Data Center Demand Response With On-Site Renewable Generation: A Bargaining Approach

Xuanyu Cao, Junshan Zhang, *Fellow, IEEE*, and H. Vincent Poor, *Fellow, IEEE*

***Abstract*— The rapid growth of cloud computing and data centers with skyrocketing energy consumption, together with the accelerating penetration of renewable energy sources, is creating both severe challenges and tremendous opportunities. Data centers offering large flexible loads in the grid, opens up a unique opportunity to smooth out the significant fluctuation and uncertainty of renewable generation and hence enable seamless integration. To take the market power of data centers into consideration, this paper proposes a bargaining solution to the market program for data center demand response when the load serving entity (LSE) has power supply deficiency. Specifically, due to the uncertainty of load flexibility of data centers incurred by the intermittent on-site renewable generation and dynamic service requests, there exists information asymmetry between the LSE and the data center, which complicates the design of the bargaining solution. Making use of the log-concavity of the (expected) utility functions, a computationally efficient method to implement the best response updates in the bargaining procedure is presented. Furthermore, it is shown analytically that the bid sequences of the LSE and the data center are guaranteed to converge and the final price clinched by the bargaining algorithm is indeed the Nash bargaining solution, which is proportionally fair. In addition, the proposed bargaining solution is compared with two other schemes, namely the Stackelberg game and the social welfare maximization schemes. Finally, extensive numerical experiments are conducted to validate the theoretical guarantees of the bargaining and to examine the impact of various model parameters. Empirical comparison indicates the fairness advantage of the bargaining approach over the other two schemes, especially when the load of the data center is not very flexible, highlighting the importance of information feedback embodied by the bargaining procedure.**

***Index Terms*— Data center, load serving entity, demand response, renewable energy, bargaining, Nash bargaining solution.**

I. Introduction

THE confluence of two powerful global trends – the rapid growth of cloud computing and data centers with skyrocketing energy consumption, and the accelerating penetration of renewable energy sources – is creating both severe challenges and tremendous opportunities. Notably, the US Department of Energy has set a goal to procure 20% of the total generation from wind/solar power by 2030, and the state of California has set a Renewable Portfolio Standard of 33% of renewable generation by 2020. Today, the uncertainty associated with renewable resources is handled by using operating reserves. The high penetration of renewable resources, however, will cause significant and random fluctuations in supply and hence introduce difficult-to-control dynamics and challenges for power system operation. There is an urgent need to develop decision support tools that can efficiently utilize renewable resources and distributed demand response products in concert with traditional grid resources. It is envisaged that smart demand response programs can potentially have very significant cost advantages over either spinning or non-spinning ramping reserve.

Data centers are especially suitable for demand response. The reasons are twofold. First, the loads of data centers are large (accounting for 1.5% of electricity consumption worldwide) [1] and are still increasing dramatically (by some ten percent each year) in recent years [2]. The total energy consumed by data centers in the United States was around 91 billion kilowatt-hours in 2013, and has been predicted to reach 140 billion kilowatt-hours by 2020. Second, part of the loads of data centers are flexible. It has been observed that 5% of the loads of data centers can be curtailed in 5 minutes and 10% of the loads can be shed in 15 minutes [1]. In fact, various workload shifting methods have been proposed to demonstrate the capability of demand response for data centers [3], [4]. Liu *et al.* [5] used workload shifting and local power generation to reduce peak loads, and Lin *et al.* [6] proposed online algorithms to turn off temporarily unused servers so that the power consumption of data centers is reduced. In addition, stochastic optimization based job scheduling and server management schemes were presented in [7] to reduce power consumption of data centers. All these works indicate the opportunities of demand response in data centers and great load curtailment can be realized by demand response programs when load service entities (LSEs) experience temporary shortage of power supply.

Since data centers are large loads, participating in demand response programs provides them with the opportunity to dramatically reduce energy costs and contribute to improv-

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X. Cao and H. V. Poor are with the Department of Electrical Engineering, Princeton University, Princeton, NJ 08544 USA (e-mail: x.cao@princeton.edu; poor@princeton.edu).

J. Zhang is with the School of Electrical, Computer and Energy Engineering, Arizona State University, Tempe, AZ 85287 USA (e-mail: junshan.zhang@asu.edu).

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ing the sustainability via seamless integration with increased renewable energy. Nevertheless, the participation of data centers in demand response would need appropriate market programs that are designed to allow for *strategic participation* of data centers, instead of *passive price taking*. Indeed, the fact that data centers represent large loads in a utility company (data centers can consume more than half of the loads in a distribution network, e.g., the Facebook data center in Oregon), makes them capable of participating actively in the markets and affecting the market prices. This fundamental difference between data centers and other consumers requires new demand response solutions tailored towards strategic players with significant market power. Furthermore, it is nontrivial to determine a data center's supply function since its workload is time-varying and it would try to maximize its cost savings without risking its performance quality.

In this paper, we advocate a bargaining approach for data center demand response, which points to a paradigm shift for data center from a passive price taker to an active price negotiator.

A. Summary of Main Results

The main contributions of this paper are summarized as follows.

- A bargaining procedure for demand response is put forth, in which an LSE and a data center settle an appropriate price for load reduction acceptable to both parties through iterative negotiations. One significant challenge lies in the information asymmetry between the LSE and the data center, which arises due to the uncertainty of the load flexibility of the data center incurred by the intermittent on-site renewable generation [8] and time-varying service loads.
- Exploiting the log-concavity of the (expected) utility functions of the LSE and the data center, we present a computationally efficient method to implement the best response updates in the bargaining. Further, we show that, under mild technical conditions, the bid sequences of the LSE and the data center converge and the final price clinched by the bargaining algorithm converges to the Nash bargaining solution (NBS), which is proportionally fair. In particular, the breakdown probability of the bargaining can be made arbitrarily small by tuning a parameter in the bargaining procedure. Moreover, the impact of various model parameters is examined numerically.
- We present a comparative study of the devised bargaining solution for data center demand response, against two other schemes based on Stackelberg game and social welfare maximization (SWM). Numerical comparison corroborates the fairness advantage of the proposed bargaining approach over these two schemes, especially when the load of the data center is not very flexible. This highlights the importance of iterative negotiation and information feedback embodied by the bargaining procedure in achieving fair outcomes. Moreover, we observe that the social welfare of the bargaining solution can be even higher than that of the SWM scheme, because the SWM designer has no knowledge of the on-site renewable generation as a third party arbitrator.

B. Related Work

Given the importance and prospect of demand response in data centers, the past few years have witnessed a surge of interest in this area. One promising approach is to use pricing for load control. Specifically, Conejo *et al.* [9] proposed algorithms to adjust the load level by responding to real-time prices. Price prediction is leveraged to minimize payment and waiting time of the operation of appliances in [10]. Since many data centers were partially driven by on-site renewable energy sources (RESs) [8], geographical load balancing was proposed to promote the usage of renewable energy in data centers by means of dynamic pricing in [11]. A more closely related work [12] studied prediction based pricing to tackle the uncertainty of the load flexibility of data centers and a social welfare maximization problem was investigated. Another interesting line of work on demand response is supply function bidding [13]. In this category, linear function bidding and supply function with capacity constraints was proposed in [14] and [15], respectively. Further, the application of supply function bidding to data centers and smart grids was considered in [16] and [17], respectively. A common requirement of supply function bidding is that the LSE and the data centers have to curtail a fixed amount of loads pre-determined in advance, in contrast to the flexible load reduction quantity in response to difference prices. Furthermore, several works examined the interaction between LSEs (utility companies) and data centers using Stackelberg game [18] or two-stage optimization [19], in which the LSEs set the prices and the data centers responded to them. In particular, for colocation data centers, the interactions between the demand response provider, the colocation operator, and data centers (tenants) were modeled by Stackelberg game in [20], and online auctions in [21]. More recently, a model predictive control based approach was proposed for reliable operation of data center activities in demand response programs [22]. A system of contracts between data centers, energy suppliers, and customers was developed in [23] to promote collaboration and economic incentives in demand response. Further, joint electricity procurement from wholesale market and geographical load balancing for data centers were optimized under uncertainty of workloads and market prices in [24]. An incentive mechanism was proposed in [25] for tenants of cloud data centers to cooperate with demand response programs. Moreover, a matching game was formulated and studied for data centers to jointly choose utility companies and schedule workloads in [26].

In the literature, the bargaining approach has been applied to various communication and networking problems, e.g., channel allocation in OFDMA networks [27], data offloading [28], Wi-Fi deployment [29], network coding [30], and routing over networks [31]. Most of them directly adopt NBS as the solution and follow an axiomatic approach for bargaining, which differs from the iterative bargaining procedure in this paper significantly. Besides, the proposed bargaining procedure is related to the strategic iterative bargaining game in the seminal works [32], [33], although the problem setups are very different, e.g., the presence of information asymmetry in the proposed bargaining approach.

The rest of this paper is organized as follows. In Section II, we elaborate on the system model for load reduction and present the bargaining procedure. In Section III, we analyze the proposed bargaining approach. In Section IV, we discuss two other schemes for data center demand response. We conclude this paper in Section V.

II. System Model and Bargaining Formulation

In this section, we present the model of data center demand response for load reduction by taking into account the information asymmetry between the LSE and the data center. Further, we propose an iterative bargaining procedure for the LSE and the data center to negotiate an appropriate price for load curtailment acceptable to both parties.

