Wind Power Integration via Aggregator-Consumer Coordination: A Game Theoretic Approach

Chenye Wu
Institute for Interdisciplinary Information Sciences
Tsinghua University
Beijing, 100084, China
Email: wucy05@mails.thu.edu.cn

Hamed Mohsenian-Rad
Department of Electrical and Computer Engineering
Texas Tech University
Lubbock, TX 79409, USA
Email: hamed.mohsenian-rad@ttu.edu

Jianwei Huang
Department of Information Engineering
The Chinese University of Hong Kong
Shatin, New Territories, Hong Kong
Email: jwhuang@ie.cuhk.edu.hk

***Abstract*—Due to the stochastic nature of wind power, its large-scale integration into the power grid requires techniques to constantly balance the load with the time-varying supply. This can be done via smart scheduling of energy consumption and storage units among end users. In this paper, we propose a game-theoretic algorithm to be implemented in an aggregator in order to coordinate the operation of demand-side resources via pricing in order to tackle the intermittency and fluctuations in wind power generation. The demand-side resources to be considered are both non-shiftable and shiftable load, in particular, electric vehicles that charge or discharge their batteries to provide extra resource management flexibility. After formulating the interactions in an aggregator-consumer system as a game, we analytically prove the existence and uniqueness of the Nash equilibrium in the formulated game model. Simulation results show that our proposed design scheme can benefit both end users (in terms of reducing energy expenses) and the power grid (in terms of integrating wind power).**

I. Introduction

The penetration level of distributed generation (DG) units has recently increased significantly, and this trend is expected to continue over the next several years. Two most popular DG schemes are *wind turbines* (renewable powers), and *combined heat and power plants* (non-renewable powers) [1]. However, wind powers (and many other renewable energy resources such as solar power) are highly stochastic and often uncontrollable, which makes it difficult to guarantee the balance between load and generation in the power grid at all times [2]. Moreover, wind generation is non-dispatchable, which means that the output of wind turbines must be taken by the grid completely rather than partially based on demand [2]. This poses great challenges to the management of wind power. Nevertheless, smart demand side management with the help of electric vehicles (EVs) may cope this challenge. EVs are likely to become very popular worldwide within the next few years. They provide a new opportunity to demand side management with their batteries serving as storage system [3]. With possibly millions of EVs, V2G system is proposed to take advantages of these EVs [4], [5]. In this regard, aggregators can be used to coordinate the operation of EVs and other load and demand-side resources in each neighborhood [6]. In this paper, we propose a game-theoretic algorithm to be implemented in an aggregator to efficiently schedule the energy consumption and storage for end-users in order to constantly maintain the balance between demand and conventional and renewable power supply with the main focus on integrating wind power.

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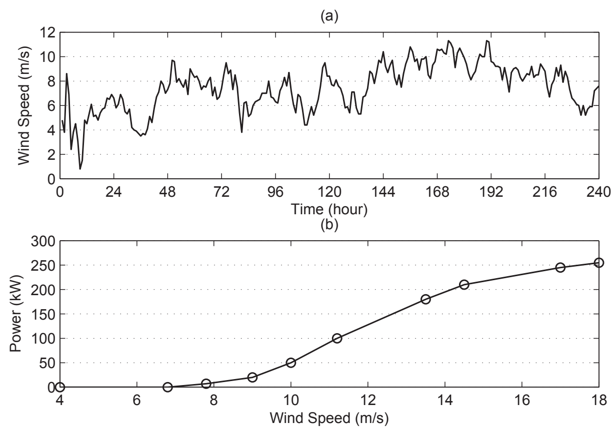

Fig. 1. Wind power prediction based on wind speed: (a) 10 days wind speed trend in Crosby County in Aug. 2009 [8]. (b) Power versus speed curve [9].

A. Wind Power Prediction

The stochastics of wind power is due to the changes in wind speed, since other on-site conditions changes are relatively slow [7]. Thus, wind speed prediction determines the wind power predication. However, predicting wind speed is not an easy task. Fig. 1(a) shows the wind speed measurements in the Crosby County in Lubbock, TX over ten days in August 2009, which is stochastic and difficult to predict precisely. With the information of wind speed, one can predict wind power using the power versus speed curve in Fig. 1(b) [7].

