both academia and industry [1], [3]–[7]. In [1], Bitar *et al.* model the contract goal as maximizing the total profit of a wind farm in the market of conventional generation. In comparison, Botterud *et al.* propose an optimal day-ahead bidding method in the wholesale electrical market based on wind energy price prediction [6]. In [5], many recent research results in current wind power systems are presented. In [4], real-time pricing in electricity markets is studied to shift peak demands to off-peak hours. Brooks *et al.* point out that plug-in hybrid electric vehicles (PHEVs) can possibly act as an AS to balance power demand and supply [7].

The renewable portfolio standard (RPS) has been proposed to further "green" the electric power grid, which makes the integration of wind energy more challenging. A RPS requires electric utilities and other retail electric providers to supply a specified minimum amount of customer load with electricity from eligible renewable energy sources. To meet the RPS requirements, small wind systems are installed in large capacity, which is expected to grow in many states, e.g., California [8]. These systems could create business opportunities for small-scale utilities that combines renewable energy with conventional generation and act as distributed energy resources (DER).

Consider a scenario of wind energy integration for an aforementioned small-scale utility, which combines wind energy and conventional energy. To fulfill the RPS, wind turbines are installed to provide renewable energy. This could be the most economic way to get RPS renewable credits because wind energy is priced high in current energy markets. To leverage the economies of scale, the conventional energy may come from electricity markets. In this scenario, the wind power integration involves scheduling constraints in two time scales, i.e., the real-time customer load provisioning and the long-term RPS compliance. As mentioned above, the wind power generation is a random variable, the cost of which depends on the real-time AS market [9]. With two-way communication infrastructure in the smart grid, the information on real-time market prices and system status can be made available timely. To address the economic feasibility of wind energy integration, we focus on designing a market-based control that maximizes the expectation of the profit.

Manuscript received January 31, 2012; revised May 08, 2012; accepted October 31, 2012. Date of publication March 07, 2013; date of current version May 18, 2013. This work was supported in part by U.S. NSF under Grant CNS-0916391. Paper no. TSG-00048-2012.

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Digital Object Identifier 10.1109/TSG.2012.2230278

In the smart grid, services in an energy market can be further classified into different categories based on the requirements for power quality. Delay-tolerant services provide flexibility to deal with fluctuating green energy. From the perspective of a utility, wind power can be potentially used for customer load or participate in green energy markets [10]. This flexibility leads to a market-based temporal integration strategy. Under the assumption that the wind capacity is larger than the minimum requirements for RPS, the utility must choose some time slots to serve load to fulfill the RPS requirements. The excess wind power can enter a green energy market to serve delay-tolerant services such as charging electrical vehicles or energy storages. Due to different power quality requirements for delay-tolerant services, the market price may be different comparing to conventional energy markets. When is the best time to choose wind power to serve customer load can be optimized according to the information such as the wind power generation, the AS price and the energy market price, etc. Following this line of thoughts, we formulate the profit maximization of the utility as a stochastic optimization problem and propose a theoretical framework to dynamically determine when to use wind energy to meet RPS requirements. The resulting scheme can provide power quality guarantee while statistically fulfilling the RPS. Besides, our scheme can be combined with any real-time pricing (RTP) scheme [4], which can shape the demand and shift the load from peak hours to non-peak hours.

The rest of the paper is organized as follows. In Section II, we describe the wind energy integration model for a market-based utility and analyze its cost for serving customer load. In Section III, we formulate the profit maximization of a utility as a stochastic optimization problem. In Section III, we solve this problem under the ergodicity assumption on system status and obtain a stationary dynamic control policy in Section IV. Section V gives numerical and simulation results, and Section VI concludes the paper.

II. System Model for Wind Energy Integration

In this section, we describe our wind energy integration model of a utility based on real-time energy markets. Since these small-scale utilities mainly act as DERs in the smart grid, we start with a brief introduction on DER and renewable energy utilities.

A. DER and Renewable Energy Utilities in Electricity Market

In the smart grid, the concept of "Microgrid" emphasizes distributed generation (DG), which makes a small-scale utility an important entity [11]. As a DER [12], the power generation sources are usually small-scale and located close to where electricity is used (e.g., a home or business), providing an alternative to or an enhancement on the traditional electric power grid.

DER technologies consist primarily of energy generation and storage systems placed at or near the point of use. Distributed energy encompasses a range of technologies including fuel cells, micro-turbines, reciprocating engines, load reduction, and other energy management technologies. DER also involves power electronic interfaces, as well as communications and control devices for efficient dispatch and operation of single generating units, multiple system packages, and aggregated blocks of power. The primary fuel for many distributed generation systems is natural gas, but hydrogen may well play an important role in the future. Renewable energy technologies, such as solar electricity, biomass power, and wind turbines, are also popular.

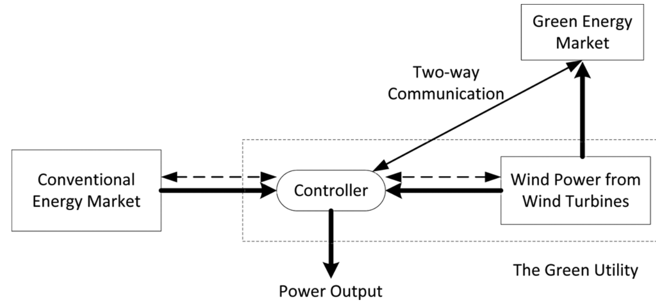

Fig. 1. System model for a green utility.