A. System Model

We consider a basic model in which two monopolists, namely an LSE and a data center, constitute the majority of the market share. With the increasing penetration of intermittent renewable energy, the power supply from the LSE can be highly fluctuant, making it difficult to meet the demand in peak periods. In particular, when the LSE experiences a supply deficit, data centers can provide demand response through workload management via dynamic server provisioning and adaptive load balancing. Suppose the LSE requests a load reduction of $D > 0$. To incentivize load shedding, the LSE compensates the data center p dollars per unit load reduction. If the realized load curtailment is $q \in [0, D]$, the LSE incurs a quadratic penalty of $\frac{C}{2}(D-q)^2$, where $C > 0$ is the penalty coefficient. Hence, the reduction of penalty relative to the case of no load curtailment is $\frac{C}{2}D^2 - \frac{C}{2}(D-q)^2$. In particular, this reduction of penalty is zero if the load curtailment q is zero. We remark that quadratic penalty/cost functions are prevalent and standard in the literature of electricity market [12], [34]–[36] to simplify analysis and to obtain engineering insights. Thus, the net utility of the LSE for unit price $p \geq 0$ and load curtailment $q \in [0, D]$ is:

$$\mathsf{S_L}(p,q) = \frac{C}{2}D^2 - \frac{C}{2}(D-q)^2 - pq \tag{1}$$

$$= (CD-p)q - \frac{C}{2}q^2. \tag{2}$$

Given the unit price $p \geq 0$, the LSE will demand an amount of load reduction that maximizes its net utility. In other words, given $p \geq 0$, the demand function of the LSE is

$$d(p) = \arg\max_{0 \leq q \leq D} \mathsf{S_L}(p,q) = \left(D - \frac{p}{C}\right)^+, \tag{3}$$

where $(x)^+ \triangleq \max\{x, 0\}$.

On the data center side, when it reduces the power load received from the LSE, it may have to degrade the QoS of its customers. Thus, when reducing loads, the data center suffers some cost, which depends on the on-site renewable generation and the customers' service request level at the data center. Specifically, if the data center collects little renewable energy or customers' service requests surge, the cost of load reduction would be high. In contrast, if the data center harvests plenty of renewables or service request level is low, the cost of load reduction becomes small. Owing to the random fluctuations of the renewable generation and service request level, the load reduction cost at the data center is also random. In this paper, following [12], the cost of reducing q amount of loads at the data center is assumed to be quadratic, given as $\frac{q^2}{2X}$, where X is a random variable uniformly distributed over the interval $(0, 2\overline{X})$ and $\overline{X} > 0$ is the expectation of X. The random variable X models the randomness of the on-site renewable generation and customers' service request level. Larger X means larger renewable generation or smaller service request level. Though seemingly restrictive, this quadratic form of cost function is standard in the electricity market literature [34]–[36]. Further, since the on-site renewable generation and service request level are private information of the data center, the realization of X is only known to the data center and is unknown to the LSE, who is only aware of the distribution of X based on the statistical information of the renewable generation and service request. This naturally gives rise to the information asymmtry between the LSE and the data center: the LSE has little knowledge about the data center's load flexibility, which is private information of the data center.

For the unit price $p \geq 0$, load reduction $q \geq 0$ and the realization of the random variable $X \in (0, 2\overline{X})$, the net utility of the data center is:

$$\mathsf{S_D}(p,q,X) = pq - \frac{q^2}{2X}. \tag{4}$$

Given the realization of X, the data center supplies an amount of load reduction that maximizes its net utility, i.e., the supply function of the data center is:

$$s(p,X) = \arg\max_{q \geq 0} \mathsf{S_D}(p,q,X) = pX. \tag{5}$$

Combining the models for the LSE and the data center, given the unit price $p \geq 0$ and the realization of X (known privately to the data center), the amount of load reduction that both parties will agree on is the minimimum of the supply and demand functions at p, i.e., the realized load reduction will be:

$$\mathsf{q}(p,X) = \min\{s(p,X), d(p)\}. \tag{6}$$

B. A Bargaining Approach to Data Center Demand Response

It is clear that a key step is for both parties to reach an agreement on the unit price p of the load reduction. Nonetheless, the interests of the two parties conflict with each other: the LSE prefers a low p to pay less while the data center wants a high p to earn more. In order to settle these conflicting interests, we advocate a bargaining approach. A well-known axiomatic solution concept for bargaining games is the Nash bargaining solution (NBS) [37]. In our model, the NBS is the optimal price given by the following optimization problem:

$$\operatorname*{Max}_{p \geq 0} \ \mathbb{E}_X\left[\mathsf{S_L}(p, \mathsf{q}(p,X))\right] \mathsf{S_D}(p, \mathsf{q}(p,X), X), \tag{7}$$

in which the LSE's utility is averaged over all possible realizations of X since the true X is unknown to him. It is infeasible to solve (7) directly and prescribe this price to the LSE and the data center, because (i) the realization of X is private information of the data center; (ii) the LSE and the

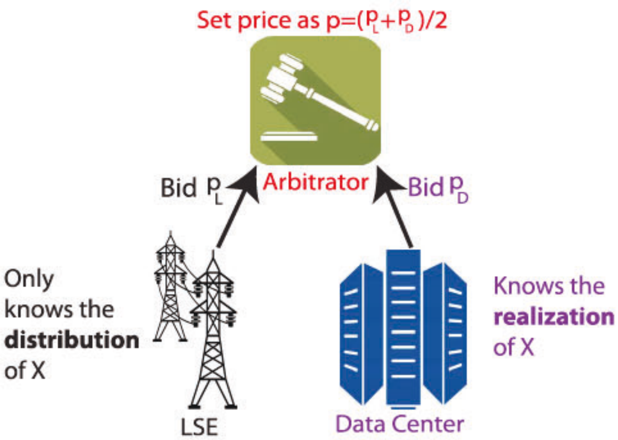

Fig. 1. An illustration of the bargaining between the LSE and the data center.

data center may not obey the prescribed solution since they aim to maximize their own (expected) utilities. This motivates us to design a bargaining procedure that respects the players' private information and selfishness. Moreover, it is possible to take the logarithm of the objective function of problem (7) and transform it to an SWM with the utility functions replaced by the logarithms of the original ones. The resulting SWM of log-utility is a convex problem due to the log-concavity of the (expected) utility functions of the LSE and the data center (to be shown in Section III). Thus, the SWM of log-utility can be solved efficiently via off-the-shelf optimization packages if the realization of X is known to the coordinator. Nevertheless, in practice, the data center may not be willing to reveal her private information about X. In addition, the LSE and the data center, both having significant market leverage, may not conform to the price prescribed by a third-party coordinator. Instead, they may want to bargain for a mutually agreeable price by themselves.

As is standard, there are three entities involved in the bargaining procedure, namely the LSE, the data center, and an independent arbitrator (see Fig. 1). The arbitrator can be an independent system operator (ISO), which coordinates the operation of the electrical power system in a local region, e.g., one or multiple US states. The unit price p is negotiated through an iterative bidding process, in which each of the LSE and the data center takes turns to propose a bid, i.e., p_{L} and p_{D} respectively, on the unit price to the arbitrator. At each iteration, the arbitrator sets the unit price as the average of the current bids of the LSE and the data center, i.e., $p = \frac{1}{2}(p_{\mathsf{L}} + p_{\mathsf{D}})$. The LSE and the data center take turns to revise their respective bids as the best responses of the opponent's bid, and the price is updated by the arbitrator accordingly. This bargaining process continues until the bids of both the LSE and the data center converge.

The arbitrator will determine the success or failure (breakdown) of the bargaining based on the stablized bids p_{L} and p_{D}. When updating their bids, the LSE and the data center will take into consideration the possibility of breakdown of the bargaining. Intuitively, the breakdown probability should depend on the spread of the final bids $p_{\mathsf{L}} - p_{\mathsf{D}}$. Formally, the arbitrator can generate a positive value ϵ from an exponential distribution with parameter λ, i.e., the probability density function (PDF) is $f(\epsilon) = \lambda e^{-\lambda\epsilon}$ and the cumulative distribution function (CDF) is $F(\epsilon) = 1 - e^{-\lambda\epsilon}$ for $\epsilon > 0$. Here, $\lambda > 0$ is some predefined positive parameter announced to the LSE and the data center prior to the start of the bargaining. If the spread of the bids $p_{\mathsf{L}} - p_{\mathsf{D}}$ exceeds ϵ, the arbitrator declares success of the bargaining and the LSE and the data center finalizes the load reduction with the final price $p = \frac{1}{2}(p_{\mathsf{L}} + p_{\mathsf{D}})$. Otherwise, if the spread $p_{\mathsf{L}} - p_{\mathsf{D}}$ is less than ϵ, the arbitrator declares failure of the bargaining and no load curtailment takes place. In such a mechanism, if $p_{\mathsf{L}} < p_{\mathsf{D}}$, the bargaining will fail deterministically. This is reasonable since it is impossible to set a price satisfying both parties in such a case. If $p_{\mathsf{L}} > p_{\mathsf{D}}$, the bargaining succeeds with positive probability and the probability of success increases with the spread $p_{\mathsf{L}} - p_{\mathsf{D}}$. In particular, as the distribution parameter λ goes to infinity, the cumulative probability distribution (CDF) of ϵ approaches a unit step function and the probability of success approaches 1 for any fixed positive spread $p_{\mathsf{L}} - p_{\mathsf{D}}$. In such a limiting case, the declaration of the arbitrator degenerates to a deterministic sign discrimination: the bargaining succeeds if and only if $p_{\mathsf{L}} > p_{\mathsf{D}}$. Later analysis manifests that a finite value of λ is crucial in establishing the convergence of the bargaining process and the bargaining converges more slowly for larger values of λ empirically. Thus, we consider finite λ in the proposed bargaining mechanism in this paper. Additionally, we note that exponential distribution has been used to model exogenous risk of breakdown in each stage of the bargaining in [33], which is very different from the breakdown mechanism used in this paper.