B. Related Work

Most related literature studying the impact of wind power on power grid appeared only in the last few years. In [10], Neely *et al.* proposed several efficient algorithms of allocating energy from renewable sources to flexible consumers. Considering the distributed storage capacity of V2G systems, Shimizu *et al.* in [11] designed a centralized load frequency control system for integration of photovoltaic and wind power. In [12], Freire *et al.* developed three different electric vehicles charging strategies to optimize the grid load balancing for the integration of renewable energy generation. In [13], Liu employed a load dispatch model for a system consisting of both thermal generators and wind turbines based on a wait-and-see approach. In [2], He *et al.* demonstrated a multiple timescale dispatch and scheduling system for smart grid with wind generation integration. To the best of our knowledge, our work is the first to design a *decentralized* smart pricing mechanism to encourage end user participation in helping integrating wind power into the smart grid.

Another body of related literature focuses on game theoretical analysis of power networks. In [14], Bhakar *et al.* used cooperative game theory to provide a stable cost allocation model in a DG embedded distribution network. In [15], Wu *et al.* modeled an optimal decentralized vehicle-to-aggregator game to provide frequency regulation to the grid. The game model studied in this paper is targeting the integration of wind power with user participation, and thus is different from those in [14], [15].

C. Our Contributions

In this paper, we assume that each user is equipped with a software agent that schedules the user's energy consumption and storage to pursue the user's best interest. The operation of each group of users in a neighborhood is coordinated by an aggregator. Such control is indirect and works based on setting the prices in response to any imbalance between supply and demand in the system. Such imbalance can particularly be due to the fluctuations in available wind power. Given the price values, the software agent for each user properly schedules energy consumption and energy storage for that user. The contributions in this paper can be summarized as follows.

- We propose a game-theoretical model that captures the rational and selfish behavior of end users when they participate in wind power integration.
- We introduce a pricing algorithm to be implemented by aggregators to encourage user participation in wind power integration. The proposed pricing leads to a unique Nash equilibrium of the resource management game constructed among each group of users and their aggregator.
- Simulation results show that our proposed scheme benefits both users and power grid. Users reduce their energy expenses while the grid experiences less mismatch between power generation and consumption.

The rest of this paper is organized as follows. The system model is explained in Section II. The optimal centralized design for wind power integration is proposed in Section III. Our game theoretic analysis is proposed in Section IV. Simulation results are presented in Section V. Future extensions and concluding remarks are discussed in Section VI.

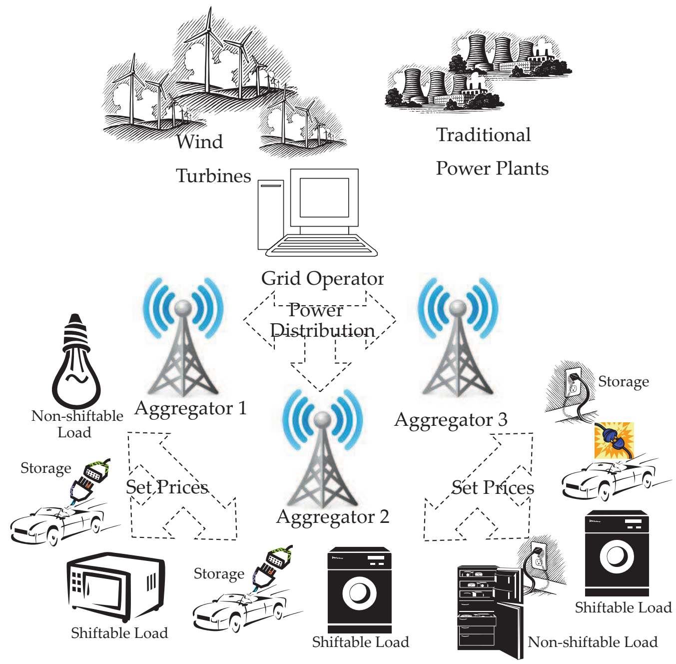

Fig. 2. The power system model considered in this paper.

II. System Model

Consider the power system in Fig. 2. It consists of seven key components: power grid operator, traditional power plants, wind turbines, aggregators, non-shiftable load, shiftable load, and appliances with storage capacity such as EVs. Both traditional power plants and wind turbines contribute to power generation. The daily operation of the grid can be divided into several time slots. The power generation of the traditional power plants can be arranged precisely ahead of time. At the beginning of each time slot, wind turbine operator predicts its generated power within the next several time slots. Such information is collected by the grid operator, and the total predicted wind power is announced to all users. In addition, users are informed about the pricing policies of the next few hours. Given the information, users then schedule their load to minimize their own energy expenses. Next we will explain the power generation and user consumptions more precisely.