RPS provides a mechanism to increase renewable energy generation using a cost-effective, market-based approach that is administratively efficient. The goal of a RPS is to stimulate market and technology development so that, ultimately, renewable energy becomes economically competitive with conventional forms of electric power. To comply with RPS, small-scale wind turbines are installed in large capacity to provide renewable energy. The variability of production from a small number of wind turbines can be high. Thus, conventional power is used in combination to maintain a reliable output. In the National Renewable Energy Laboratory (NREL) green power marketing report [13], there have been a large number of renewable energy utilities participating in the renewable energy market as DERs. Most of these utilities combine two or more kinds of energy sources and generating units are typically small-scale, i.e., in the range of 3 kW to 50 MW. In this paper, we term the utilities complying with RPS requirement as "green utilities".

B. Wind Energy Integration Model for Green Utilities

We consider wind energy integration in a green utility with available two-way communication infrastructure, as shown in Fig. 1. In this figure, power flows are illustrated by solid lines while information flows of two-way communications between system components by dash lines. The direction on a solid line indicates the direction of the power flow. The total power output comes from the conventional power bought from the electricity market and the green power produced by wind turbines.

The wind energy has already been an optional power source for a long time. Due to its random and energy-limited nature, conventional generators are simultaneously used to provide power. When the wind power is not appropriate to serve customer load due to its availability and quality, the excess power can be sold to a separate energy market, which can be a green energy market, used for delay-tolerant services such as charging PHEVs, etc. In this case, conventional energy may be used to serve all customer load.

With the two-way communication infrastructure in place, the information such as real-time wind power generation, power demand and market prices can be timely made available. Therefore, fine-grained control on integrating wind energy can be done on the order of minutes. We consider a time slotted system

TABLE I
NOTATIONS

t	:	the time slot index.
$D(t)$	:	the total customer load of the green utility at the beginning of slot t.
$W(t)$	:	the wind power generation forecast.
$W_b(t)$	:	the true value of wind power generation.
$G(t)$	:	the conventional power bought from the RT market at slot t.
σ_t	:	the absolute error measured as a percentage of the wind power forecast at slot t.
T	:	the total time slots considered in the cost minimization.
q_t	:	the unit cost of regulation required by wind power at slot t.
p_t	:	the unit price of energy in the conventional energy market at slot t.
k_t	:	the unit price of energy in the green energy market at slot t.
Q	:	the control policy for wind power integration.
Q^*	:	the optimal control policy for wind power integration. If $Q = w$, wind power is chosen to serve load. If $Q = c$, wind power is sold as green energy.
$I_{\{Q=w\}}(t)$	:	the indicator of choosing wind power to serve load at slot t. If $I_{\{Q=w\}}(t) = 1$, wind power serves load at slot t.
r	:	the wind power integration percentage required by RPS.
$f_{p,\sigma,q,k}(w,u,v)$	:	the joint distribution of p_t, σ_t, q_t, and k_t.
U_w^t	:	the utility defined for wind at slot t.
U_c^t	:	the utility defined for conventional at slot t.
$\vec{U}^t$	:	the utility vector at slot t defined as $\vec{U}^t = [U_w^t, U_c^t]$.
α_i^*	:	the parameters used to describe the wind power integration control policy, where $\alpha_i^* \in [1, +\infty)$, and $i = \{w, c\}$.

and let $t \in \{0, 1, 2, \ldots, T-1\}$ denote the index of operating time slots. The notations are listed in Table I.

Conventional energy of a green utility is purchased from a conventional power pool participating in energy markets that are cleared and settled by the market operator, such as an Independent System Operator (ISO) or Regional Transmission Organization (RTO). A common energy market consists of two successive ex-ante markets: a day-ahead (DA) forward market and real-time (RT) market [14]. The system price in a DA market is, in principle, determined by matching offers from generators to bids from consumers at each node to develop a classical supply and demand equilibrium price, usually on an hourly interval. The schedules cleared in a DA market are the initial operations to balance load and supply, which are subject to deviation penalties. Due to system status forecast errors and contingencies, RT market is employed to ensure the balance between load and supply in real-time by allowing market participants to adjust their DA schedules based on more accurate wind and load forecasts. An RT market is cleared 5 to 15 minutes before the operating interval, which is on the order of five minutes.

Energy related commodities managed by market operators to ensure reliability are considered ASs, including spinning reserve, non-spinning reserve, operating reserve, responsive reserve, regulation up, regulation down, and installed capacity. Some of the energy markets and AS markets are integrated while some are separately managed. In this paper, we do not differentiate market management scheme, but use price to characterize market statistics. A green utility is assumed to be a price taking participant due to its small-scale, thus the market clearing price (MCP) is not affected by the bid of the utility in RT electricity and AS markets.

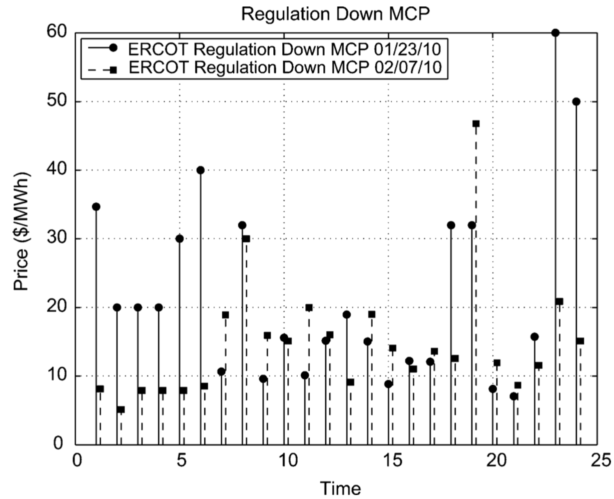

Fig. 2. ERCOT market clearing price for regulation down.

In the United States, control area operators/balancing authorities follow two controlled performance standards, i.e., CPS-1 and CPS-2. Due to the randomness of wind energy production, wind energy should be compensated by ASs if feeding into an electric grid. ASs are in three time frames: regulation in seconds to minutes, load-following in tens of minutes to hours and scheduling in hours or a day [15]. Prices should be more volatile in real time than day ahead because of all the unexpected events that may occur in real time, including forced outages of generation and transmission equipment and sudden weather changes [4].