In a nutshell, the bargaining procedure for load curtailment can be summarized in Algorithm 1. A few remarks on the proposed bargaining procedure are in order. First, when updating their bids, the LSE and the data center aim at maximizing their own utilities by taking the possibility of the breakdown of the bargaining into consideration. This conforms to the rationality and selfishness of both parties and contrasts with the social welfare maximization formulation in [12]. Second, owing to information asymmetry, the LSE does not know the realization of X, which is private information of the data center. Thus, when updating bids, the LSE maximizes its expected utility averaged over all possible realizations of X (c.f. (8)) while the data center maximizes its utility at the true value of X (c.f. (9)). Third, when implementing the bargaining, there are various possible conditions for convergence judgement, e.g., $\left|p_{\mathsf{L}}^{(k)} - p_{\mathsf{L}}^{(k-2)}\right| < \beta$ and $\left|p_{\mathsf{D}}^{(k-1)} - p_{\mathsf{D}}^{(k-3)}\right| < \beta$ for odd k and some predefined threshold β. Fourth, in practice, the local independent system operator (ISO) can serve as the arbitrator. When the LSE has sufficient power supply, she operates normally according to existing market schemes. Whenever the LSE encounters an energy deficit and cannot sustain the current load, she can request the ISO to set up a load curtailment bargaining procedure with a data center with large load. The LSE may request multiple bargainings with multiple data centers if the load reduction from one single data center is not enough to compensate for the energy deficit. With the proposed bargaining approach, the LSE

TABLE I
NOTATIONS

Notations	Definitions
C	The coefficient of the penalty function of the LSE
D	The amount of load that the LSE aims to curtail
X	The reciprocal of the random coefficient of the cost function of the data center
$\mathsf{S}_{\mathsf{L}}(p,q)$	The utility function of the LSE
$\mathsf{S}_{\mathsf{D}}(p,q,X)$	The utility function of the data center
$\mathsf{q}(p,X)$	The realized load reduction
ϵ	A random variable with exponential distribution of parameter λ
$f(\cdot)$, $F(\cdot)$, $G(\cdot)$	The PDF, CDF, and log-CDF of ϵ
$\phi(p)$	The logarithm of the expected utility function of the LSE
$\gamma_X(p)$	The logarithm of the utility function of the data center

becomes much more robust to a temporary energy deficit by exploiting the load flexibility of data centers in an intelligent manner. Fifth, we note that the proposed bargaining approach differs significantly from the traditional supply function bidding method [13]–[15]. In supply function bidding, a fixed amount of load reduction needs to be fulfilled, in contrast to the flexible load reduction quantity negotiated by the LSE and the data center in advocated bargaining. Additionally, in supply function bidding, the data centers may be either price-taking or price-anticipating, i.e., taking the impact of their bids on prices into consideration. Nevertheless, unlike the bargaining approach, the data centers cannot directly negotiate the prices with the LSE and the prices are set by the LSE unilaterally based on submitted bids. Overall, the bargaining framework endows the data centers with more market power than the supply function bidding does. This is in accordance with the large loads contributed by the data centers. The notations of this paper are summarized in Table I.

Given the proposed bargaining procedure in Algorithm 1, we seek to answer the following questions. Firstly, are the best responses of the LSE and the data center unique, i.e., do the optimal solutions to problems (8) and (9) exist and if yes are they unique? If so, how to compute them efficiently so that the bargaining can be implemented readily? Secondly, can the bidding sequences of the LSE and the data center converge so that the bargaining procedure will be terminated after finite number of iterations? Thirdly, if the bidding sequences are convergent, how can we characterize the final unit price clinched by the bargaining? In the next section, we will study the bargaining procedure thoroughly. A major technical novelty lies on how to tackle the challenge due to the information asymmetry between the LSE and the data center. Since the LSE does not know the value of X, she has to take expectations over all possible realizations of X in order to make optimal decisions. This complicates the analytical form of the expected utility of the LSE and makes the properties (e.g., contraction mapping) of the best response of the LSE difficult to analyze. Nevertheless, as will be elaborated in the next section, we manage to show that the expected utility of the LSE is strictly log-concave and the best response of the LSE is a contraction mapping, which leads to the convergence of the proposed bargaining procedure.

Algorithm 1 The Bargaining Procedure of Load Curtailment

Initialization: The arbitrator announces a positive number λ to the LSE and the data center. Then, the data center initializes its bid $p_{\mathsf{D}}^{(0)} \in [0, CD)$ arbitrarily. Set $k = 1$.
while convergence is not reached **do**
  if k is odd **then**
    The LSE updates its bid as the best response of the current bid of the data center, i.e.,

$$p_{\mathsf{L}}^{(k)} = \arg\max_{p_{\mathsf{L}}\geq 0} \left\{ F\left(p_{\mathsf{L}} - p_{\mathsf{D}}^{(k-1)}\right) \cdot \mathbb{E}\left[\mathsf{S}_{\mathsf{L}}\left(\frac{p_{\mathsf{L}}+p_{\mathsf{D}}^{(k-1)}}{2}, \mathsf{q}\left(\frac{p_{\mathsf{L}}+p_{\mathsf{D}}^{(k-1)}}{2}, X\right)\right)\right]\right\}. \quad (8)$$

  else
    The data center updates its bid as the best response of the current bid of the LSE, i.e.,

$$p_{\mathsf{D}}^{(k)} = \arg\max_{p_{\mathsf{D}}\geq 0} \left\{ F\left(p_{\mathsf{L}}^{(k-1)} - p_{\mathsf{D}}\right) \cdot \mathsf{S}_{\mathsf{D}}\left(\frac{p_{\mathsf{L}}^{(k-1)}+p_{\mathsf{D}}}{2}, \mathsf{q}\left(\frac{p_{\mathsf{L}}^{(k-1)}+p_{\mathsf{D}}}{2}, X\right), X\right)\right\}. \quad (9)$$

  end if
  $k \leftarrow k + 1$.
end while
Once the bids of the LSE and the data center converge to p_{L}^* and p_{D}^*, respectively, the arbitrator generates a value ϵ from exponential distribution with parameter λ. If $p_{\mathsf{L}}^* - p_{\mathsf{D}}^* \geq \epsilon$, the arbitrator declares success of the bargaining. Otherwise, it declares failure of the bargaining.

III. Analysis of the Bargaining Game

In this section, we analyze the bargaining procedure in Algorithm 1. Specifically, we first prove the strict log-concavity of the utility function of the data center and the (expected) utility function of the LSE. Based on this, we show the existence and the uniqueness of the best responses in problems (8) and (9) and derive an efficient method to compute them. Further, we prove the convergence of the bid sequences in the bargaining under the assumption that the distribution parameter λ is sufficiently large. In addition, we show that the final unit price clinched by the bargaining procedure converges to the Nash bargaining solution (NBS), i.e., the price maximizes the product of the utility of the data center and the expected utility of the LSE. Moreover, we show that the breakdown probability of the bargaining can be made arbitrarily small by choosing λ sufficiently large. Finally, numerical results are presented to corroborate the proposed bargaining approach. For clarity of presentation, all proofs are presented in the supplementary material.

A. Strict Log-Concavity of (Expected) Utility Functions

We first study the properties of the utility function of the data center $\mathsf{S}_{\mathsf{D}}(p, \mathsf{q}(p, X), X)$ defined over $p \in [0, +\infty)$. It can be shown that $\mathsf{S}_\mathsf{D}(p, \mathsf{q}(p, X), X)$ is positive for $p \in (0, CD)$ and is zero for $p = 0$ or $p \geq CD$. Thus, we can define $\gamma_X(p) \triangleq \ln \mathsf{S}_\mathsf{D}(p, \mathsf{q}(p, X), X)$ for $p \in (0, CD)$. Its derivative can be computed as:

$$\gamma'_X(p) = \begin{cases} \frac{2}{p}, \text{ if } 0 < p \leq \frac{CD}{1+CX}, \\ \frac{2CX+1}{(2CX+1)p - DC} - \frac{1}{DC - p}, \text{ if } \frac{CD}{1+CX} < p < CD, \end{cases} \tag{10}$$

which has the following property.

Lemma 1: For any realization of X in $(0, 2\overline{X})$, $\gamma'_X(p)$ is continuous and strictly decreasing over the interval $(0, CD)$. $\gamma''_X(p) < 0$ for any $p \in (0, CD) \backslash \left\{\frac{CD}{1+CX}\right\}$.

Next, we examine the properties of the expected utility function of the LSE. It can be shown that, for $p \in [0, +\infty)$:

$$\mathbb{E}[\mathsf{S}_\mathsf{L}(p, \mathsf{q}(p, X))] = \begin{cases} (CD - p)p\overline{X} - \frac{2}{3}Cp^2\overline{X}^2, \text{ if } 0 \leq p \leq \frac{CD}{2C\overline{X}+1}, \\ -\frac{Cp^2}{12\overline{X}}\left(\frac{D}{p} - \frac{1}{C}\right)^3 + \frac{Cp^2}{2}\left(\frac{D}{p} - \frac{1}{C}\right)^2, \\ \qquad \text{if } \frac{CD}{2C\overline{X}+1} < p < CD, \\ 0, \text{ if } p \geq CD. \end{cases} \tag{11}$$

We have the following lemma.

Lemma 2: $\mathbb{E}[\mathsf{S}_\mathsf{L}(p, \mathsf{q}(p, X))]$ is positive for $p \in (0, CD)$ and is zero for $p = 0$ or $p \geq CD$. Further, $\mathbb{E}[\mathsf{S}_\mathsf{L}(p, \mathsf{q}(p, X))]$ is continuous on $p \in [0, +\infty)$.

