Optimal Wind Power Integration in Microgrid: A Dynamic Demand Response Game Approach

Fengchao Chen(✉), Xin Zhang, Zejian Qiu, and Junwei Zhao

Dongguan Power Supply Bureau, Guangdong Power Grid Corporation, Dongguan 523000, Guangdong, China
csgcfc@126.com

Abstract. The large-scale integration of renewables is very challenging due to their intermittency and fluctuations. With the growing interest in smart grids and smart metering systems, one promising option to tackle these challenges is to design demand-side management (DSM) algorithms. Such algorithms can shape the load to follow renewable energy generation, which is the focus of this paper. Based on field data, we model such intertemporal variations of the available wind power as a Markov chain. We formulate a dynamic potential game for efficient cost sharing among users to encourage user cooperation and participation in DSM programs to coordinate load with wind power generation. Further, we analyze the designed dynamic game over a long period and investigate the efficiency of the constructed game model at equilibrium. Then, we develop a *strategy proof* mechanism, which will reach a Nash equilibrium of the designed game. Simulation results show that, on average, the Nash equilibrium of the proposed game can reduce the generation cost by 25% compared to the case without demand side management. For the case of a windy day, the generation cost further reduces up to 91%.

Keywords: Smart Grid · Wind Power Integration · Demand Side Management · Markov Chain · Dynamic Game · Microgrid

1 Background

Renewable energy sources, particularly wind power, are becoming significant power generation technologies worldwide. However, wind power output's intermittency and inherent stochastic nature become the major bottleneck to reaching a considerable market penetration. One promising solution is to use fast-responding generators to compensate for the wind turbines' output fluctuations. Alternatively, we can implement advanced demand-side management (DSM) programs that adjust the controllable load to match the amount of available renewable power. We focus on the latter case. In an isolated microgrid, we want

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to study how to balance supply and demand efficiently [10] in the presence of wind power generation. An isolated microgrid comprises multiple local loads, local conventional generators, and local renewable generators. Therefore, understanding wind power integration in a microgrid can offer the first step toward large-scale penetration of renewable energy sources in a smart grid.

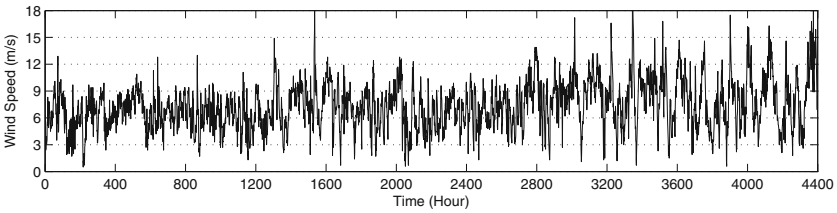
Integrating wind power into smart grid is already a well investigated topic. Cui *et al.* investigate forecast competition in energy imbalance market, taking the uncertainty of wind power into consideration in [4]. Furthermore, Cui *et al.* design the architecture of energy imbalance market with wind power in the form of blockchain in [3]. Gu *et al.* study deployment of power electronic devices into the distribution network, which can incentivize the distributed wind power integration in [9]. Wu *et al.* explore storage control with uncertainties of wind power generation in the framework of deep learning in [19]. Lu *et al.* conduct efficient economic dispatch via accurate wind power forecasting in the framework of end-to-end learning in [12]. Different from the previous work, our focus here is on applying game theory [8] to design a *decentralized* demand side management system, where users in a microgrid are independent decision makers and are interested in managing its own load to minimize its own energy expenses. A decentralized approach assures that users participate in the integration of renewable energy sources *voluntarily*.

Demand side management problem and demand response have also been explored by many researchers. Broadly speaking, demand side will adjust its load flexibly to obtain more benefits, such as [2,13]. Also, the vulnerability and robustness of demand side is also a significant problem, such as [5,6,11] and so on. Unlike the existing works, we address the demand side management design problem with focus on characterizing the interactions among users rather than generations. Furthermore, in this work, we apply dynamic game models which allows us to consider the decision dependencies over multiple periods of time. We feel that such consideration is critical for the integration of renewable energy resource, mainly due to the intermittency and inter-temporal variations such resource such as wind power.