The hourly regulation down prices for two days in ERCOT are shown as examples in Fig. 2[9]. In this figure, large fluctuation is observed at different hours in a day and during the same time period in different days.

Integration of wind energy should consider economic returns and feasibility. Deep wind penetration will further increase the demand of ASs, as studied in [16]–[18]. It is intuitively not economical to use wind power to serve load demand during price pikes as shown in Fig. 2. With high penetration of wind power, an AS price could be even higher.

C. System Cost Model

In this section, we model the cost of the aforementioned green utility. Since wind power is considered as non-dispatchable in current power systems, we consider the integration scheme of the wind power as a 0–1 control, i.e., to decide whether to use wind power to serve load or sell it to energy markets during slot t based on the information of market prices and system status. Let Q represent arbitrary control scheme and $\{Q = c\}$ denote that wind power is sold to energy markets while let $\{Q = w\}$ denote that wind power is integrated as part of the system output. The diagram of the wind energy integration is illustrated in Fig. 3. In this diagram, $D(t)$ is the total customer load of the green utility at the beginning of slot t and assumed to be constant during a slot. It is assumed that $D(t)$ is a random variable across different time slots, but can be known at the beginning of slot

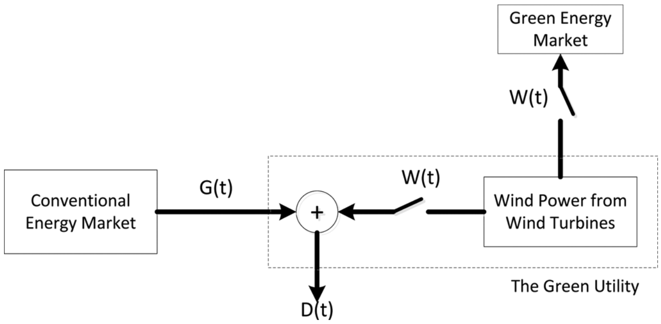

Fig. 3. Wind energy integration diagram.

t. The wind power generation forecast is denoted by $W(t)$ and the true value of wind power generation is denoted by $W_b(t)$. The conventional power purchased from RT markets is denoted by $G(t)$, which is a system variable to be determined.

Customer load needs to be balanced by the power output of the green utility for every slot. Therefore, if the wind energy is not used for serving load at slot t, the conventional power $G(t) = D(t)$. Otherwise, we have $D(t) = G(t) + W(t)$ for slot t. To avoid trivial cases, we assume that $D(t) \geq W(t)$ always holds. Then, we have

$$D(t) = W(t)I_{\{Q=w\}}(t) + G(t), \tag{1}$$

where $I_A \in \{0, 1\}$ is the indicator function of event A, and $I_{\{Q=w\}}(t) = 1$ denotes that wind energy will be used to serve part of customer load at slot t, which is also a system variable to be determined in the wind energy integration. Similarly, $I_{\{Q=c\}}(t) = 1$ represents that the wind energy is sold on energy markets at slot t. Obviously, we have

$$I_{\{Q=c\}}(t) + I_{\{Q=w\}}(t) = 1. \tag{2}$$

It is intuitive that the cost of wind energy is related to the fluctuation of wind energy production, which can be reflected by the wind forecast error. One useful model for wind energy and system analysis is the SIVAEL model [5]. In the updated SIVAEL, stochastic wind energy description is included to simulate the need of regulation. To make our paper focused, we use a simpler model to characterize the wind power forecast error. To capture the randomness of wind generation and prediction, we assume that $W_b(t)$ and $W(t)$ are random variables across different time slots, but stay constant during a slot. The wind power prediction error is captured by the normalized absolute error $\sigma_t \in [0, 1]$, which is the absolute error measured as a percentage of the wind power forecast. Then, the real-time wind energy generation satisfies

$$W_b(t) = (1 \pm \sigma_t)W(t), \tag{3}$$

where σ_t is assumed to be independent of $W(t)$. In [19], it has been shown that the distribution of σ_t can be obtained by combining beta distributions with parameters estimated from historic data. A larger wind forecast error can be due to large variation in wind power output, so the distribution of σ_t contains information about the real-time fluctuation of wind power.

The cost of using wind power can be evaluated as one to compensate forecast error of wind power generation. For example, if $W_b(t) > W(t)$, the wind energy output needs a regulation-down service and vice versa. For simplicity, we do not differentiate the regulation-up and regulation-down service price. Let q_t denote the unit cost of regulation required by wind power. The cost of the wind energy is modeled to be proportional to the absolute value of the wind forecast error σ_t. For the power purchased from conventional energy markets, the unit price is determined by the bids of market participants, which is a random variable across different time slots and denoted by p_t. Let k_t be the green energy market price that the wind energy can be sold at if not used for serving load. It is assumed that the market prices p_t, q_t and k_t are known at the beginning of slot t. Then the cost of total power generation in time slot t can be calculated as

$$p_t G(t) + q_t \sigma_t W(t) I_{\{Q=w\}}(t) - k_t W(t) I_{\{Q=c\}}(t), \tag{4}$$

where the last term of (4) is the income from selling wind energy, which is considered as a negative cost. Note that k_t is different from p_t because they are from different energy markets.

Substituting (1) and (2) into (4), we obtain the total cost of the green utility as

$$\begin{aligned} &p_t G(t) + q_t \sigma_t W(t) I_{\{Q=w\}}(t) - k_t W(t) I_{\{Q=c\}}(t) \\ &\quad = p_t G(t) - k_t W(t) + (q_t \sigma_t + k_t) W(t) I_{\{Q=w\}}(t) \\ &\quad = p_t W(t) I_{\{Q=c\}}(t) + (q_t \sigma_t + k_t) W(t) I_{\{Q=w\}}(t) \\ &\qquad + p_t [D(t) - W(t)] - k_t W(t). \end{aligned} \tag{5}$$

In this paper, we regard the operational cost of wind turbines as constant during a long period of time, which can be optimized independently of wind energy integration process.