Based on Lemma 2, we define $\phi(p) \triangleq \ln \mathbb{E}[\mathsf{S}_\mathsf{L}(p, \mathsf{q}(p, X))]$ for $p \in (0, CD)$. The derivative of $\phi(p)$ can be computed as:

$$\phi'(p) = \begin{cases} \frac{1}{p} - \frac{1+\frac{2}{3}C\overline{X}}{CD - p(1+\frac{2}{3}C\overline{X})}, \text{ if } 0 < p \leq \frac{CD}{2C\overline{X}+1}, \\ \frac{2}{p} - \frac{2D}{p^2} \cdot \frac{1}{\frac{D}{p} - \frac{1}{C}} + \frac{D}{p^2} \cdot \frac{1}{6\overline{X} - (\frac{D}{p} - \frac{1}{C})}, \\ \qquad \text{if } \frac{CD}{2C\overline{X}+1} < p < CD. \end{cases} \tag{12}$$

Then, we have the following property for $\phi(p)$.

Lemma 3: $\phi'(p)$ is continuous and strictly decreasing over the interval $(0, CD)$. $\phi''(p)$ is negative and continuous over the interval $(0, CD)$.

Lemmas 1 and 3 demonstrate the strict log-concavity of the utility function of the data center $\mathsf{S}_\mathsf{D}(p, \mathsf{q}(p, X), X)$ and the expected utility function of the LSE $\mathbb{E}[\mathsf{S}_\mathsf{L}(p, \mathsf{q}(p, X))]$, both over the interval $p \in (0, CD)$. These properties play critical roles in computing the best responses in (8) and (9) efficiently.

B. Best Response Updates

In this subsection, we investigate the existence and uniqueness of the best responses in the updates (8) and (9) and characterize the optimality conditions, based on which an efficient method of finding the best responses is presented. We first study the LSE's best response update. Denote $G(y) = \ln F(y)$ for any positive y.

Lemma 4:

1) *For any given $p_\mathsf{D} \in [0, CD)$, the following optimization problem with respect to p_L:*

$$\underset{p_\mathsf{L} \geq 0}{\text{Max.}}\ F(p_\mathsf{L} - p_\mathsf{D})\mathbb{E}\left[\mathsf{S}_\mathsf{L}\left(\frac{p_\mathsf{L} + p_\mathsf{D}}{2}, \mathsf{q}\left(\frac{p_\mathsf{L} + p_\mathsf{D}}{2}, X\right)\right)\right] \tag{13}$$

has a unique optimal point, which is denoted as $\mathsf{B}_\mathsf{L}(p_\mathsf{D})$.

2) *For any $p_\mathsf{D} \in [0, CD)$, we have $\mathsf{B}_\mathsf{L}(p_\mathsf{D}) \in (p_\mathsf{D}, 2CD - p_\mathsf{D}) \subset (0, 2CD)$. Thus, the mapping B_L satisfies $\mathsf{B}_\mathsf{L} : [0, CD) \mapsto (0, 2CD)$.*

3) *For any $p_\mathsf{D} \in [0, CD)$, we have:*

$$G'(\mathsf{B}_\mathsf{L}(p_\mathsf{D}) - p_\mathsf{D}) + \frac{1}{2}\phi'\left(\frac{\mathsf{B}_\mathsf{L}(p_\mathsf{D}) + p_\mathsf{D}}{2}\right) = 0. \tag{14}$$

Next, we examine the best response update of the data center as follows.

Lemma 5: For any realization of X in $(0, 2\bar{X})$, the following statements hold.

1) *For any given $p_\mathsf{L} \in (0, 2CD)$, the following optimization problem with respect to p_D:*

$$\underset{p_\mathsf{D} \geq 0}{\text{Max.}}\ F(p_\mathsf{L} - p_\mathsf{D})\mathsf{S}_\mathsf{D}\left(\frac{p_\mathsf{L} + p_\mathsf{D}}{2}, \mathsf{q}\left(\frac{p_\mathsf{L} + p_\mathsf{D}}{2}, X\right), X\right) \tag{15}$$

has a unique optimal point, which is denoted as $\mathsf{B}_\mathsf{D}(p_\mathsf{L}; X)$.

2) *For any $p_\mathsf{L} \in (0, 2CD)$, we have $\mathsf{B}_\mathsf{D}(p_\mathsf{L}; X) \in [0, \min\{p_\mathsf{L}, 2CD - p_\mathsf{L}\}) \subset [0, CD)$. Thus, the mapping $\mathsf{B}_\mathsf{D}(\cdot; X)$ satisfies $\mathsf{B}_\mathsf{D}(\cdot; X) : (0, 2CD) \mapsto [0, CD)$.*

3) *For any $p_\mathsf{L} \in (0, 2CD)$, we have:*
   - *If $-G'(p_\mathsf{L}) + \frac{1}{2}\gamma'_X\left(\frac{p_\mathsf{L}}{2}\right) \leq 0$, then $\mathsf{B}_\mathsf{D}(p_\mathsf{L}; X) = 0$.*
   - *If $-G'(p_\mathsf{L}) + \frac{1}{2}\gamma'_X\left(\frac{p_\mathsf{L}}{2}\right) > 0$, then $\mathsf{B}_\mathsf{D}(p_\mathsf{L}; X) \in (0, \min\{p_\mathsf{L}, 2CD - p_\mathsf{L}\})$ satisfies:*

$$-G'(p_\mathsf{L} - \mathsf{B}_\mathsf{D}(p_\mathsf{L}; X)) + \frac{1}{2}\gamma'_X\left(\frac{p_\mathsf{L} + \mathsf{B}_\mathsf{D}(p_\mathsf{L}; X)}{2}\right) = 0. \tag{16}$$

The strict log-concavity of the (expected) utility functions of the LSE and the data center plays crucial role in the proofs of Lemmas 4 and 5. For example, the uniqueness of the optimal solution to problems (13) and (15) follows directly from the strict concavity of the log-utility functions, or equivalently the strict monotonicity of their derivatives. Additionally, thanks to the strict monotonicity of the derivatives of the log-utility, we can readily analyze the signs of the derivatives of the log-objective functions in problems (13) and (15). This leads to the simple characterization of the optimal solutions in Lemmas 4-(3) and 5-(3). Without the log-concavity of the utility functions, problems (13) and (15) are still nonconvex after taking logarithms and there may exist multiple local minima so that simple characterizations of the optimal solutions are not available.

Combining Lemmas 4 and 5, together with the initial condition $p_\mathsf{D}^{(0)} \in [0, CD)$, we know by induction that:

$$p_\mathsf{L}^{(k)} = \mathsf{B}_\mathsf{L}\left(p_\mathsf{D}^{(k-1)}\right) \in (0, 2CD),\ \forall k = 1, 3, 5, \cdots, \tag{17}$$

$$p_\mathsf{D}^{(k)} = \mathsf{B}_\mathsf{D}\left(p_\mathsf{L}^{(k-1)}; X\right) \in [0, CD),\ \forall k = 2, 4, 6, \cdots. \tag{18}$$

Computationally, owing to the monotonicity of the L.H.S. of the optimality conditions (14) and (16) with respect to the unknowns ($\mathsf{B}_\mathsf{L}(p_\mathsf{D})$ and $\mathsf{B}_\mathsf{D}(p_\mathsf{L}; X)$, respectively), the best responses can be found via a simple bisection method efficiently. Therefore, the bargaining procedure presented in

Algorithm 2 Implementation of the Bargaining Procedure

Initialization: The same as in Algorithm 1.
while convergence is not reached **do**
  if k is odd **then**
    The LSE solves the following equation:

$$G'\left(p_{\mathsf{L}}^{(k)} - p_{\mathsf{D}}^{(k-1)}\right) + \frac{1}{2}\phi'\left(\frac{p_{\mathsf{L}}^{(k)} + p_{\mathsf{D}}^{(k-1)}}{2}\right) = 0$$

    by using bisection method to update its bid $p_{\mathsf{L}}^{(k)}$.
  else
    if $-G'\left(p_{\mathsf{L}}^{(k-1)}\right) + \frac{1}{2}\gamma'_X\left(\frac{p_{\mathsf{L}}^{(k-1)}}{2}\right) \le 0$ **then**
      The data center updates its bid as $p_{\mathsf{D}}^{(k)} = 0$.
    else
      The data center solves the following equation:

$$-G'\left(p_{\mathsf{L}}^{(k-1)} - p_{\mathsf{D}}^{(k)}\right) + \frac{1}{2}\gamma'_X\left(\frac{p_{\mathsf{L}}^{(k-1)} + p_{\mathsf{D}}^{(k)}}{2}\right) = 0$$

      by using bisection method to update its bid $p_{\mathsf{D}}^{(k)}$.
    end if
  end if
  $k \leftarrow k+1$.
end while
The arbitrator determines the success or failure of the bargaining in a way detailed in Algorithm 1.

Algorithm 1 is amenable to easy implementation, which is summarized in Algorithm 2.

C. Convergence Analysis

In this subsection, we analyze the convergence of the proposed bargaining procedure under the assumption that λ is sufficiently large, which indicates that the breakdown probability of the bargaining for any fixed positive spread $p_{\mathsf{L}} - p_{\mathsf{D}}$ is sufficiently small. This is reasonable in practice since the arbitrator is able to set a unit price satisfying both parties (LSE and data center) whenever $p_{\mathsf{L}} > p_{\mathsf{D}}$.

We first define several key quantities as follows. Define $\xi_{\mathsf{D}}(X) \triangleq \frac{(CX+1)DC}{2CX+1}$ and $\widetilde{\xi}_{\mathsf{D}} \triangleq \xi_{\mathsf{D}}(2\overline{X}) = \frac{(2C\overline{X}+1)DC}{4C\overline{X}+1}$. One can easily check that $\gamma'_X(\xi_{\mathsf{D}}(X)) = 0$ and $\xi_{\mathsf{D}}(X)$ is indeed the unique root of γ'_X, which is strictly decreasing. Further, since ϕ' is strictly decreasing over the interval $(0, CD)$, we can denote its unique root as $\xi_{\mathsf{L}} \in (0, CD)$, i.e., $\phi'(\xi_{\mathsf{L}}) = 0$. We note that ξ_{L} and $\widetilde{\xi}_{\mathsf{D}}$ are constants in $(0, CD)$ while $\xi_{\mathsf{D}}(X)$ is a function of the random variable X. Then, we have the following relationship between these quantities.