2 System Model

A microgrid usually consists of local generators such as small-scale combined heat and power equipments, along with photovoltaic modules, small wind turbines, other renewable energy sources, heat and electricity storages, and controllable loads. Microgrids are expected to play a significant role in future electricity supply [10]. Our focus in this paper is on a simplified isolated microgrid, where a set of $\mathcal{N} = \{1, \ldots, N\}$ users. These users are supported by two kinds of generating resources. The first one is a conventional fast-responding generator, such as a gas turbines or a coal fired generator, whereas the other one is a wind turbine.

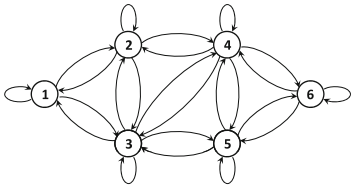
We design the demand side management problem for a period of time. And we divide the time period of interest into H time slots, *i.e.,* $\mathcal{H} = [1, \ldots, H]$. For example, we may choose $H = 24$ for daily planning. Other granularity, *e.g.,* 15 min time slots, may also be considered if needed.



(a) Wind Speed Over the Period of Interest.

State	1	2	3	4	5	6
1	0.60	0.38	0.02	0.00	0.00	0.00
2	0.06	0.74	0.20	0.01	0.00	0.00
3	0.00	0.13	0.76	0.11	0.00	0.00
4	0.00	0.01	0.25	0.68	0.06	0.00
5	0.00	0.00	0.02	0.28	0.66	0.05
6	0.00	0.00	0.00	0.09	0.31	0.60

(b) Markov Transition Matrix.



(c) Markov Chain State Model.

Fig. 1. The Markov chain model used in this study. The data are collected from [1].

2.1 Power Generation

The *total* generated power at each time slot $h \in \mathcal{H}$ includes the power generated by the conventional fast-responding fuel generator, denoted as v^h, and the power generated by the wind turbine, denoted as w^h. Note that the conventional power is used to supplement the gap between available wind power and users' total power demand.

We first characterize the wind power outputs. We assume the wind power outputs follow a stochastic process according to the wind speed. Specifically, we consider a simplified model where once the wind speed is given, the wind power output can be obtained according to the wind power versus wind speed curve. Figure 1(a) plots a sample measurement of the wind speed to highlight the volatility.

We employ the Markov chain to enable wind power output prediction. Based on field data, we identify six states. The first state is the case where the wind turbine output is between 0 and 30 kW. The other five states can be defined accordingly. We obtain the Markov chain transition probabilities as shown in Fig. 1(b) based on the collected data. We can observe that the transition probability matrix is, in fact, very sparse. That is, with a very high probability, the Markov chain will either stay at the current state or jump to an adjacent state, as illustrated in Fig. 1(c). The transition probability matrix enables the wind power output prediction at upcoming time slots. This is crucial for demand-side management as well as its associated decision-making. To the best of our knowledge, this is the first paper that integrates an explicit Markov chain model based on actual data for wind power in demand-side management.

2.2 Power Consumption

Denote x_n^h user $n \in \mathcal{N}$'s load at time slot h. To make the formulation neat, we assume that each user exactly owns a single appliance with a controllable load. This appliance and the controllable load are required to be met during the period of interest $\mathcal{H}$. Specifically, for each user $n \in \mathcal{N}$, the desirable load scheduling by the start time α_n and the end time β_n. For example, after lunch, the user may set α_n = 1:00 PM and β_n= 5:00 PM for the dishwasher. Thus, the dishwasher could wash all the lunch dishes before dinner. Similar examples include washers and more recently, electric vehicles [14]. To fulfill the users' load scheduling needs, it is required that

$$\sum\nolimits_{h=\alpha_n}^{\beta_n} x_n^h = E_n, \quad \forall n \in \mathcal{N}, \tag{1}$$

where E_n stands for the total energy consumption, which user n's appliance needs to consume for finishing the task. The energy profile x_n^h outside the time frame $[\alpha_n, \beta_n]$ should be zero. That is,

$$\begin{cases} x_n^h \geq 0, & \alpha_n \leq h \leq \beta_n, \\ x_n^h = 0, & \text{otherwise}, \end{cases} \quad \forall n \in \mathcal{N}. \tag{2}$$