III. Profit Maximization of a Green Utility

In this section, we formulate the profit maximization of the green utility as a stochastic optimization problem under the constraints of RPS. Currently, the average unit cost of wind energy is still higher than that of conventional power generation. The RPS requires the integration ratio of renewable power to the total power consumed be above a threshold. However, it may not be economically feasible to satisfy this requirement in the near future due to the variation of wind energy generation. Intuitively, by utilizing wind energy when it is available with lower cost, the green utility company may increase profit as well as meeting the required integration percentage of wind energy in a long run.

Following this intuition, we model this control process as a stochastic optimization problem to statistically exploit the temporal "opportunities" in the variation of wind energy and AS markets. Define the optimized variable as $\vec{I} = [I_{\{Q=w\}}(t)]$ ($t \in \{0, 1, 2, \ldots, T-1\}$), where $[\cdot]$ is the tensor notation. Since the income of a utility is independent of the control scheme, to maximize the expectation of the profit is equivalent to minimizing the expectation of the cost of a green utility. Note that the term $p_t[D(t) - W(t)] - k_t W(t)$ of (5) is independent of the variables in $\vec{I}$, thus to minimize the expectation of the generation cost, we only need to minimize the expectation of the first two term in (5).

Since $W(t)$ and $D(t)$ are random variables, our objective is to minimize the time averaged expectation of the cost of power generation over a long time period of T as below

$$(\mathbf{P1}): \min_{Q} \lim_{T\to\infty} \frac{1}{T}\Big\{ \sum_{t=0}^{T-1} \mathbb{E}\big[p_t W(t) I_{\{Q=c\}}(t) + (q_t\sigma_t + k_t) W(t) I_{\{Q=w\}}(t)\big]\Big\}, \tag{6a}$$

s.t.

$$\frac{\sum_{t=0}^{T-1} \mathbb{E}[W(t) I_{\{Q=w\}}(t)]}{\sum_{t=0}^{T-1} \mathbb{E}[D(t)]} \ge r, \tag{6b}$$

$$I_{\{Q=w\}}(t) + I_{\{Q=c\}}(t) = 1, \quad \forall t \tag{6c}$$

where (6b) is the constraint on the integration percentage of wind energy with respect to total power consumption and $r \in [0,1)$ is a parameter indicating the minimum integration percentage of wind energy required by RPS. A larger r means a stronger attempt to use wind energy.

(P1) is challenging to solve due to the following two reasons: 1) the wind energy generation is a random variable, and the available wind energy cannot be predicted precisely. The bias of wind energy forecast can be large, which makes it difficult to solve **(P1)** by approaches such as dynamic programming; 2) RPS constraint (6b) introduces temporal correlation among time slots, which considerably increases the complexity of this problem. In Section IV, we simplify and solve **(P1)** under the ergodicity assumption, which generally holds in practical systems.

IV. Long-Term Performance Evaluation

In this section, we simplify **(P1)** under the assumption that the wind energy generation $W_b(t)$, prediction $W(t)$ and demand $D(t)$ are ergodic across time slots, as well as the market prices p_t, q_t and k_t. This assumption is usually valid because the power load, wind energy generation and market behaviors statistically recur in some daily or seasonal patterns, which will normally yield that the time-average is equal to the ensemble-average. We refer this to as system ergodicity as commonly defined.

Here, we focus on stationary control schemes, which are practical and easy to implement online. By stationary control policy, we mean that the decision for slot t only depends on the system status and does not explicitly depend on time. With the ergodicity assumption, **(P1)** can be rewritten as

$$(\mathbf{P2}): \min_{Q} \mathbb{E}\big[(q_t\sigma_t + k_t) W(t) I_{\{Q=w\}}(t) + p_t W(t) I_{\{Q=c\}}(t)\big], \tag{7a}$$

s.t.

$$\mathbb{E}\big[W(t) I_{\{Q=w\}}(t)\big] \ge \mathbb{E}[D(t)], \tag{7b}$$

$$I_{\{Q=w\}}(t) + I_{\{Q=c\}}(t) = 1. \tag{7c}$$

To simplify notations, we define:

$$U_w^t = (q_t\sigma_t + k_t) W(t), U_c^t = p_t W(t), \tag{8}$$

and $\vec{U}^t = [U_w^t, U_c^t]$. **(P2)** is intuitive. Since p_t is the unit cost of conventional power, the second term captures the cost when using conventional energy. Since $q_t\sigma_t$ is the unit cost of wind power and k_t can be regarded as the opportunity cost when using wind energy to serve the work load instead of selling to energy markets, $q_t\sigma_t + k_t$ reflects the total unit cost when using wind power.

(P2) is analogous to a user-selection problem over a shared wireless channel under performance guarantees [20]. To solve **(P2)**, we follow the strategy in [20] and define a stationary control policy Q^*. A stationary policy is a policy whose decision does not depend on the slot index t explicitly, but the value of $\vec{U}^t$. Define

$$Q^*(\vec{U}^t) = \arg\min_i (\alpha_i^* U_i^t), i \in \{w, c\} \tag{9}$$

where $\{\alpha_i^*\}$ ($\alpha_i^* \in [1, +\infty)$) are real parameters to be determined later. From (9), we observe that Q^* controls the power integration according to a $\{\alpha_i^*\}$ modified version of $\vec{U}^t$. An example of the parameter setting is that $\alpha_c^* > 1$ and $\alpha_w^* = 1$ under the assumption that $\mathbb{E}[p_t] < \mathbb{E}[q_t\sigma_t + k_t]$. The performance of Q^* is stated in Theorem 1.