A. Power Generation

Let w^t denote the generated wind power at time slot t. Using a short-term prediction method [16], the total wind power to be generated within the next H time slots (from time slot t) is predicted as $\hat{w}^1, \cdots, \hat{w}^H$, where H is the prediction horizon. We assume that the prediction error $n \sim N(0, \sigma^2)$, *i.e.,* follows a zero-mean Gaussian distribution [2]. Then we have:

$$w^h = \hat{w}^h + n^h. \tag{1}$$

Thus, the *total* generated power within the next H time slots are predicted as $\hat{w}^1 + v^1, \ldots, \hat{w}^H + v^H$, where $v^1, \ldots, v^H$ denote the amount of traditional/non-renewable power generation available, *e.g.,* from fossil-fuel and nuclear power plants.

B. Users Power Consumption

Users may own a variety of appliances, such as washer, dryer, dishwasher, refrigerator, air conditioner, and a few appliances with storage capacity such as electric vehicles (EVs). Appliances can be divided into *two* groups based on the characteristics of their power consumption: *non-shiftable load* and *shiftable load*. A typical example for non-shiftable load is refrigerator, which needs to be always on. An example of shiftable load is dishwasher, which needs to be on for a certain total time, while the exact on time is flexible as long as the job is done before certain deadline (say dinner time). Note that appliances with storage capacity are shiftable load with the additional possibility of having *negative* energy consumption at the time of discharging.

Consider one aggregator and set $\mathcal{N} = \{1, \ldots, N\}$ of all end users connected to it. For each user $n \in \mathcal{N}$, let $\gamma_n = [\gamma_n^1, \cdots, \gamma_n^H]$ be the energy consumption profile of all his non-shiftable load in the next H time slots. Also let $\mathcal{L}_n$ denote the set of user n's shiftable loads that can be scheduled. For each load $l \in \mathcal{L}_n$, we denote its total energy consumption as $E_{l,n}$. For example, for an EV, $E_{l,n} = 16$kWh [17]. The beginning and end of the valid scheduling time frame for the shiftable load are denoted by $a_{l,n}$ and $b_{l,n}$, that is, a valid scheduling should make sure that the load is satisfied during this period. For example, for a dishwasher after lunch, we can set $a_{l,n}$ = 1:00 PM and $b_{l,n}$= 5:00 PM, such that we can assure washing the dishes before dinner. Finally, we denote the minimum and the maximum schedulable energy consumption level of the appliance at each time slot by $x_{l,n}^{\min}$ and $x_{l,n}^{\max}$, respectively. In summary, a valid scheduling should meet the following constraints:

$$x_{l,n}^{\min} \leq x_{l,n}^h \leq x_{l,n}^{\max}, \forall l \in \mathcal{L}_n, \ \forall n \in \mathcal{N}, \ 1 \leq h \leq H \quad (2)$$

$$\sum_{h=a_{l,n}}^{b_{l,n}} x_{l,n}^h = E_{l,n}, \forall l \in \mathcal{L}_n, \ \forall n \in \mathcal{N}. \quad (3)$$

Note that, the equality constraint in (3) means that each appliance needs to consume a predefined total amount of energy between time slots $a_{l,n}$ and $b_{l,n}$.

While (2) and (3) are applicable to all appliances, the appliances with storage capacity require some additional constraints. Let $\mathcal{L}_n^s$ denote the set of appliances with storage capacity. Note that $\mathcal{L}_n^s \subset \mathcal{L}_n$. For each appliance $l \in \mathcal{L}_n^s$, *e.g.,* the battery of an EV, a charging or discharging schedule $x_{l,n}^h$ should also depend on the scheduling plan in previous time slots, *i.e.,* $x_{l,n}^1, \cdots, x_{l,n}^{h-1}$. As an example, let us denote the total capacity of a battery as C. If the initial battery level at the beginning of time slot 1 is $35\%C$, and the charging upper and lower limits are $80\%C$ and $20\%C$, respectively, then the battery can supply at most $15\%C$ to the grid and consume at most $45\%C$ accumulatively. To mathematically represent the constraints, we can denote $y_{l,n}^{\min}$ and $y_{l,n}^{\max}$ as the overall energy that the battery can provide and consume. In the previous example, we have $y_{l,n}^{\min} = -15\%C$ and $y_{l,n}^{\max} = 45\%$.