Let $\boldsymbol{x}_n$ denote user n's energy consumption profile vector:

$$\boldsymbol{x}_n = [x_n^1, \cdots, x_n^H]. \tag{3}$$

User n's energy consumption feasible set can be characterized as follows:

$$\mathcal{X}_n = \left\{ \boldsymbol{x}_n \middle| \text{Constraints (1) and (2)} \right\}. \tag{4}$$

Finally, at each time slot h, the total load in the system summing over all users is denoted by

$$l^h = \sum\nolimits_{n \in \mathcal{N}} x_n^h. \tag{5}$$

2.3 Generation Cost

If the supply matches the demand in real-time, then clearly, it is not necessary to use the conventional backup generator. Otherwise, the microgrid operator must use the traditional generator to compensate for the supply-demand mismatch, which is primarily caused by the inaccurate forecast of renewable generation outputs. At each time slot h, the total conventional power needed can be calculated as follows $v^h = l^h - w^h$. Without loss of generality, we assume that the traditional generator available in the microgrid is a thermal generator. Thus, at each time slot h, we can model the power generation cost as a quadratic function [18]:

$$C(l^h - w^h) = k\,(l^h - w^h)^2 + s, \tag{6}$$

where the generation and maintenance cost of the wind power plant is assumed to be fixed and represented by the constant $s > 0$, as a *sunk cost*. That is, such a cost is independent of the exact value of wind power output [17]. Hence, as for demand side management, the model in (6) characterizes the total generation cost of the microgrid at time slot h to supply the total load l^h. From (6), we can observe that the microgrid operator will penalize any deviation (no matter whether the deviation is positive or negative) of load l^h from renewable energy supply w^h. For the case when $l^h < w^h$, the penalty comes from the fact that the *excessive* generated power challenges the power quality in the microgrid by deviating the voltage amplitude and frequency from their nominal values [16]. Therefore, the microgrid operator seeks to keep the total load at each time slot *as close as* possible to the total wind power outputs.

2.4 Centralized DSM Planning

Suppose we are allowed to adopt a centralized control. In that case, the microgrid coordinator can directly select $\boldsymbol{x} = (\boldsymbol{x}_n,\ \forall n \in \mathcal{N})$ and schedule the controllable load such that the load are kept as close as possible to the *expected* wind power outputs. Specifically, in a centralized design approach, we seek to solve the minimization problem as follows:

$$\begin{aligned} \mathbf{P1}: \quad & \underset{\boldsymbol{x}_n,\ \forall n \in \mathcal{N}}{\textbf{minimize}} \quad \mathbb{E}\left\{\sum\nolimits_{t=1}^{H}\left[k\left(l^t - w^t\right)^2 + s\right]\right\} \\ & \textbf{subject to} \quad \boldsymbol{x}_n \in \mathcal{X}_n, \qquad\qquad \forall n \in \mathcal{N}. \end{aligned} \tag{7}$$

Note that problem **P1** is a static optimization problem. Next, we introduce its dynamic version where the centralized controller will decide each user's load profile time slot by time slot. For notational simplicity, we denote all the users' load profile from time slot l to time slot m as $\mathcal{U}_{t=l}^{m}$, that is

$$\mathcal{U}_{t=l}^{m} = \{x_n^t,\ \forall n \in \mathcal{N}\}_{t=l}^{m}. \tag{8}$$

Thus, mathematically, at time slot h, given all the users' load profile history, *i.e.*, $\mathcal{U}_{t=1}^{h-1}$ and the wind power history $\{w^t\}_{t=1}^{h-1}$, the controller tries to solve the following problem **P2**(h):

$$\begin{aligned} \mathbf{P1}(\mathrm{h}): \quad & \underset{\mathcal{U}_{t=h}^{H}}{\textbf{minimize}} \quad \mathbb{E}\left\{\sum\nolimits_{t=h}^{H}\left[k\left(l^h - w^h\right)^2 + s\right] \middle| w^{h-1}\right\} \\ & \textbf{subject to} \quad \mathcal{U}_{t=h}^{H} \in \mathcal{X}^h, \end{aligned} \tag{9}$$

where $\mathcal{X}^h$ is the refined feasible solution set for $\mathcal{U}_{t=h}^{H}$. It can be obtained by the following two steps:

- For each $\mathcal{X}_n$, if $h \leq \alpha_n$, construct $\mathcal{X}_n^h = \mathcal{X}_n$. Otherwise, given user n's load profile history $\{x_n^t\}_{t=1}^{h-1} \in \mathcal{U}_{t=1}^{h-1}$, we could change constraint (1) to

$$\sum\nolimits_{t=h}^{\beta_n} x_n^t = E_n - \sum\nolimits_{t=\alpha_n}^{h-1} x_n^t. \tag{10}$$

Note in (10), $\{x_n^t\}_{t=\alpha_n}^{h-1}$ can be considered as the known constants. Hence, the only variables in (10) are the decision variables $\{x_n^t\}_{t=h}^{H} \in \mathcal{U}_{t=h}^{H}$. Together with constraint (2), we construct $\mathcal{X}_n^h$. That is

$$\mathcal{X}_n^h = \begin{cases} \mathcal{X}_n, & h \leq \alpha_n, \\ \{\{x_n^t\}_{t=h}^{H} | \text{Constraints (2) and (10)}\}, & \text{otherwise.} \end{cases} \tag{11}$$

- Construct

$$\mathcal{X}^h = \bigcup\nolimits_{n\in\mathcal{N}} \mathcal{X}_n^h. \tag{12}$$

Both problem **P1** and problem **P2**(h) can be solved in a centralized fashion using various optimization methods [7]. However, in practice, users are independent decision makers and their behavior is not directly controlled by a centralized controller. Therefore, next, we propose an alternative approach that can lead to a distributed yet efficient solution to integrate renewable energy sources using dynamic game theory.

3 Cost-Sharing Game

In this section, we design a *decentralized* mechanism for efficient cost sharing. In the mechanism, we assume that each user, on his own, decides his energy consumption schedule at the beginning of each time slot. Specifically, each user decides to maximize its payoff based on the forecasts of wind power generation outputs based on the developed Markov chain. We want to emphasize that such decision-making is also coupled with other users' decisions. To share the total generation cost among all users in the microgrid, we define, at each time slot h, each user n's payoff function $f_n^h(\boldsymbol{x}_n, \boldsymbol{x}_{-n})$ as proportional to its total energy consumption over time interval $\mathcal{H}$:

$$f_n^h(x_n^h, x_{-n}^h) = \frac{-E_n}{\sum_{m\in\mathcal{N}} E_m} \mathbb{E}\left\{k\left(l^h - w^h\right)^2 + s\right\}, \tag{13}$$

where x_{-n}^h indicates the energy consumption scheduling profiles for all users *other than* user n at time slot h. We can see that each user's payoff function depends on not only the user's own load profile, but also other users' load profiles. This leads to a dynamic game model among users. In this paper, we consider a game with complete information, that is, at each time slot h, all the users have access to the wind power generation history, *i.e.,* $\{w^t\}_{t=1}^{h-1}$ and all the users' load profile history, *i.e.,* $\mathcal{U}_{t=1}^{h-1}$. Based on such information, the users can try to maximize their *expected* payoff during the rest of the game with the help of the Markov chain model. This yields our cost sharing game for microgrid (CSGM).

The solution concept for a dynamic game is the subgame perfect equilibrium.

3.1 Potential Game

For each subgame of *CSGM* at time slot $h \in \mathcal{H}$, we can verify that

$$\Phi(l^h, \ldots, l^H | w^{h-1}) = -\sum\nolimits_{t=h}^{H} \mathbb{E}\left\{k\left(l^h - v^h\right)^2 + s | w^{t-1}\right\}$$

is in fact an ordinal potential function for *CSGM*. A game with an ordinal potential function is called an ordinal potential game (OPG). Thus, each subgame of *CSGM* at time slot $h \in \mathcal{H}$ is a finite-player OPG with several interesting properties that we will explain next.

3.2 Nash Equilibria Characterization of Subgames

For a finite-player OPG, a strategy profile is a Nash equilibrium *if and only if* it is a maximizer of the ordinal potential functions [15]. From this, together with (14), we can directly derive the following theorem.