Theorem 1: The policy Q^* defined in (9) is a solution to **(P2)**, i.e., it minimizes the expected cost of the green utility described above under the constraint on minimum integration percentage of wind energy in (7b).

Proof: The proof of Theorem 1 is given in the Appendix. ■

In light of (9), Q^* can be simplified as follows. If $\alpha_c^* p_t < \alpha_w^*(\sigma_t q_t + k_t)$, serve the customer load by conventional power and sell the wind power to green energy markets. The power $G(t)$ purchased from the conventional energy market can be calculated by (1). In essence, Q^* is a dynamic threshold-based control policy, which is easy to implement online. The explanation of control policy Q^* is intuitive. To maximize the profit, the green utility uses wind energy whenever the sum of total unit cost of wind energy is less than $\alpha_c^*/\alpha_w^* p_t$. If the regulation service is priced high, $\{\alpha_c > 1, \alpha_w = 1\}$ helps increase the integration percentage of green energy, so as to satisfy the constraint (7b).

From the perspective of energy markets, our model reflects the role of markets in balancing the demand and supply. For example, when AS is needed in large amount, the AS price q_t is high and the green utility tends to sell the wind power and purchase more conventional power to meet the customer load. This decision further prevents the fluctuation brought in by wind power serving the load, and alleviates the requirement of AS. On the other hand, when AS is priced low, which means there is less demand for AS. Wind power can be used at lower cost and the green utility schedule it to serve the customer load and earn renewable credits from RPS fulfillment.

In addition, the effect of the quality of wind power can also be captured in our model by the prediction error. Larger wind power fluctuation usually incurs larger prediction error, thus higher regulation cost, as reflected by σ_t. It is obviously more effective to island distributed wind power generating units from the electric power grid when their outputs fluctuate severely, which reduces the demand of AS and increases the profit of the green utility. It is also implied by (9) that the advance of wind prediction helps improve the efficiency of wind power integration.

To calculate the parameters $\{\alpha_i^*\}, i \in \{w, c\}$, (7b) can be re-written as

$$\mathbb{E}\left[W(t)I_{\{Q=c\}}(t)\right] \leq \mathbb{E}[W(t)] - r\mathbb{E}[D(t)]. \tag{10}$$

Observe that (9) is equivalent to $\alpha_c^* p_t < \alpha_w^*(\sigma_t q_t + k_t)$, independent of $W(t)$. The normalized absolute prediction error σ_t is independent of $W(t)$ by assumption. In addition, the price-taking assumption implies that $W(t)$ is independent of p_t, q_t and k_t. Thus, the left hand side of (10) can be simplified as

$$\begin{aligned}\mathbb{E}\left[W(t)I_{\{Q^*=c\}}(t)\right] &= \mathbb{E}\left[W(t)\right]\mathbb{E}[I_{\{Q^*=c\}}(t)] \\ &= \mathbb{E}\left[W(t)\right] P\left\{(q_t\sigma_t + k_t) \leq \frac{\alpha_c^*}{\alpha_w^*}p_t\right\},\end{aligned} \tag{11}$$

where $P\{A\}$ indicates the probability of event A. Equation (11) is due to the fact that the definition of Q^* does not involve $W(t)$, but the statistics of p_t, q_t, σ_t and k_t, and these four random variables are independent of $W(t)$ as observed above. Substituting (11) into (10), we obtain

$$\begin{aligned}&P\left\{(q_t\sigma_t + k_t) \leq \frac{\alpha_c^*}{\alpha_w^*}p_t\right\} \\ &= \int_0^{(q_t\sigma_t+k_t)/p_t \leq \alpha_c^*/\alpha_w^*} f_{p,\sigma,q,k}(x,w,u,v)dxdvdudw \\ &\leq 1 - \frac{r\mathbb{E}[D(t)]}{\mathbb{E}[W(t)]},\end{aligned} \tag{12}$$

where $f_{p,\sigma,q,k}(x,w,u,v)$ is the probability density function of the joint distribution of p_t, σ_t, q_t, and k_t.

Let $F(a) = \int_0^{(q_t\sigma_t+k_t)/p_t \leq a} f_{p,\sigma,q,k}(x,w,u,v)dx\, dv\, du\, dw$, $a \in [1, +\infty)$. Since $F(a)$ is non-decreasing, let $F^{-1}(\cdot)$ denote the inverse function of $F(a)$. Then the optimal parameter α_c^*/α_w^* can be written as

$$\frac{\alpha_c^*}{\alpha_w^*} = F^{-1}\left[1 - \frac{r\mathbb{E}[D(t)]}{\mathbb{E}[W(t)]}\right]. \tag{13}$$

From (13), we can see that α_c^*/α_w^* depends on the joint distribution of power price p_t, q_t, σ_t and k_t as well as the integration percentage r. To ensure that the integration percentage r can be achieved, $\mathbb{E}[D(t)]/\mathbb{E}[W(t)] \in [0, 1/r]$ should be guaranteed.

Our scheme can be readily extended to the situation where there are several kinds of renewable resources, such as solar energy and hydro-power, required to be integrated into the smart grid by percentage. In this case, the parameter $\{\alpha_i^*\}$ cannot be calculated in close-form, but can be estimated numerically. We refer the readers to [20] for more details.

In summary, wind power integration with conventional power can be controlled as follows. According to the joint distribution of p_t, q_t, k_t, calculate the parameters α_c^*/α_w^* based on (13), where $\mathbb{E}[D(t)]$, $\mathbb{E}[W(t)]$ and the RPS level r are known. Because $D(t)$ and $W(t)$ are assumed to be ergodic, the parameter α_c^*/α_w^* only needs to be estimated once. At the beginning of slot t, calculate $\alpha_c^* p_t$ and $\alpha_w^*(\sigma_t q_t + k_t)$. If $\alpha_c^* p_t \geq \alpha_w^*(\sigma_t q_t + k_t)$, use wind to serve customer load in this slot. Otherwise, sell the wind energy to the energy market in this slot.