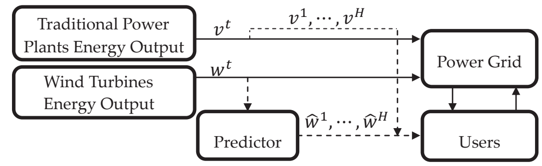

Fig. 3. Block diagram of the power system. The solid lines indicate the power flow and the dashed lines show information flow.

Thus, in addition to (2) and (3), we need to also have:

$$y_{l,n}^{\min} - \sum_{s=1}^{h-1} x_{l,n}^s \leq x_{l,n}^h, \ 1 \leq h \leq H, \ \forall l \in \mathcal{L}_n^s, \ \forall n \in \mathcal{N}, \quad (4)$$

$$y_{l,n}^{\max} - \sum_{s=1}^{h-1} x_{l,n}^s \geq x_{l,n}^h, \ 1 \leq h \leq H, \ \forall l \in \mathcal{L}_n^s, \ \forall n \in \mathcal{N}. \quad (5)$$

With constraints (4) and (5), we assure that the batteries will not be over-charged or over-discharged at any time slot. Together, constraints (2)-(5) define a feasible set for a scheduling plan. For each user n, the feasible set is denoted by $\mathcal{X}_n$.

III. Centralized Design

For each user $n \in \mathcal{N}$ and for any of his shiftable appliances $l \in \mathcal{L}_n^s$, let $\boldsymbol{x}_{l,n}$ denote the corresponding energy consumption scheduling vector during the next H time slots:

$$\boldsymbol{x}_{l,n} = [x_{l,n}^1, \cdots, x_{l,n}^H]. \quad (6)$$

User n's energy profile for *all* his appliances becomes

$$\boldsymbol{x}_n = [\boldsymbol{x}_{1,n}, \cdots, \boldsymbol{x}_{L_n,n}]. \quad (7)$$

If a centralized control was feasible, then the grid coordinator would directly select $\boldsymbol{x} = (\boldsymbol{x}_n, \ \forall n \in \mathcal{N})$ and schedule the shiftable load for all users in order to balance the load and the *expected* power supply. It would particularly set the load to minimize the expected difference between available power, *i.e.,* $w^h + v^h$, and the scheduled power consumption (both shiftable and non-shiftable), *i.e.,* $\sum_{n \in \mathcal{N}} \gamma_n^h + \sum_{n \in \mathcal{N}} \sum_{l \in \mathcal{L}_n} x_{l,n}^h$, for $h = 1, \cdots, H$. However, solving such a problem requires the knowledge of the variance of wind power predication error, which can be difficult to obtain. Instead, we consider minimizing the difference between expected available power, *i.e.,* $\hat{w}^h + v^h$, and the scheduled power consumption. It's easy to see that these two formulations share the same solution, yet the latter is more practical. Thus, we can formulate the following optimization problem:

$$\begin{aligned} &\underset{\boldsymbol{x}}{\textbf{minimize}} \ \sum_{h=1}^{H} \left\| \hat{w}^h + v^h - \sum_{n \in \mathcal{N}} \gamma_n^h - \sum_{n \in \mathcal{N}} \sum_{l \in \mathcal{L}} x_{l,n}^h \right\|_2^2 \\ &\textbf{subject to} \ \ \boldsymbol{x}_n \in \mathcal{X}_n, \qquad \forall n \in \mathcal{N}. \end{aligned} \quad (8)$$

The objective function in problem (8) is convex and quadratic. Therefore, it can be solved efficiently using various convex programming techniques such as the *interior point method* [18]. The overall diagram, along with the energy and information flows in the system, is shown in Fig. 3.

IV. Decentralized Design Using Game Theory

In most practical scenarios, the centralized design described in Section III is not feasible, as users are independent decision makers pursuing their own interests and are not controlled by the grid operator. Therefore, in this section, we propose an alternative *decentralized* mechanism to achieve the same desired performance as with the optimal solution of problem (8). The key idea is to introduce a smart pricing model that aligns users behavior with the needs of the grid.