Theorem 1. *At each time slot $h \in \mathcal{H}$, given the history profiles $\mathcal{U}_{t=1}^{h-1}$ and $\{w^t\}_{t=1}^{h-1}$, a strategy profile $\mathcal{U}_{t=h}^{H}$ is a Nash equilibrium of the subgame of* CSGM *at time slot h* if and only if *it is a maximizer to the optimization problem **P2**(h).*

However, since for a potential game, only the total load at each time slot h, *i.e.,* l^h matters, we reformulate the optimization problem **P2**(h) with the constraints only depend on the total load $\{l^t\}_{t=h}^{H}$. By such replacement, we want to obtain a clearer insight of the game. First, at each time slot t, we define

$$\mathcal{N}_{\alpha}^{t} = \{\text{user } n | \alpha_n \leq t\}; \tag{14}$$

$$\mathcal{N}_{\beta}^{t} = \{\text{user } n | \beta_n \leq t\}. \tag{15}$$

Lemma 1. *At time slot $h \in \mathcal{H}$, given the history profiles $\mathcal{U}_{t=1}^{h}$, for any $\mathcal{U}_{t=h}^{H} \in \mathcal{X}^h$,* i.e., *any feasible solution for problem **P2**(h), there exists an $\boldsymbol{l}^h = (l^h, \ldots, l^H)$ that satisfies the following set of constraints:*

$$\sum_{n \in \mathcal{N}_{\beta}^{p}} E_n \leq \sum_{t=1}^{h} l^t + \sum_{t=h}^{p} l^t \leq \sum_{n \in \mathcal{N}_{\alpha}^{p}} E_n, \ h \leq p \leq H. \tag{16}$$

$$l^p \geq 0, \ h \leq p \leq H. \tag{17}$$

Note that, in Lemma 1, there could exist several different combinations of users' individual energy consumption schedules $\boldsymbol{x}$ that can lead to the same total load $\boldsymbol{l}$. We are now ready to characterize the subgame perfect equilibria (SPE) of *CSGM* in the following key theorem.

3.3 Subgame Perfect Equilibrium of CSGM

Theorem 2. *The total load profile* $\boldsymbol{l}^* = (l^{1*}, \ldots, l^{H*})$ *corresponding to any SPE* $\mathcal{U}_{t=1}^{*H}$ *of* CSGM*is the unique maximizer to the following sequence of optimization problem* ***P3****(h):*

$$\textbf{\textit{P3}}(h): \quad \underset{l^t,\ h\le t\le H}{\textbf{\textit{maximize}}} \quad -\mathbb{E}\left\{\sum_{t=h}^{H}\left[k\left(l^t-w^t\right)^2+s\right]\middle| w^{h-1}\right\}$$

$$\textbf{\textit{subject to}} \quad \sum_{n\in\mathcal{N}_\beta^p} E_n \le \sum_{t=1}^{p} l^t \le \sum_{n\in\mathcal{N}_\alpha^p} E_n, h\le p\le H, \tag{18}$$

$$l^p \ge 0,\ h\le p\le H. \tag{19}$$

That is, each l^{h*} *in* $\boldsymbol{L}^*$ *is determined by the corresponding optimization problem* ***P3****(h).*

Note that problem **P3**(h) has to be solved time slot by time slot, since the wind power prediction will be updated at each time slot.

We conclude the section with the following remarks. First, we note that Theorems 2 provide an analytical approach to characterize the SPE of *CSGM*. Second, if *perfect predictions* are available on future wind power generation, then by solving problem **P1**, we can obtain the SPE for *CSGM* directly. However, since the wind power predictions are updated based on the new wind power measurements, *i.e.,* wind power generation history profile, as the game moves from one time slot to the next one, at each time slot $h \in \mathcal{H}$, the users may use and implement the SPE solution obtained by problem **P3**(h) only at the current time slot h. As time goes by, the SPE will be updated according to the new wind power measurements and predictions. Finally, we note that any $\boldsymbol{l}^*$ obtained from Theorems 2 characterizes the SPE in terms of the *total* load. However, there could exist several different combinations of users' *individual* energy consumption schedules $\boldsymbol{x}^*$ that can lead to the same aggregate load $\boldsymbol{l}^*$. Therefore, we also need to investigate individual load distributions at each equilibrium. This is what we will do next using mechanism design.