TABLE II
PARAMETERS

$\mu_q = \$15$/MWh	$\sigma_q = \$9$/MWh
$\mu_k = \$12$/MWh	$\sigma_k = \$10$/MWh
$\mu_p = \$\{5, 10, 15\}$/MWh	$\sigma_p = \$5$/MWh
$\mathbb{E}[W(t)]/\mathbb{E}[D(t)] = 0.5$	$\rho_1 = 0.2$
$\rho_2 = 0.4$	$\rho_3 = 0.4$
$a = 2$	$b = 5$

V. Case Study and Simulation Results

In this section, we present the numerical results for the parameter estimation in the stationary control Q^* and the simulation results for the control policy.

A. Simulation Setting

We choose the time slot interval as one hour and simulate the hourly wind power integration. The market prices of regulation q_t, the green energy k_t and conventional generation p_t are assumed to be market clearing price (MCP), which are correlated as studied in [21]. To capture their randomness and correlation, p_t, q_t and k_t are assumed to be multi-dimensional truncated normal distribution in the interval $[0, p_m] \times [0, q_m] \times [0, k_m]$ with parameter (μ, Σ) as the mean vector and the covariance matrix, where p_m, q_m and k_m are the maximums of p_t, q_t and k_t. Let $\rho_1, \rho_2\ \rho_3$ denote the correlation coefficients between p_t and and k_t, q_t and k_t, and p_t and q_t, respectively. The customer load and the forecasted wind energy $W(t)$ are assumed to be uniformly distributed with $\mathbb{E}[D(t)]/\mathbb{E}[W(t)] = 2$. The absolute value of wind energy forecast error is assumed to be beta distributed with parameter $\{a, b\}$. This simulation setting by no means captures all the characteristics of a liberalized power market. However, we want to use this simple example for illustration purpose.

The statistical model of energy market price has been investigated in [22], [23]. We refer readers to these works for a detailed characterization of energy market prices. The parameters used in this simulation is listed in Table II, where $\mu = [\mu_p\ \mu_k\ \mu_q]$. These parameters are chosen according to the curve fitting to the hourly price data in ERCOT [9] from 01/01/2011 to 03/31/2011 by normal distribution. Here, we choose the slot interval as one hour for illustrative purpose because the current hourly prices are available in the energy markets such as ERCOT and PJM. However, the slot interval can be adjustable in the smart grid.

B. Performance Analysis

The parameter α_w^*/α_c^* is estimated by simulating Q^* for $\mathrm{T} = 1000$ hours and calculating the probability in (12). The parameter α_w^*/α_c^* vs. r is shown in Fig. 4, where the conventional energy price is chosen as \$5, \$10, and \$15/MWh, respectively. It is intuitive that α_w^*/α_c^* decreases with the wind energy integration ratio r, as a larger r will increase the probability of using wind energy to serve the work load. To fulfill the same wind energy integration percentage r, the parameter α_w^*/α_c^* is increasing with conventional energy price. According to (12), α_w^*/α_c^* increases with p_t when r is a constant. The largest achievable wind energy integration percentage is 50% under these three scenarios in Fig. 4, which agrees with a priori study that $\mathbb{E}[W(t)]/\mathbb{E}[D(t)] = 0.5$ in this simulation. The case that there is no requirement on wind energy integration percentage is equivalent to $\alpha_c = 1$. This implies that we determine

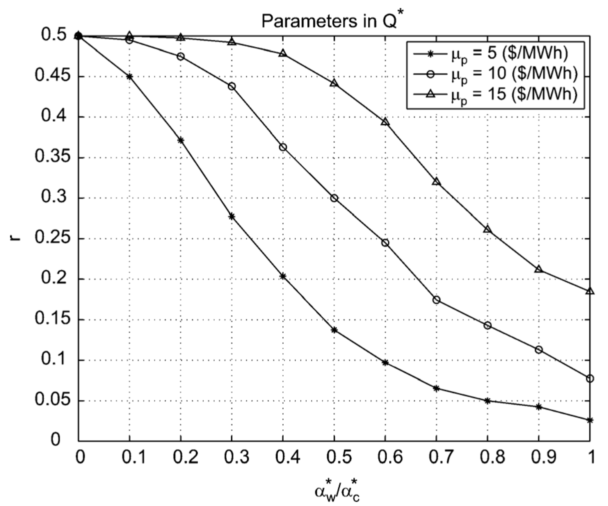

Fig. 4. Parameter in the control policy Q^* vs. integration ratio.

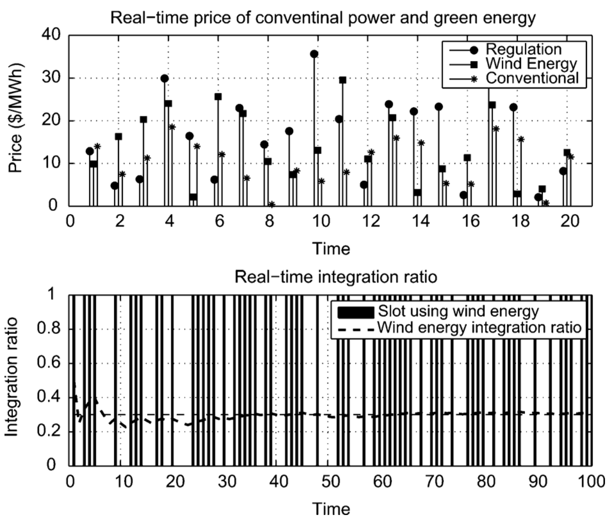

Fig. 5. Real-time power integration.

the role of wind energy only by price. Under this condition, the integration percentage is about 20% with $p_t = \$15/\mathrm{MWh}$ and only 3% with $p_t = \$5/\mathrm{MWh}$, indicated by the curves in Fig. 4.