A. Pricing Model

At each time slot t, we assume that the grid operator updates the electricity price p^t as follows:

$$p^t = p^t_{base} - \lambda \left(w^t + v^t - \sum_{n\in\mathcal{N}} \gamma_n^t - \sum_{n\in\mathcal{N}} \sum_{l\in\mathcal{L}_n} x^t_{l,n} \right). \quad (9)$$

Here, p^t_{base} is the base electricity price at time slot t and $\lambda > 0$ is a design parameter and is independent of time. From (9), if the total power generation is greater than the total load, then the price of electricity p^t becomes *less* than the base price p^t_{base}. This encourages users to consume more energy to balance supply and demand. On the other hand, if the total power generation is less than the total load, then the price of electricity p^t becomes *greater* than the base price p^t_{base} to encourage users to consume less energy or even supply energy back to the grid. Clearly, those users that supply electricity in this scenario will gain profit.

B. Payoff Functions

From (9), for each user n, its electricity cost in the next H time slots is obtained as

$$\begin{aligned} f_n(\boldsymbol{x}_n, \boldsymbol{x}_{-n}) &= -\mathbb{E}\left\{ \sum_{h=1}^{H} \left(p^h \left(\gamma_n^h + \sum_{l\in\mathcal{L}_n} x^h_{l,n} \right)\right)\right\} \\ = -\sum_{h=1}^{H} \Bigg\{ \Bigg[p^h_{base} - \lambda\Bigg(&\mathbb{E}\left\{w^h\right\} + v^h - \sum_{m\in\mathcal{N}} \gamma_m^h \\ &- \sum_{m\in\mathcal{N}} \sum_{i\in\mathcal{L}_m} x^h_{i,m} \Bigg)\Bigg] \left(\gamma_n^h + \sum_{l\in\mathcal{L}_n} x^h_{l,n} \right) \Bigg\}, \end{aligned} \quad (10)$$

where $\boldsymbol{x}_{-n}$ is the energy consumption scheduling profiles for all users *other than* user n. Note that, due to (1), we have $\mathbb{E}\{w^h\} = \mathbb{E}\{\hat{w}^h + n^h\} = \hat{w}^h$. Thus, we can rewrite (10) as:

$$\begin{aligned} f_n(\boldsymbol{x}_n, \boldsymbol{x}_{-n}) = -\sum_{h=1}^{H} \Bigg\{ \Bigg[p^h_{base} - \lambda\Bigg(&\hat{w}^h + v^h - \sum_{m\in\mathcal{N}} \gamma_m^h \\ &- \sum_{m\in\mathcal{N}} \sum_{i\in\mathcal{L}_m} x^h_{i,m} \Bigg)\Bigg] \left(\gamma_n^h + \sum_{l\in\mathcal{L}_n} x^h_{l,n} \right) \Bigg\}. \end{aligned} \quad (11)$$

Since the electricity price p^t depends on all users' energy consumption profiles, user n's payment function in (11) depends on not only user n's energy consumption profile $\boldsymbol{x}_n$, but also all other users' behavior $\boldsymbol{x}_{-n}$. This leads to a game among the users as we will explain next.

C. Game Model

We can now introduce an *Energy Consumption and Storage Game* among end users as follows:

ECS Game (Energy Consumption and Storage Game):

- ***Players***: Set $\mathcal{N}$ of all end users.
- ***Strategies***: For each user n, energy consumption scheduling vector $\boldsymbol{x}_n \in \mathcal{X}_n$.
- ***Payoffs***: For each user n, $f_n(\boldsymbol{x}_n, \boldsymbol{x}_{-n})$ as in (11).

D. Best Response and Nash Equilibrium

We first consider the *best response strategy*, which is a user's choice to maximize his own payoff function assuming that all other users' strategies are *fixed*. For each user $n \in \mathcal{N}$, his best response strategy is:

$$\boldsymbol{x}_n^{best}(\boldsymbol{x}_{-n}) = \arg\max_{\boldsymbol{x}_n\in\mathcal{X}_n} \ f_n(\boldsymbol{x}_n, \boldsymbol{x}_{-n}). \quad (12)$$

Next, we define Nash equilibrium, which is a vector of all players' strategies such that no player has an incentive to deviate *unilaterally*.