Lemma 6: For any realization of $X \in (0, 2\overline{X})$, we have:

$$\xi_{\mathsf{D}}(X) \ge \widetilde{\xi}_{\mathsf{D}} > \max\left\{\xi_{\mathsf{L}}, \frac{DC}{2}\right\}. \tag{19}$$

For large enough λ, we can restrict the range space of $\mathsf{B_L}$ to a smaller set as in the following lemma.

Lemma 7: For sufficiently large λ, we have, $\forall p_{\mathsf{D}} \in [0, CD)$:

$$\xi_{\mathsf{L}} < \mathsf{B_L}(p_{\mathsf{D}}) \le \widetilde{\xi}_{\mathsf{D}} + \max\left\{\xi_{\mathsf{L}}, \frac{CD}{2}\right\}, \tag{20}$$

i.e., the mapping $\mathsf{B_L}$ satisfies

$$\mathsf{B_L} : [0, CD) \mapsto \left(\xi_{\mathsf{L}}, \widetilde{\xi}_{\mathsf{D}} + \max\left\{\xi_{\mathsf{L}}, \frac{CD}{2}\right\}\right]. \tag{21}$$

When p_{L} is in the range described in (20), the corresponding best response for the data center p_{D} must be an interior optima, i.e., it fits the second senario of part 3 of Lemma 5, so that the optimality condition (16) holds. This is formally shown in the following lemma.

Lemma 8: For sufficiently large λ, we have that, for any realization of $X \in (0, 2\overline{X})$ and any $p_{\mathsf{L}} \in \left(\xi_{\mathsf{L}}, \widetilde{\xi}_{\mathsf{D}} + \max\left\{\xi_{\mathsf{L}}, \frac{CD}{2}\right\}\right]$:

$$\mathsf{B_D}(p_{\mathsf{L}}; X) \in (0, \min\{p_{\mathsf{L}}, 2CD - p_{\mathsf{L}}\}), \tag{22}$$

$$-G'(p_{\mathsf{L}} - \mathsf{B_D}(p_{\mathsf{L}}; X)) + \frac{1}{2}\gamma'_X\left(\frac{p_{\mathsf{L}} + \mathsf{B_D}(p_{\mathsf{L}}; X)}{2}\right) = 0. \tag{23}$$

From Lemmas 7 and 8 together with the initial condition $p_{\mathsf{D}}^{(0)} \in [0, CD)$, by induction, we observe that:

$$p_{\mathsf{L}}^{(k)} \in \left(\xi_{\mathsf{L}}, \widetilde{\xi}_{\mathsf{D}} + \max\left\{\xi_{\mathsf{L}}, \frac{CD}{2}\right\}\right], \ \forall k = 1, 3, 5, \cdots, \tag{24}$$

$$p_{\mathsf{D}}^{(k)} \in (0, CD), \ \forall k = 2, 4, 6, \cdots, \tag{25}$$

as long as λ is sufficiently large. Thus, Lemma 8 excludes the possibility of a boundary best response for the data center in the bargaining procedure and ensures that the optimality condition (23) must hold. This will be used in later convergence analysis. Next, we show that $\mathsf{B_L}(\cdot)$ is a contraction mapping.

Lemma 9: There exists a positive constant $\theta < 1$ such that, for any $p_{\mathsf{D}}, \widehat{p}_{\mathsf{D}} \in [0, CD)$, we have:

$$|\mathsf{B_L}(p_{\mathsf{D}}) - \mathsf{B_L}(\widehat{p}_{\mathsf{D}})| \le \theta |p_{\mathsf{D}} - \widehat{p}_{\mathsf{D}}|. \tag{26}$$

Furthermore, we can provide an analogous but weaker result for $\mathsf{B_D}(\cdot; X)$ as follows.

Lemma 10: For sufficiently large λ, we have that, for any realization of $X \in (0, 2\overline{X})$ and $p_{\mathsf{L}}, \widehat{p}_{\mathsf{L}} \in \left(\xi_{\mathsf{L}}, \widetilde{\xi}_{\mathsf{D}} + \max\left\{\xi_{\mathsf{L}}, \frac{CD}{2}\right\}\right]$:

$$|\mathsf{B_D}(p_{\mathsf{L}}; X) - \mathsf{B_D}(\widehat{p}_{\mathsf{L}}; X)| \le |p_{\mathsf{L}} - \widehat{p}_{\mathsf{L}}|. \tag{27}$$

Now, we are ready to present a main result for the proposed bargaining algorithm as follows.

Theorem 1: For sufficiently large λ, there exist $p_{\mathsf{L}}^* \in \left(\xi_{\mathsf{L}}, \widetilde{\xi}_{\mathsf{D}} + \max\left\{\xi_{\mathsf{L}}, \frac{CD}{2}\right\}\right]$ and $p_{\mathsf{D}}^* \in [0, CD)$ such that the bid sequence of the LSE converges to p_{L}^* and the bid sequence of the data center converges to p_{D}^*, i.e.,

$$\lim_{t\to\infty} p_{\mathsf{L}}^{(2t+1)} = p_{\mathsf{L}}^*, \ \textit{and} \ \lim_{t\to\infty} p_{\mathsf{D}}^{(2t)} = p_{\mathsf{D}}^*. \tag{28}$$

The convergence result in Theorem 1 ensures the feasibility of Algorithm 1: the bargaining will indeed terminate within finite number of iterations. Further, when the bids of the LSE and the data center both reach convergence, the final unit price set by the arbitrator converges to $p^* \triangleq \frac{1}{2}(p_{\mathsf{L}}^* + p_{\mathsf{D}}^*)$, which has the following interesting characterization.

Theorem 2: For sufficiently large λ, the final unit price $p^* \triangleq \frac{1}{2}(p_{\mathsf{L}}^* + p_{\mathsf{D}}^*)$ coincides with the Nash bargaining solution (NBS) of the bargaining between the LSE and the data

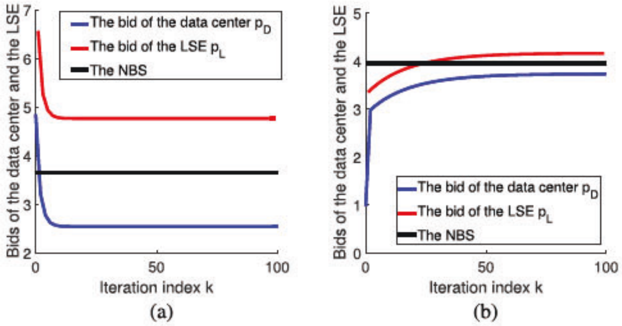

Fig. 2. Convergence of the proposed bargaining procedure. (a) One realization when $\lambda = 1$. (b) One realization when $\lambda = 10$.

center, i.e.,

$$p^* = \arg\max_{p \geq 0} \mathbb{E}[\mathsf{S}_\mathsf{L}(p, \mathsf{q}(p, X))]\mathsf{S}_\mathsf{D}(p, \mathsf{q}(p, X), X), \quad (29)$$

for any realization of $X \in (0, 2\overline{X})$.

Remark 1: Theorem 2 manifests an interesting relation between the outcome of the proposed bargaining procedure and that of the NBS. While the former is the ramification of an iterative bargaining process, the latter is based on an axiomatic framework (NBS is the unique solution satisfying the four reasonable axioms postulated by Nash in [37]). It is interesting that the bargaining solutions based on iterative methods and axiomatic frameworks coincide in the data center demand response problem under study. Related results have been obtained in [33], which justifies the axiomatic NBS as perfect equilibrium of some strategic bargaining game. Nevertheless, the problem setup in [33] is very different from that of the this paper, particularly due to the presence of information asymmetry. Moreover, we note that the final unit price clinched by the proposed bargaining is a proportionally fair *outcome for load curtailment. This is desirable since one of the main goals of bargaining is to realize fair resource allocation.*

Both Theorems 1 and 2 presume that λ is sufficiently large. In fact, this means λ needs to satisfy the following two conditions (c.f. the proofs of Lemmas 7 and 8 in the supplementary file):

$$G'\left(\widetilde{\xi}_\mathsf{D} - \frac{DC}{2}\right) < -\frac{1}{2}\phi'\left(\frac{\widetilde{\xi}_\mathsf{D} + \xi_\mathsf{L}}{2}\right), \quad (30)$$

$$G'(\xi_\mathsf{L}) < \min\left\{\frac{1}{CD}, \frac{1}{2}\gamma'_{2\overline{X}}\left(\frac{\widetilde{\xi}_\mathsf{D} + \max\left\{\xi_\mathsf{L}, \frac{CD}{2}\right\}}{2}\right)\right\}, \quad (31)$$

where $G'(y) = \frac{\lambda}{e^{\lambda y} - 1}$ for $\lambda, y > 0$. It can be shown that $\lim_{\lambda \to +\infty} G'(y) = 0$ and the right hand sides of (30) and (31) are both positive constants independent of λ. So, (30) and (31) must hold for sufficiently large λ. These conditions on λ are cumbersome and are only sufficient conditions for the convergence results in Theorems 1 and 2. Empirically, λ need not be too large at all and $\lambda = 1$ is more than enough for the convergence of the bargaining, c.f. Fig. 2-(a).

According to the arbitrator's mechanism, when the bids of the LSE and the data center reach convergence, the probability of success of the bargaining is $F(p_\mathsf{L}^* - p_\mathsf{D}^*)$, in which both the CDF $F(\bullet)$ and the final spread $p_\mathsf{L}^* - p_\mathsf{D}^*$ depends on λ. An interesting question is how the probability of success behaves when λ is large. This is answered by the following proposition.