4 Mechanism Design

In this section, we design a mechanism to reach one SPE of *CSGM*. Our focus is to obtain the exact energy consumption schedule for each individual user. Note that, although *CSGM* may have multiple SPE, they are the same in terms of maximizing the potential function and hence minimizing the total generation cost in the system. Therefore, as long as all users choose their energy consumption schedules according to one of the SPE obtained in Sect. 3.2, optimal performance is guaranteed. However, the difficulty is to assure that users announce their local information truthfully. This can be tackled by developing mechanism design as we discuss next.

In order to reach the SPE of *CSGM* in a distributed fashion, it is required for each user $n \in \mathcal{N}$ to broadcast its own total energy consumption E_n, start time α_n and the end time β_n at the beginning such that all other users can also adjust their energy consumption schedules accordingly later on. Moreover, at each time slot h, the wind turbine needs to broadcast the upcoming expected wind power based on the new measure data w^{h-1}, *i.e.,* $\mathbb{E}\{w^h|w^{h-1}\}, \ldots, \mathbb{E}\{w^H|w^{h-1}\}$. The proposed DSM mechanism includes the following stages.

1. Each user n broadcasts E_n, α_n and β_n at time slot 1.
2. At each time slot h,
   - The wind turbine broadcasts the upcoming wind power to all the users.
   - Each user constructs $\mathcal{N}_h$ as the set of active users n whose $\alpha_n \leq h$ and $\beta_n \geq h$. That is,
   $$\mathcal{N}_h = \{\text{user } n | \alpha_n \leq h \leq \beta_n\}. \tag{20}$$
   - Each user computes the desirable total load at the Nash equilibrium, denoted by l_0^h, by solving **P3**(h).
   - Each user sorts the members in set $\mathcal{N}_h$ based on their end times β_n in an ascending order. Starting from the first with smallest finishing time, for the k^{th} user in the sorted list, denoted by n_k, we also denote the available total energy consumption at the decision time slot is l_{k-1}^h. Then, set
   $$x_{n_k}^h = \max\left\{0, \min\left\{E_{n_k} - \sum\nolimits_{t=1}^{h-1} x_{n_k}^t, l_{k-1}^h\right\}\right\}, \tag{21}$$
   - Update the available total energy consumption l_{k-1}^h to l_k^h according to the following equation:
   $$l_k^h = l_{k-1}^h - x_{n_k}^h. \tag{22}$$
   - Continue the process for the $k + 1^{th}$ user in the sorted list until $l_k^h = 0$.
   - Each user n consumes x_n^h amount of power.

Note that, the second stage us implemented at each time slot h, *e.g.,* at every hour. At each time slot h, after the wind turbine broadcasts the upcoming wind power, each user computes its own load profile locally. They need keep a history of the previous computation results, *i.e.,* $\mathcal{U}_{t=1}^{h-1}$ to ensure the adequate information for the local computation in time slot h.

Next, we prove the optimality of this mechanism by showing that it achieves one SPE of *CSGM*. By Theorem 2, we can obtain the optimality of this mechanism in terms of minimizing the total energy cost in the system.

Theorem 3. *The designed mechanism will reach one SPE of* CSGM.

In our mechanism, we assume that based on the actual operating cost of the wind generator and conventional generator, the shared cost of each user will be collected at the end of the day. Then, we have the following theorem:

Theorem 4. *The designed mechanism is strategy proof.*

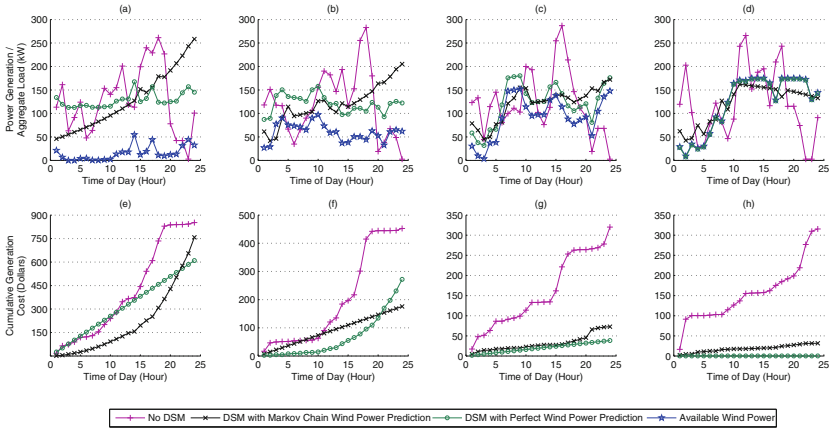


Fig. 2. Empirical results to highlight the performance of the proposed demand side management scheme. Subfigures (a)–(d) examine the performance under four weather conditions: (a) light/gentle breeze, (b) moderate/fresh breeze, (c) strong wind, and (d) (moderate) gale. Subfigures (e)–(h) investigates the corresponding cumulative power generation cost for these 4 weather conditions, respectively.

Proof. Notice that in our designed game, all the SPE coincide with the maximizer of the potential function. Based on Theorem 3, the designed mechanism will lead to one SPE of *CSGM*. Therefore, any cheating will only deviate the aggregated strategy profile from SPE and cannot lead to a better payoff for any user. In particular, the shared cost for each user is based on the actual energy one consumes during the day, instead of the amount of energy each user announces in the mechanism. ■

We note that Theorem 4 is *not* a general conclusion for every OPG, as in general, the players' payoff functions may not always coincide with the OPG's potential function.

5 Simulation Results

The numerical study considers a one-day energy consumption scheduling in a microgrid with $N = 1,000$ users. For each user, the daily load is selected randomly between 1 kWh to 5 kWh. We evaluate the performance of our proposed algorithm in terms of generation cost under different weather conditions. Specifically, we compare three approaches. First, we consider the case without any demand-side management. In this case, each user n arbitrarily schedules its energy consumption within interval $[\alpha_n, \beta_n]$. We implement our proposed distributed dynamic game-theoretic algorithm in the second case based on the Markov Chain model developed in Sect. 2.1. Third, we employ the same approach as in the second case except assuming we now have access to the perfect

wind power prediction. Note that this last case is a very good benchmark. This benchmark provides an upper bound for the overall system performance.

We consider the following weather conditions: light/gentle breeze (wind speed less than 6 m/s), moderate/fresh breeze (wind speed between 6 m/s and 10.6 m/s), strong wind (wind speed between 10.7 m/s and 13.6 m/s), and (moderate) gale (wind speed between 13.7 m/s and 20.6 m/s). The results for these conditions in terms of the aggregate load schedule are shown in Fig. 2(a)–(d), respectively. The corresponding cumulative power generation costs for four considered weather conditions are illustrated in Fig. 2(e)–(h), respectively. For the case of a light breeze, our proposed algorithm reduces the total daily generation cost by 11% at the equilibrium compared with the case when no demand side management program is implemented. Improving the wind power prediction can further reduce the total power generation cost up to 17%. For the case of a moderate breeze, our algorithm reduces the generation cost by 40% at the equilibrium. One can further reduce the cost by 21% by improving the prediction accuracy. For the case of a strong wind, the saving in the generation cost is 77%. Finally, for the case of a moderate gale, our proposed algorithm works very well and can save up to 91% in the cost of generation at the equilibrium of *CSGM* compared with the scenario where no demand side management strategy is used. From the simulation results in Figs. 2, we can conclude the following remarks:

- The proportion of the reduced generation cost increases as the available wind power increases. This is intuitive and verifies the suitability of our design.
- Comparing the results when our design uses Markov Chain-based wind power prediction versus perfect wind power prediction, we can see that the curves converge when high wind power is available. This suggests that our proposed algorithm is particularly efficient in places such as West Texas, where wind speed is high in several days every year. Based on the six-month field data in West Texas, our simulation results show that on average, our algorithm can reduce the generation cost by 25%. By deploying more accurate wind power prediction models, one can further reduce the generation cost by 18%.