According to the curves in Fig. 4, with the integration ratio $r = 0.3$ and the conventional energy price $\mu_p = \$10/\mathrm{MWh}$, the parameter α_c^*/α_w^* is about 0.48. Then we simulate the wind power integration procedure for 200 independent slots. This can be regarded as the integration procedure for several consecutive days. The real-time power prices of conventional generation and wind power are shown in Fig. 5(a) in the first 20 hours. Fig. 5(b) shows the real-time role of wind power determined by control Q^*. The bars indicate the slots when the wind power is used to serve the customer load. The curve illustrates the real-time integration percentage in Fig. 5(b). We can see that after a period of time, say, 30 slots, the green energy integration percentage is fulfilled.

To evaluate the time averaged system cost under Q^*, we compare it with a randomized control scheme and a deterministic scheme where wind power is used to serve load for all the slots. Both the randomized and the deterministic control schemes comply with RPS. The randomized control scheme chooses a random fraction of slots to sell wind energy to markets and use the rest of slots to serve customer load. For example, when $r = 30\%$ and $\mathbb{E}[W(t)]/\mathbb{E}[D(t)] = 0.5$, the randomized control policy randomly chooses 40% of the slots to sell wind power to energy markets. The time-averaged energy cost is shown in Fig. 6. The system cost is reduced by about 15% using control scheme Q^* compared to the randomized scheme, which does not utilize the opportunity of time-varying market prices. Obviously, the deterministic scheme results in the highest cost because it does not leverage the information of wind power generation and energy markets.

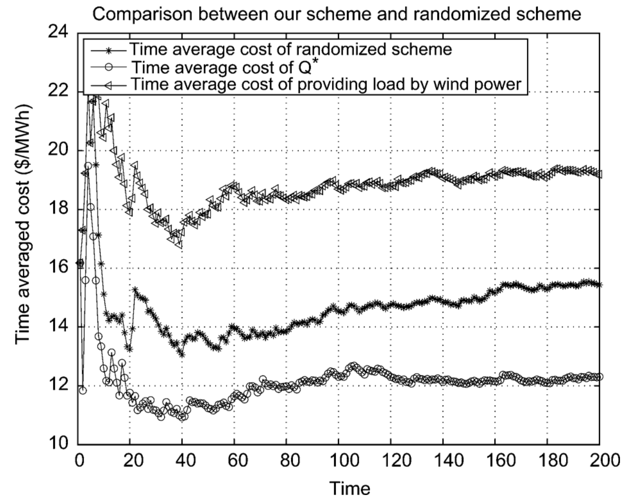

Fig. 6. Time-averaged cost.

VI. Conclusion and Future Work

In this paper, we consider the problem of statistically integrating wind energy into the smart grid for green utilities complying with RPS. The profit maximization of the green utility is formulated as a stochastic optimization problem. By utilizing the real-time information of wind power generation and energy markets, we propose a stationary dynamic threshold based scheme to alternate the role of wind power in electric power systems. Under this scheme, wind energy is used to serve the customer load when it is available with low cost. Alternatively, wind power is sold to green energy markets when it is priced high. As a result, the profit of the system is maximized and the RPS requirements are fulfilled statistically.

Our results provide the key insights into the trade-off between wind energy integration percentage and the cost of wind energy integration. Besides, this work emphasizes the benefits brought in by two-way communication and control techniques in the integration of renewable resources, which are key features of the smart grid.

Appendix

Proof of Theorem 1: Recall that the parameters $\{\alpha_i\}$, $i \in \{w, c\}$ defined in Q^* satisfy $\alpha_i \in [1, +\infty)$. To prove Theorem 1, we define the following auxiliary variables:

1) Define

$$m_c = \mathbb{E}[p_t | I_{\{Q^*=c\}}(t) = 1]\,(\mathbb{E}[W(t)] - r\mathbb{E}[D(t)])$$
$$m_w = \max_Q \mathbb{E}[U_w^t I_{\{Q^*=w\}}(t)];$$

2) For all i, $\mathbb{E}\left[U_i^t I_{\{Q^*=i\}}(t)\right] \le m_i$, $i \in \{w, c\}$;

3) For all i, if $\mathbb{E}\left[U_i^t I_{\{Q^*=i\}}(t)\right] < m_i$, then $\alpha_i^* = 1$.

We prove Theorem 1 by two steps. First, we show that Q^* is an optimal solution to the problem below

$$P3: \quad \min_Q \mathbb{E}[U_Q^t] \tag{14}$$
$$s.t. \quad \mathbb{E}[U_i^t I_{\{Q=i\}}(t)] \le m_i,$$
$$I_{\{Q=w\}}(t) + I_{\{Q=c\}}(t) = 1 \tag{15}$$

where $\{U_i^t\}(i=1,2\ldots,N)$ are N utilities indexed by i, and $\mathbb{E}\left[U_Q^t\right] = \sum_{i=1}^N \mathbb{E}\left[U_i^t I_{\{Q=i\}}(t)\right]$ is the expected system utility achieved by control policy Q at slot t with $\sum_{i=1}^N I_{\{Q=i\}}(t) = 1$, and $\{m_i\} \in \mathcal{R}$ are the same as those defined in Q^*, where $\mathcal{R}$ is the set of m_i when (14) is feasible. Here, we do not discuss the feasibility of (14) due to space limitation. After showing the optimality of Q^*, we then demonstrate the equivalence between (6b) and (15).

The optimality of Q^* is discussed in a general situation where the control policy chooses from $\{1,2,\ldots,N\}$ according to $\{U_i^t\}$. Let Q be any control policy satisfying (15) and $\sum_{i=1}^N I_{\{Q=i\}}(t) = 1$.