Definition 1: A Nash equilibrium is any set of energy scheduling profile $x_n^* \in \mathcal{X}_n$ for all $n \in \mathcal{N}$ such that

$$f_n(\boldsymbol{x}_n^*, \boldsymbol{x}_{-n}^*) \geq f_n(\boldsymbol{x}_n, \boldsymbol{x}_{-n}^*), \forall n \in \mathcal{N}, \forall \boldsymbol{x}_n \in \mathcal{X}_n.$$

A Nash equilibrium is a fixed point of all players' best responses, *i.e.,* $\boldsymbol{x}_n^{best}(\boldsymbol{x}_{-n}^*) = \boldsymbol{x}_n^*$ for *all* $n \in \mathcal{N}$. It represents a stable solution of the game. We can show that

Theorem 2: There always exists a Nash equilibrium for the *ECS Game*. The Nash equilibrium is unique.

The proof for Theorem 2 is provided in Appendix A. Simulation results in Section V show that the network performance at the Nash equilibrium of the *ECS Game* is close to the optimal solution of the optimization problem in (8) with proper choice of the pricing parameter.

V. Simulation Results

A. Wind Speed Prediction

There are a variety of methods available to predict wind speed u^t [16]. Here, we adopt a simple autoregressive model:

$$u^{t+1} = u^t + \xi n^t, \quad (13)$$

where n^t is the standard Gaussian noise. According to real wind speed data at Crosby County in July and August, 2009, we have $\xi = 1.0808$. The calculation of wind power output with respect to wind speed is based on Fig. 1(b).

We consider a total of $N = 20$ end users in the system. The number of non-shiftable appliances of each user is randomly selected between 10 to 20. Such appliances may include computers (daily usage of 1.92 kWh for laptops and 12 kWh for desktop computers), refrigerators (daily usage of 1.32 kWh), and televisions (daily usage of 6 kWh) [19]. Each user also has 3 to 5 shiftable appliances, which can be scheduled. Such appliances may include dishwashers (daily usage of 1.44

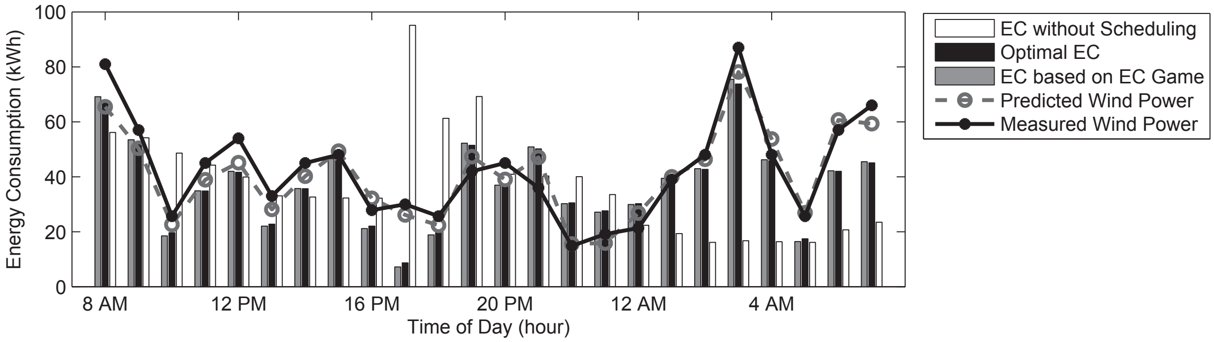

Fig. 4. Simulation Results with 20 user participation of daily energy consumption (EC) scheduling to integrate wind power

kWh), clothes dryers (daily usage of 2.50 kWh), and EVs (daily usage of 9.9 kWh) [17], [19]. In our simulations, the energy consumption of each appliance is uniformly distributed around the typical daily usage. With the increasing popularity of EVs, we assume each user has one EV. From [20], we set the base electricity price to be 11.58 cents/kWh as in Texas. We set parameter $\lambda = 1$. Each time slot is 1 hour. We assume that the output of traditional power plants is fixed at $v^t \equiv 10$ kW for all time slots. The 1-day simulation result is shown in Fig. 4. The unique Nash equilibrium of the *ECS Game* can be found numerically based on [21, Theorem 10].