Proposition 1: The probability of success of the bargaining $F(p_\mathsf{L}^* - p_\mathsf{D}^*)$ converges to 1 as $\lambda \to \infty$.

Proposition 1 asserts that the breakdown probability of the bargaining can be made arbitrarily small if λ is sufficiently large. Nevertheless, λ still needs to be finite so that the bargaining procedure will converge. In particular, the larger the value of λ, the slower the bargaining procedure converges, as will be confirmed by numerical experiments. Thus, in practice, the value of λ should be set to balance the breakdown probability and the convergence speed.

The analysis in this paper mainly relies on two assumptions: (i) the penalty/cost functions of load reduction for the LSE and the data center take quadratic forms; and (ii) X is uniformly distributed. We believe that the analysis can be extended to more general bargaining settings with incomplete information or information asymmetry. As long as the (expected) utility functions of the bargaining parties are strictly log-concave, the uniquess and analogous first-order characterizations of the best responses (c.f. Lemmas 4 and 5) should still hold. Under certain technical conditions, the best responses may still be contraction mappings and the convergence of the bargaining procedure can still follow from the Banach fixed-point theorem. Details of the general bargaining model are worth studying thoroughly in future work.

To implement the bargaining procedure in Algorithm 1, at each iteration, the LSE or the data center needs to solve a maximization problem by using simple bisection method (c.f. Algorithm 2). In practice, if the LSE or the data center cannot even afford the low-complexity bisection method, the best response updates in (8) and (9) can be replaced with projected gradient ascent steps of the corresponding maximization problems after taking logarithms of the objective functions. In such a case, for odd k, the LSE updates its bid as

$$p_\mathsf{L}^{(k)} = \left[p_\mathsf{L}^{(k-2)} + \alpha^{(k)}\left(G'\left(p_\mathsf{L}^{(k-2)} - p_\mathsf{D}^{(k-1)}\right) + \frac{1}{2}\phi'\left(\frac{p_\mathsf{L}^{(k-2)} + p_\mathsf{D}^{(k-1)}}{2}\right)\right)\right]^+, \quad (32)$$

where $x^+ = \max\{x, 0\}$ and $\alpha^{(k)} > 0$ is the stepsize at iteration k. For even k, the data center updates its bid as

$$p_\mathsf{D}^{(k)} = \left[p_\mathsf{D}^{(k-2)} + \alpha^{(k)}\left(-G'\left(p_\mathsf{L}^{(k-1)} - p_\mathsf{D}^{(k-2)}\right) + \frac{1}{2}\gamma'_X\left(\frac{p_\mathsf{L}^{(k-1)} + p_\mathsf{D}^{(k-2)}}{2}\right)\right)\right]^+. \quad (33)$$

We conjecture that, under appropriate technical conditions, the simplified bargaining iterations in (32) and (33) still converge and the final price clinched is still the NBS. The essential idea of the bargaining framework is that the mutual best responses can be gradually achieved by the gradient ascent updates.

With appropriate adaptations, the proposed bargaining framework may be adopted by other distributed energy resources such as electric vehicles (EVs) and distributed storage. Some important changes are discussed as follows. For instance, in EV charging, the LSE faces many distributed EVs (each contributing a small load) with heterogeneous load reduction/shifting costs and requirements, instead of one single data center with large load in the setup of this paper. To bargain with the heterogeneous EVs, the LSE needs to aggregate the heterogeneous bids submitted by the EVs and respond optimally. The bargaining procedure should be decentralized so that an EV does not need to know other EVs' private information, e.g., charging requirements. Additionally, since the EV charging often lasts for a relatively long period, the energy deficit or surplus at the LSE may vary and may not be predicted accurately by the LSE. This uncertainty of energy conditions further complicates the bargaining design. In the literature, decentralized EV charging has been studied in the seminal work [38], where the EVs fully collaborate and update their charging profiles according to an algorithm designed by the utility. EVs' economic incentives have also been considered under a game-theoretic framework. A contract-theoretic approach is proposed in [39], where each EV selects a payment-charging rate combination from a list of contracts designed by the utility. Moreover, an auction method is developed in [40], where the EVs submit bids to compete for the energy resources. Neither approach allows the EVs to directly negotiate prices with the LSE, which is the most prominent feature of the bargaining procedure in this paper. Overall, the bargaining approach can endow the EVs with greater market leverage, in concert with the increasing penetration of EVs in power grids.

D. Numerical Evaluation

In this subsection, extensive numerical experiments are implemented to validate the proposed bargaining approach. Specifically, numerical results corroborating the theoretical findings (Theorems 1 and 2 and Proposition 1) are presented. Furthermore, we demonstrate the impact of various system parameters on the performance of the bargaining procedure to shed engineering insights on the design of data center demand response programs.

Consider an LSE and a data center bargaining for load curtailment as specified in Algorithm 1. We set the model parameters as $C = 1$, $D = 10$, $\overline{X} = 2$. The initial bid $p_{\mathrm{D}}^{(0)}$ of the data center is randomly generated within $[0, CD)$. First, we study the convergence behaviors of the bargaining in Fig. 2. We consider two values of the distribution parameter λ, namely $\lambda = 1$ in Fig. 2-(a) and $\lambda = 10$ in Fig. 2-(b). For each value of λ, the evolution of the bids $p_{\mathrm{L}}, p_{\mathrm{D}}$ for one realization of X is shown. We observe that, for both scenarios of λ, the bids $p_{\mathrm{L}}, p_{\mathrm{D}}$ converge to some $p_{\mathrm{L}}^*, p_{\mathrm{D}}^*$, respectively, after some iterations of bargaining, as guaranteed in Theorem 1. We further plot the NBS, i.e., the optimal point of problem (7), in Fig. 2. We remark that, as promised by Theorem 2, the final unit price $p^* = \frac{1}{2}(p_{\mathrm{L}}^* + p_{\mathrm{D}}^*)$ coincides with the NBS. Thus, the two main theoretical results, i.e., Theorems 1 and 2, are verified numerically. Moreover, comparing Fig. 2-(a) with Fig. 2-(b), we observe that the bargaining procedure converges

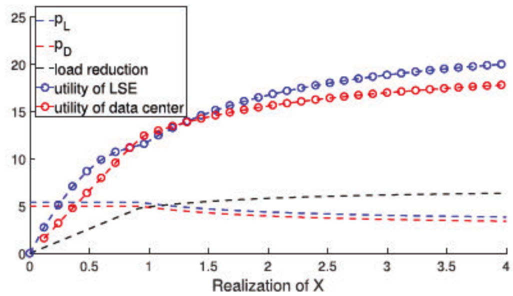

Fig. 3. Impact of the realization of X.

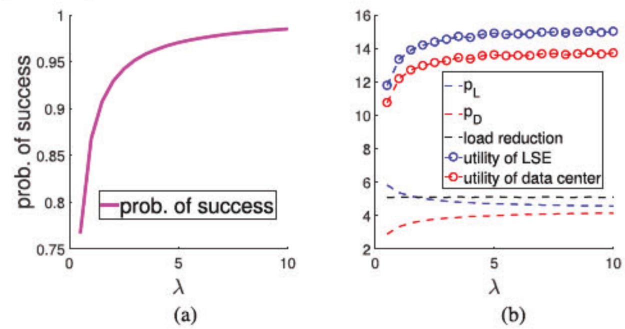

Fig. 4. Impact of the distribution parameter λ. (a) Impact on the probability of success of the bargaining. (b) Impact on the bids, the load reduction and the utilities.

slower for larger values of λ. Therefore, the choice of λ should balance the tradeoff between the convergence speed of the bargaining and the breakdown probability (c.f. Proposition 1).

Next, we investigate the impact of the realization of the random variable X on the steady-state (i.e., after convergence of the bids) performance of the bargaining in Fig. 3. We set $\lambda = 10$ and let the realization of X vary between 0 and $2\overline{X} = 4$. We observe that the steady-state bids remain the same for small values of X and then decreases with X. This can be explained as follows. Note that, in the proof of Theorem 2, the steady-state bids p_{L}^* and p_{D}^* depend on X only through the term $\gamma_X'(p^*)$. Recall the expression of $\gamma_X'(\cdot)$ in (10). For a given p, if X is small, $\gamma_X'(p) = \frac{2}{p}$, which does not depend on X. In this regime, p_{L}^* and p_{D}^* does not depend on X. For this regime to hold, according to (10), we need $p^* \leq \frac{CD}{1+CX}$, where $p^* = 5.2075$ since $p_{\mathrm{L}}^* = 5.406$ and $p_{\mathrm{D}}^* = 5.009$ as shown in Fig. 3. Equivalently, the condition for X is $X \leq 0.9203$, which matches the turning point of the bids in Fig. 3. After this turning point, as X increases further, the cost of the data center decreases (recall that X is the reciprocal cost coefficient of the data center). Therefore, the data center needs less compensation for load curtailment and the price (thus bids) decreases. Furthermore, from Fig. 3, we see that the realized load reduction increases with X. This is reasonable because, as the cost for load reduction decreases, the data center is willing to curtail more loads. In addition, from Fig. 3, we observe that the utilities of both the LSE and the data center increases with X. This is also unsurprising since the decrease of the cost of the data center will benefit the data center directly and the LSE indirectly (through increasing load reduction and decreasing prices).