The expected system utility satisfies

$$\begin{aligned}
&\mathbb{E}\left[U_Q^t\right] \\
&\ge \mathbb{E}\left[U_Q^t\right] + \sum_{i=1}^N (\alpha_i^* - 1)\left(\mathbb{E}\left[U_i^t I_{\{Q=i\}}(t)\right] - m_i\right) \\
&= \sum_{i=1}^N \mathbb{E}\left[U_i^t I_{\{Q=i\}}(t)\right] + \sum_{i=1}^N (\alpha_i^* - 1)\mathbb{E}\left[U_i^t I_{\{Q=i\}}(t)\right] \\
&\quad - \sum_{i=1}^N (\alpha_i^* - 1) m_i \\
&= \sum_{i=1}^N \mathbb{E}\left[\alpha_i^* U_i^t I_{\{Q=i\}}(t)\right] - \sum_{i=1}^N (\alpha_i^* - 1) m_i,
\end{aligned} \tag{16}$$

where the first inequality comes from that $(\alpha_i^* - 1)\left(\mathbb{E}\left[U_i^t I_{\{Q=i\}}(t)\right] - m_i\right) \le 0$ for any i.

By the definition of Q^* in (9), we obtain that

$$\sum_{i=1}^N \alpha_i^* U_i^t I_{\{Q=i\}}(t) \ge \sum_{i=1}^N \alpha_i^* U_i^t I_{\{Q^*=i\}}(t).$$

Thus, we have

$$\begin{aligned}
\mathbb{E}\left[U_Q^t\right] &\ge \sum_{i=1}^N \mathbb{E}\left[\alpha_i^* U_i^t I_{\{Q^*=i\}}(t)\right] - \sum_{i=1}^N (\alpha_i^* - 1) m_i \\
&= \sum_{i=1}^N (\alpha_i^* - 1)\left(\mathbb{E}\left[U_i^t I_{\{Q^*=i\}}(t)\right] - m_i\right) + \mathbb{E}\left[U_{Q^*}^t\right] \\
&= \mathbb{E}\left[U_{Q^*}^t\right]
\end{aligned} \tag{17}$$

where (17) follows from

$$\sum_{i=1}^N (\alpha_i^* - 1)\left(\mathbb{E}[U_i^t I_{\{Q^*=i\}}(t)] - m_i\right) = 0,$$

because

$$\alpha_i^* \begin{cases} = 1, & \text{if } \mathbb{E}[U_i^t I_{\{Q^*=i\}}(t)] < m_i \\ > 1, & \text{if } \mathbb{E}[U_i^t I_{\{Q^*=i\}}(t)] = m_i. \end{cases}$$

In addition, $\mathbb{E}[U_w^t I_{\{Q^*=w\}}(t)] \le m_w$ always holds.

Hence, with (8) and $N = 2$ as a special case of (14), the optimality of Q^* is proved. Now we show that the constraint (6b) on the integration percentage of wind energy is equivalent to (15).

Substituting (8) into $Q^* = \arg\min_i(\alpha_i^* U_i^t)$, we obtain

$$Q^* = \arg\min_i\{\alpha_c^* p_t, \alpha_w^*(q_t\sigma_t + k_t)\} \tag{18}$$

which is independent of the forecast wind energy generation $W(t)$ at time t. Then (15) can be re-written as

$$\begin{aligned}
&\mathbb{E}\left[p_t W(t) I_{\{Q^*=c\}}(t)\right] \\
&\quad = \mathbb{E}[W(t)]\mathbb{E}\left[p_t I_{\{Q^*=c\}}(t)\right] \\
&\quad \le m_c,
\end{aligned} \tag{19}$$

where we have used the fact that $W(t)$ is independent of Q^* and p_t. In addition, Q^* satisfies (7b) and we have

$$\begin{aligned}
\mathbb{E}\left[W(t) I_{\{Q^*=c\}}(t)\right] &= \mathbb{E}[W(t)]\mathbb{E}[I_{\{Q^*=c\}}(t)] \\
&\le \mathbb{E}[W(t)] - r\mathbb{E}[D(t)].
\end{aligned} \tag{20}$$

Comparing (19) with (20), we only need the following

$$\frac{\mathbb{E}[W(t)] - r\mathbb{E}[D(t)]}{\mathbb{E}[I_{\{Q^*=c\}}(t)]} = \frac{m_c}{\mathbb{E}[p_t I_{\{Q^*=c\}}(t)]}. \tag{21}$$

Since

$$I_{\{Q^*=c\}} = \begin{cases} 1, & \text{if } \alpha_w^*(q_t\sigma_t + k_t) \ge \alpha_c^* p_t \\ 0, & \text{otherwise,} \end{cases}$$

we obtain

$$\begin{aligned}
&\mathbb{E}\left[p_t I_{\{Q^*=c\}}(t)\right] \\
&\quad = P\{\alpha_w^* q_t \ge \alpha_c^* p_t\}\mathbb{E}[(q_t\sigma_t + k_t) | I_{\{Q^*=c\}}(t) = 1]
\end{aligned} \tag{22}$$

which is a constant and can be calculated from the distribution of p_t, q_t, σ_t and k_t. Recall that $\mathbb{E}[I_{\{Q^*=c\}}(t)] = P\{\alpha_w^*(q_t\sigma_t + k_t) \ge \alpha_c^* p_t\}$, and we have $m_c = \mathbb{E}[p_t | I_{\{Q^*=c\}}(t) = 1]\left(\mathbb{E}[W(t)] - r\mathbb{E}[D(t)]\right)$, which yields (21). This completes the proof of Theorem 1.

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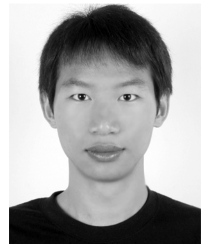

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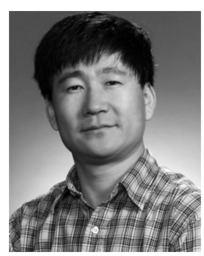

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