In order to evaluate the efficiency of our proposed distributed design, we define an efficiency parameter μ as

$$\mu = \frac{\sum_{h=1}^{H} \left\| \hat{w}^h + v^h - \sum_{n\in\mathcal{N}} \gamma_n^h - \sum_{n\in\mathcal{N}} \sum_{l\in\mathcal{L}} x_{l,n}^{*,h} \right\|_2^2}{\sum_{h=1}^{H} \left\| \hat{w}^h + v^h - \sum_{n\in\mathcal{N}} \gamma_n^h - \sum_{n\in\mathcal{N}} \sum_{l\in\mathcal{L}} x_{l,n}^{opt,h} \right\|_2^2}, \tag{14}$$

where $\boldsymbol{x}^* = (\boldsymbol{x}_n^*, \forall n \in \mathcal{N})$ denotes the Nash equilibrium of *ECS Game*, and $\boldsymbol{x}^{opt} = (\boldsymbol{x}_n^{opt}, \forall n \in \mathcal{N})$ denotes the solution to the centralized optimization problem (8). Note that the numerator in (14) is the obtained objective value in problem (8) at the unique Nash equilibrium of the *ECS Game* and the denominator is the optimal objective value obtained by a centralized design. Clearly, we always have $\mu \geq 1$. Simulation results show that $\mu = 1.13$, which means that the distributed scheme only leads to 13% mismatch between supply and demand than the optimal solution. As shown in Fig. 5, a large range of the parameter λ (*e.g.,* $[0.2, 2]$) can guarantee a small value of μ, which means that our decentralized scheme has a robust performance in terms of the choice of parameter. The only requirement is that parameter λ should not be too small, otherwise the price will be dominated by the based price, and does not lead to proper incentives of the users.

Now let us look at the benefits of the grid. Simulation results show that the maximum mismatch is 70.3 kW without scheduling. *ECS Game* can reduce this gap to 22.8 kW, and thus benefit the power grid with wind power integration.

End users can also benefit from participating the proposed *ECS Game* shown by simulation results. For each user, the average daily energy expense is 7.51 dollars without scheduling, and 2.15 dollars with decentralized strategy based on *ESC Game*. That is, each user saves 5.19 dollars a day on average by participating in the proposed game. Note that due to the stochastic nature of wind power, there is still a mismatch between the supply and load even under a centralized optimization. Such mismatch can be handled by the grid operators using techniques such as frequency regulation [15].

VI. Future Work and Conclusions

This paper addresses the problem of integrating wind power into the grid by smart scheduling of end users' energy consumption and storage using a game-theoretic pricing algorithm to be implemented by an aggregator among each group of users in a neighborhood. In this regard, we develop an energy consumption and storage game model, where self-interested end users can schedule their energy consumption profiles to minimize the energy cost. By adopting a smart pricing policy based on the wind power availability and fluctuations, we show that the distributed behaviors of self-interested users can achieve close to optimal performance as if they are centrally controlled to match power supply and load demand.

This paper can be extended in several directions. For example, we can consider the case where the accuracy of the wind speed predication of later time slots can be improved based on the observed actual wind speed in earlier time slots. This makes the wind prediction a Markov process within H time slots. In that case, the introduced *ECS Game* will be stochastic and dynamic, making it significantly more difficult to analyze. On possible approach would be using Competitive Markov Decision Process (MDP) techniques [22]. We also want to further extend the introduced game model design to include uncertainty about other users' behaviors. That is, instead of knowing the explicit information of other users'

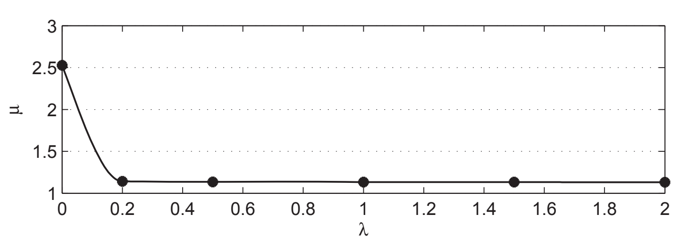

Fig. 5. System optimality index μ verses parameter λ.

energy consumption and storage, each end user only knows the typical distribution of other users' daily energy schedules.