We further examine the impact of the distribution parameter λ on the expected (expectation over X) steady-state performance of the bargaining solution. All results are the

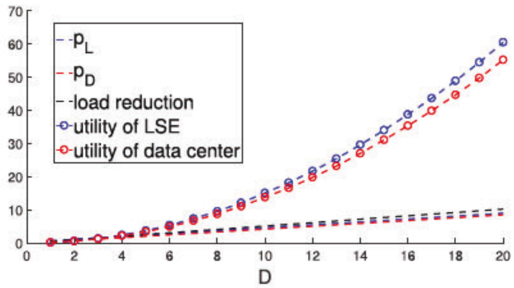

Fig. 5. Impact of the desired load curtailment by the LSE D.

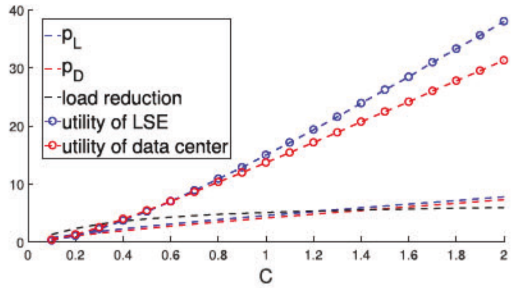

Fig. 6. Impact of the penalty coefficient of the LSE C.

average of 10000 Monte Carlo trials. In Fig. 4-(a), we see that the probability of success of the bargaining converges to 1 as λ increases, corroborating the theoretical result in Proposition 1. In Fig. 4-(b), we observe that, as λ increases, the steady-state bid of the LSE p_{L}^* decreases while the steady-state bid of the data center p_{D}^* increases. In other words, the gap between p_{L}^* and p_{D}^* decreases while the average of them, i.e., the finalized unit price p^*, remains unchanged. This can be explained as follows. We first note that, according to Theorem 2, p^* is indeed the NBS, which does not depend on λ. In addition, when λ is small, to obtain a relatively large probability of success $F(p_{\mathrm{L}}^* - p_{\mathrm{D}}^*)$, the spread $p_{\mathrm{L}}^* - p_{\mathrm{D}}^*$ needs to be large. As λ increases, a small spread is enough to guarantee a large probability of success. Thus p_{L}^* decreases and p_{D}^* increases while their average p^* remains the same. From Fig. 4-(b), we further see that the load reduction remains the same as λ increases. This is because the load reduction depends only on the final price p^*, which does not depend on λ. Moreover, as λ increases, the probability of success of the bargaining increases and thus so do the expected utilities of the LSE and the data center, which gradually saturate as the probability of success is approaching 1.

Next, we study the impact of the desired load curtailment by the LSE D on the steady-state performance of the bargaining solution in Fig. 5. As D increases, the LSE desires more load reduction. Hence, the realized load reduction increases, as can be seen in Fig. 5. Additionally, for the data center to supply more load reduction, the unit price (thus the bids p_{L}^* and p_{D}^*) must also increase, as observed in Fig. 5. Moreover, the increase in unit price facilitates the increase of the utility of the data center. Besides, according to (1), increasing D can also potentially boost the utility of the LSE as long as the unit price is not too high. The increase of the utilities of the LSE and the data center are confirmed in Fig. 5.

In addition, we investigate the impact of the penalty coefficient of the LSE C on the steady-state performance in Fig. 6.

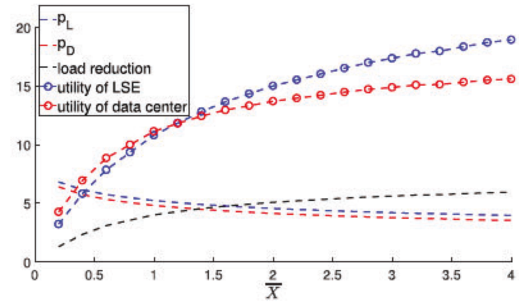

Fig. 7. Impact of $\overline{X}$.

According to (1), as C increases, the utility of the LSE increases, as shown in Fig. 6. Thus, the LSE is willing to compensate the data center with higher unit prices so that the bids p_{L}^* and p_{D}^* increase, as can be seen in Fig. 6. The increase of unit price further boosts the utility of the data center and elicits more load reduction supply from it, as shown in Fig. 6.

Finally, we examine the impact of the expected reciprocal cost coefficient $\overline{X}$ on the steady-state performance in Fig. 7. As $\overline{X}$ increases, the cost of the data center decreases so that it is willing to shed more loads at a lower unit price (thus lower $p_{\mathrm{L}}^*, p_{\mathrm{D}}^*$), as can be observed in Fig. 7. With lower cost, the utility of the data center also increases. The lower unit price also enhances the utility of the LSE, as can be seen in Fig. 7.

IV. Comparison With Stackelberg Game and Social Welfare Maximization Schemes

In this section, we discuss two other popular schemes, namely Stackelberg game and social welfare maximization (SWM), for load reduction in data center demand response. Further, these two schemes are compared with the proposed bargaining approach numerically.

A. Stackelberg Game Scheme

In what follows, we consider a model where the LSE proposes a one-shot (i.e., no opportunity to revise) tentative unit price p_{L} to the data center. After observing p_{L}, the data center also proposes a tentative unit price p_{D} in response. Finally, an independent arbitrator sets a finalized unit price to be $p = \frac{1}{2}(p_{\mathrm{L}} + p_{\mathrm{D}})$ and declares success of the load reduction if and only if the spread $p_{\mathrm{L}} - p_{\mathrm{D}}$ is greater than ϵ, which is an exponentially distributed random number (with parameter λ) generated after p_{L} and p_{D} are determined. This two-stage scheme (one for the LSE and one for the data center) is indeed a Stackelberg game formulation [41] with the LSE being the leader and the data center being the follower.

The main difference between the proposed iterative bargaining procedure and the Stackelberg game scheme is that the latter scheme is bound to terminate after two iterations (one for the LSE to propose p_{L} and the other for the data center to propose p_{D}) and there is no opportunity to revise the proposed tentative prices. This renders Stackelberg game more efficient in terms of execution time than the bargaining procedure, which has to iterate until convergence. This execution efficiency of Stackelberg game comes at the expense of fairness loss due to the leader's (LSE's in this case) advantage, which will be confirmed numerically later (c.f. Fig. 8-(d)(f)).

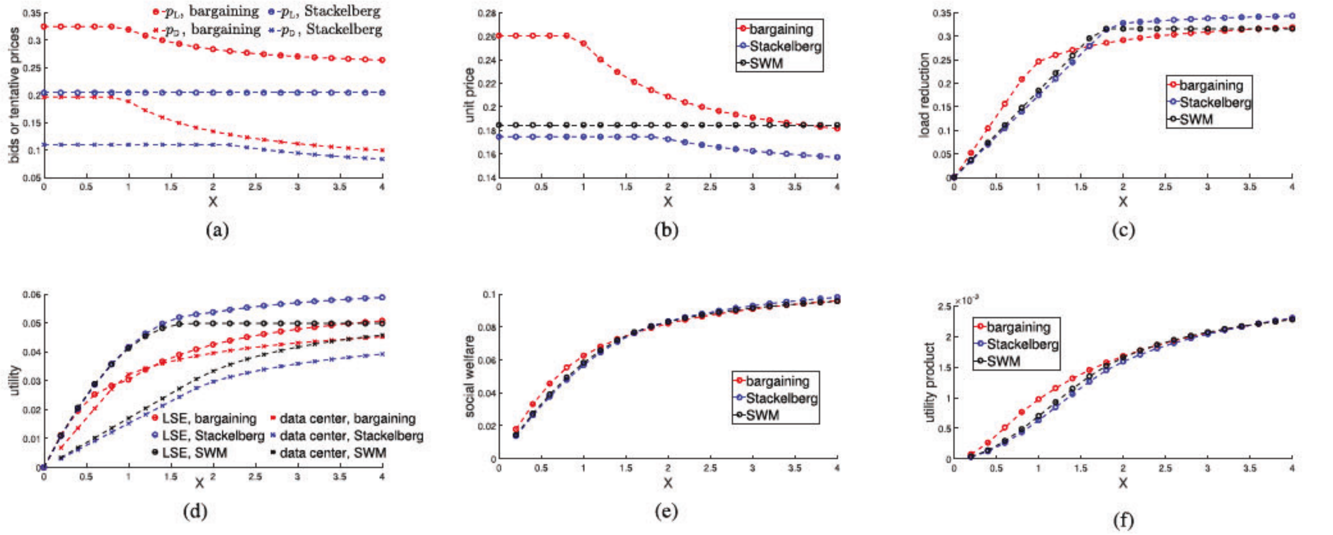

Fig. 8. Comparison between the proposed bargaining, the Stackelberg game, and the social welfare maximization schemes. (a) Bids in the bargaining and tentative prices in the Stackelberg game. (b) Comparison of unit prices. (c) Comparison of realized load reduction. (d) Comparison of the utilities. (e) Comparison of the social welfare (note that, in the SWM scheme, the social designer is unaware of the on-site renewable generation X). (f) Comparison of the utility product.