6 Concluding Remarks

This paper considers an isolated microgrid. The microgrid consists of N users, and these users obtain energy from two sources: a renewable power generator and a backup conventional power plant. We review a dynamic scenario of users' interactions in which these N users share the total energy cost. Note that such a cost is due to the use of the traditional power plant to balance supply and demand. This approach can effectively minimize the total generation cost. Furthermore, we assess its performance via simulation.

References

1. Alternative Energy Institute, West Texas A&M University. https://www.windenergy.org/

2. Cui, J., Wu, C.: On the consumer behavior management in tier price. In: 2021 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), p. 1. IEEE (2021)
3. Cui, J., Gu, N., Wu, C.: Blockchain enabled data transmission for energy imbalance market. IEEE Trans. Sustain. Energy **13**(2), 1254–1266 (2022). https://doi.org/10.1109/TSTE.2021.3108170
4. Cui, J., Gu, N., Zhao, T., Wu, C., Chen, M.: Forecast competition in energy imbalance market. IEEE Trans. Power Syst. **37**(3), 2397–2413 (2022). https://doi.org/10.1109/TPWRS.2021.3117967
5. Cui, J., Wang, H., Wu, C., Yu, Y.: Vulnerability analysis for data driven pricing schemes. In: 2020 IEEE Power Energy Society General Meeting (PESGM), pp. 1–5 (2020). https://doi.org/10.1109/PESGM41954.2020.9281848
6. Cui, J., Wang, H., Wu, C., Yu, Y.: Robust data-driven profile-based pricing schemes. In: 2021 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), pp. 1–5. IEEE (2021)
7. Filar, J., Vrieze, K.: Competitive Markov Decision Processes. Springer, Heidelberg (1997). https://doi.org/10.1007/978-1-4612-4054-9
8. Fudenberg, D., Tirole, J.: Game Theory. MIT Press, Cambridge (1991)
9. Gu, N., Cui, J., Wu, C.: Power-electronics-enabled transactive energy market design for distribution networks. IEEE Trans. Smart Grid 1 (2021). https://doi.org/10.1109/TSG.2021.3127544
10. Hatziargyriou, N., Asano, H., Iravani, R., Marnay, C.: Microgrids. IEEE Power Energ. Mag. **5**(4), 78–94 (2007)
11. Jiang, G., Cui, J., Wu, C.: Role of prediction in data-driven pricing schemes. In: 2021 5th International Conference on Smart Grid and Smart Cities (ICSGSC), pp. 125–129 (2021). https://doi.org/10.1109/ICSGSC52434.2021.9490484
12. Lu, C., Jiang, W., Wu, C.: Effective end-to-end learning framework for economic dispatch. IEEE Trans. Netw. Sci. Eng. 1 (2022). https://doi.org/10.1109/TNSE.2022.3168845
13. Lu, C., Wang, Z., Wu, C.: Storage-aided service surcharge design for EV charging stations. In: 2021 60th IEEE Conference on Decision and Control (CDC), pp. 5653–5658 (2021). https://doi.org/10.1109/CDC45484.2021.9683047
14. Mohsenian-Rad, A.H., Leon-Garcia, A.: Optimal residential load control with price prediction in real-time electricity pricing environments. IEEE Trans. Smart Grid **1**(2), 120–133 (2010). https://doi.org/10.1109/TSG.2010.2055903
15. Monderer, D., Shapley, L.S.: Potential games. Games Econom. Behav. **14**(1), 124–143 (1996). https://doi.org/10.1006/game.1996.0044
16. Rebours, Y.G., Kirschen, D.S., Trotignon, M., Rossignol, S.: A survey of frequency and voltage control ancillary services mdash; part I: technical features. IEEE Trans. Power Syst. **22**(1), 350–357 (2007). https://doi.org/10.1109/TPWRS.2006.888963
17. van de Wekken, T.: Distributed generation and renewables: wind farm case study. Power Quality and Utilisation Guide (2007)
18. Wood, A.J., Wollenberg, B.F.: Power Generation, Operation, and Control. Wiley-Interscience (1996)
19. Wu, J., Lu, C., Wu, C.: Learning-aided framework for storage control facing renewable energy. IEEE Syst. J. 1–12 (2022). https://doi.org/10.1109/JSYST.2022.3154389