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Appendix

A. Proof for Theorem 2

Since each user n's payoff function is concave with respect to $\boldsymbol{x}_n$ and the strategy set defined by linear constraints is convex, the existence of Nash equilibrium directly follows [21, Theorem 1]. Next, we prove the uniqueness of Nash equilibrium. From [21, Theorem 4] and [21, Theorem 6], a sufficient condition for Nash Equilibrium uniqueness in a concave game is that matrix $F(\boldsymbol{x})+F^T(\boldsymbol{x})$ is negative definite, where $F(\boldsymbol{x})$ is the Jacobian matrix for payoff functions,

$$F(\boldsymbol{x}) = \begin{pmatrix} \frac{\partial^2 f_1}{\partial^2 \boldsymbol{x}_1} & \frac{\partial^2 f_1}{\partial \boldsymbol{x}_1 \partial \boldsymbol{x}_2} & \cdots \\ \frac{\partial^2 f_2}{\partial \boldsymbol{x}_2 \partial \boldsymbol{x}_1} & \ddots & \\ \vdots & & \end{pmatrix}. \tag{15}$$

Note that the payoff functions for all users are defined in (10). We can obtain the derivatives as follows:

$$\frac{\partial^2 f_n}{\partial x_{l,n}^h \partial x_{k,n}^h} = -2\lambda,\ \forall l,k \in \mathcal{L}_n,\ \forall n \in \mathcal{N}, 1 \le h \le H. \tag{16}$$

$$\frac{\partial^2 f_n}{\partial x_{l,n}^h \partial x_{k,m}^h} = -\lambda,\ \forall l \in \mathcal{L}_n,\ k \in \mathcal{L}_m,\ \forall n,m \in \mathcal{N}, \quad n \neq m, 1 \le h \le H. \tag{17}$$

$$\frac{\partial^2 f_n}{\partial x_{l,n}^h \partial x_{k,m}^r} = 0,\ \forall l \in \mathcal{L}_n,\ k \in \mathcal{L}_m,\ \forall n,m \in \mathcal{N}, \quad 1 \le h,r \le H,\ h \neq r. \tag{18}$$

Let $\boldsymbol{A}_{m\times n}^H$ be an $m\,H \times n\,H$ block diagonal matrix:

$$\boldsymbol{A}_{m\times n}^H = \begin{pmatrix} \mathbf{1}_{m\times n} & 0 & 0 & \cdots \\ 0 & \mathbf{1}_{m\times n} & 0 & \cdots \\ 0 & 0 & \mathbf{1}_{m\times n} & \ddots \\ \vdots & \ddots & \ddots & \ddots \end{pmatrix}, \tag{19}$$

where $\mathbf{1}_{m\times n}$ is the $m \times n$ matrix with each entry being 1. Based on (16)-(18), we have

$$F(\boldsymbol{x}) = -\lambda \begin{pmatrix} 2\boldsymbol{A}_{L_1\times L_1}^H & \boldsymbol{A}_{L_1\times L_2}^H & \boldsymbol{A}_{L_1\times L_3}^H & \cdots \\ \boldsymbol{A}_{L_2\times L_1}^H & 2\boldsymbol{A}_{L_2\times L_2}^H & \boldsymbol{A}_{L_2\times L_3}^H & \cdots \\ \boldsymbol{A}_{L_3\times L_1}^H & \boldsymbol{A}_{L_3\times L_1}^H & 2\boldsymbol{A}_{L_3\times L_3}^H & \ddots \\ \vdots & \ddots & \ddots & \ddots \end{pmatrix}. \tag{20}$$

For an arbitrary $H\sum_{n\in\mathcal{N}} L_n \times 1$ non-zero vector z, we have

$$\begin{aligned} & z^T(F(\boldsymbol{x}) + F^T(\boldsymbol{x}))z \\ & = -2\lambda \left(\sum_{h=1}^{H} \left(\sum_{n\in\mathcal{N}} \left(\sum_{l\in\mathcal{L}_n} z_{l,n}^h \right)^2 + \left(\sum_{n\in\mathcal{N}} \sum_{l\in\mathcal{L}_n} z_{l,n}^h \right)^2 \right) \right) \\ & < 0. \end{aligned} \tag{21}$$

Hence, $F(\boldsymbol{x}) + F^T(\boldsymbol{x})$ is negative definite. Thus, from [21, Theorem 4] and [21, Theorem 6], the introduced *ECS Game* has indeed a unique Nash equilibrium. ■