Now, we detail the implementation of the Stackelberg game scheme in the following. We first note that the LSE will not propose a p_{L} greater than $2CD$, otherwise the finalized price p will be greater than CD for any $p_{\mathsf{D}} \geq 0$, which implies that the realized load reduction $\mathsf{q}(p, X)$ (and thus the utility of the LSE) will be identically zero. Given $p_{\mathsf{L}} \in (0, 2CD)$, the data center (the follower in the Stackelberg game), being aware of its private information X, will choose p_{D} to be:

$$\begin{aligned}&\mathsf{B}_{\mathsf{D}}(p_{\mathsf{L}}; X)\\ &= \arg\max_{p_{\mathsf{D}} \geq 0} F(p_{\mathsf{L}} - p_{\mathsf{D}})\mathsf{S}_{\mathsf{D}}\left(\frac{p_{\mathsf{L}}+p_{\mathsf{D}}}{2}, \mathsf{q}\left(\frac{p_{\mathsf{L}}+p_{\mathsf{D}}}{2}, X\right), X\right),\end{aligned}$$

which is the same best response used in the bargaining procedure and thus can be solved in the same way as in Algorithm 2. The LSE (the leader), anticipating the response of the data center, will choose a p_{L} to maximize its expected utility (since it does not know X), i.e., p_{L} will be chosen as the optimal solution of the following probelm:

$$\begin{aligned}\underset{0 < p_{\mathsf{L}} < 2CD}{\text{Max.}} \ \mathbb{E}\Bigg[F(p_{\mathsf{L}} - \mathsf{B}_{\mathsf{D}}(p_{\mathsf{L}}; X))\mathsf{S}_{\mathsf{L}}\Bigg(&\frac{p_{\mathsf{L}} + \mathsf{B}_{\mathsf{D}}(p_{\mathsf{L}}; X)}{2},\\ &\mathsf{q}\left(\frac{p_{\mathsf{L}} + \mathsf{B}_{\mathsf{D}}(p_{\mathsf{L}}; X)}{2}, X\right)\Bigg)\Bigg]. \quad (34)\end{aligned}$$

We observe that (34) is different from the LSE's update (8) in the bargaining procedure because the LSE knows that the Stackelberg game is bound to terminate after two iterations and thus takes the best response of the data center into consideration. Different from (8), the objective function in (34) is no longer log-concave in p_{L} due to the presence of the data center's response function $\mathsf{B}_{\mathsf{D}}(p_{\mathsf{L}}; X)$. In fact, it is hard to even evaluate the expectation in the objective function of (34) in closed-form for a given p_{L}, not to mention solving (34) analytically. Therefore, to implement the Stackelberg game scheme, we will use the average of Monte Carlo trials to approximate the expectation in (34) and conduct exhaustive search to solve (34). The exhaustive search method is feasible in this case since the optimization is over one single variable p_{L} located in the bounded interval $(0, 2CD)$.

B. Social Welfare Maximization Scheme

Next, we presume the existence of a SWM designer whose decision the LSE and the data center must obey. In such a case, to reduce loads, the designer sets a unit price p, which the LSE and the data center have to accept. What the LSE and the data center can decide is only the demand response $d(p)$ and $s(p, X)$ given the unit price p. The designer, *being unaware of the data center's on-site renewable generation X*, aims to maximize the expected social welfare, i.e., it chooses a unit price p by solving the following problem:

$$\underset{p \geq 0}{\text{Max.}} \ \mathbb{E}[\mathsf{S}_{\mathsf{L}}(p, \mathsf{q}(p, X))] + \mathbb{E}[\mathsf{S}_{\mathsf{D}}(p, \mathsf{q}(p, X), X)], \quad (35)$$

in which $\mathbb{E}[\mathsf{S}_{\mathsf{L}}(p, \mathsf{q}(p, X))]$ is evaluated in Lemma 2 and $\mathbb{E}[\mathsf{S}_{\mathsf{D}}(p, \mathsf{q}(p, X), X)]$ can be evaluated as follows:

$$\begin{aligned}&\mathbb{E}[\mathsf{S}_{\mathsf{D}}(p, \mathsf{q}(p, X), X)]\\ &= \begin{cases}\frac{1}{2}p^2\overline{X}, \text{ if } 0 \leq p \leq \frac{CD}{1+2C\overline{X}},\\ -\frac{3\left(D-\frac{p}{C}\right)^2}{8\overline{X}} + p\left(D - \frac{p}{C}\right) - \frac{\left(D-\frac{p}{C}\right)^2}{4\overline{X}}\ln\left(\frac{2\overline{X}}{\frac{D}{p}-\frac{1}{C}}\right),\\ \qquad\qquad \text{if } \frac{CD}{1+2C\overline{X}} < p < CD,\\ 0, \text{ if } p \geq CD.\end{cases}\end{aligned}$$

We remark that the social welfare maximization (SWM) problem in (35) is different from the one considered in [12]. In [12], given an announced price, the realized load reduction depends only on the data centers' supply functions. The LSE does not have a demand function to affect the realized load curtailment. In contrast, in the SWM (35) of this paper, the LSE and the data center possess demand function and supply function, respectively, and the minimum of the two, i.e., $\mathsf{q}(p, X) = \min\{s(p, X), d(p)\}$, is the finalized load curtailment. Furthermore, since problem (35) is non-convex, we will use exhaustive search to solve it. We note that when $p \geq CD$, both terms in the objective function of (35), i.e., both expected utilities of the LSE and the data center, are zero. So, we can focus on the bounded interval $p \in [0, CD]$ only, which makes the exhaustive search method feasible.

C. Performance Comparison via Numerical Study

In this subsection, extensive numerical comparisons between different data center demand response schemes are carried out. In Fig. 8, for different realization of X, we compare various expected steady-state performance of the proposed bargaining approach, the Stackelberg game scheme, and the social welfare maximization (SWM) scheme. We change D to be 0.5 to see the impact of X more conspicuously while other parameters are the same as in Subsection III-D. We first compare the (steady-state) bids in the bargaining with the tentative prices in the Stackelberg game in Fig. 8-(a). As X increases, the bids of the bargaining first remain unaltered and then decreases, as have been observed and explained in Fig. 3. The tentative price of the LSE in the Stackelberg game does not depend on X since the LSE has no knowledge of it. The tentative price of the data center in the Stackelberg game first remains unchanged and then decreases due to similar reasons for the bids of the bargaining. We observe that the tentative prices of the Stackelberg game are lower than the bids of the bargaining. Thus, the finalized unit prices of the Stackelberg game are also lower than those of the bargaining. This highlights a *leader's advantage* of the Stackelberg game [41]: low prices benefit the LSE, i.e., the leader of the Stackelberg game. This is further confirmed in Fig. 8-(b), in which we compare the unit prices of the bargaining, the Stackelberg game, and the SWM. The Stackelberg game yields the lowest unit price and thus benefits the LSE the most. The unit price of the SWM does not depend on X because the social designer does not know X. Further, we note that the unit prices of the bargaining are larger than that of the SWM for most realizations of X, especially when X is small. The reason is as follows. When the realization of X is small, the cost of the data center is high so that it asks for higher price of compensation during the iterative bargaining procedure. In contrast, in SWM scheme, the designer is unaware that the realization of the data center's cost turns out to be high. So, the designer still prescribes a relatively low unit price.

Additionally, we compare the realized load reduction of the three schemes in Fig. 8-(c). When X is small, the load reduction realized by the bargaining is the highest among the three schemes. This is explained as follows. When X is small, through iterative bargaining, the data center can ask for high unit price to compensate its high cost so that the unit price of bargaining is the highest among the three schemes, as have been observed in Fig. 8-(b). The high unit price in turn elicits relatively high load reduction supply from the data center even when its cost is also high. In contrast, in the Stackelberg game and the SWM, the decision makers of the schemes are not well aware that X is small (so that the cost of data center is high). In fact, in the Stackelberg game, the LSE does not know X when it is making a one-shot decision on its tentative price (unlike bargaining, there is no iterative negotiation or information feedback to inform the LSE about X gradually), while in the SWM, the sole decision maker, i.e., the social designer, is completely unaware of the realization of X. As such, in Stackelberg game and SWM, the unit prices are relatively low even when the cost of data center is high. This leads to low load reduction supply from the data center.

Furthermore, we compare the utilities of the LSE and the data center in the three schemes in 8-(d). All utilities increase with X as larger X implies low cost of the data center, which benefit the data center directly and the LSE indirectly through low prices. Besides, we observe that the gap between the utilities of the LSE and the data center is the highest for Stackelberg game, which verifies the leader's advantage again. In contrast, this utility gap of the bargaining is the smallest since it realizes the NBS, a proportionally fair outcome. This highlights the fairness of the bargaining approach, which is reached through iterative negotiation between the LSE and the data center.

Moreover, in Fig. 8-(e), we compare the social welfare, i.e., the sum of the utilities of the LSE and the data center, of the three schemes. Somewhat surprisingly, the bargaining approach, instead of the SWM, yields the greatest social welfare when X is small. This can be explained as follows. In bargaining, though the direct goal is not to maximize the social welfare, one of the decision makers, the data center, knows the value of X and informs the LSE about X gradually through iterative negotiation. This is an information advantage over the SWM scheme, in which the sole decision maker, i.e., the social designer, does not know X. This advantage is especially significant when the realization of X is small. Recall that the load reduction cost of the data center is proportional to $1/X$ (c.f. (4)), which decreases dramatically when X is small. As such, when X is small, the realization of X is very valuable information in the bargaining since the realized utility of the data center is far from its mean value for random X. This renders the bargaining approach superior to the SWM scheme in terms of social welfare. To further confirm the social welfare benefits of the bargaining, we change the load reduction cost of the data center to be $\frac{q^2 Y}{2}$, wherer Y is uniformly distributed over $[\underline{y}, \overline{y}]$ with $\overline{y} \geq \underline{y} \geq 0$. In other words, the load reduction cost of the data center is linear in the random variable Y (as oppposed to being inversely proportional to X in the original model), whose realization is privately known to the data center. In such a case, the utility function of the data center becomes

$$\widetilde{\mathsf{S}}_{\mathsf{D}}(p, q, Y) = pq - \frac{q^2 Y}{2}, \tag{36}$$

and the supply function of the data center becomes

$$\widetilde{s}(p, Y) = \arg\max_{q \geq 0} \widetilde{\mathsf{S}}_{\mathsf{D}}(p, q, Y) = \frac{p}{Y}. \tag{37}$$

We note that the log-concavity of the (expected) utility functions of the LSE and the data center no longer holds for this model. Thus, problem (7) becomes nonconvex after taking the logarithm and the NBS can only be computed numerically with exhaustive search. The social welfare of the bargaining, Stackelberg game, and SWM schemes is shown in Fig. 9

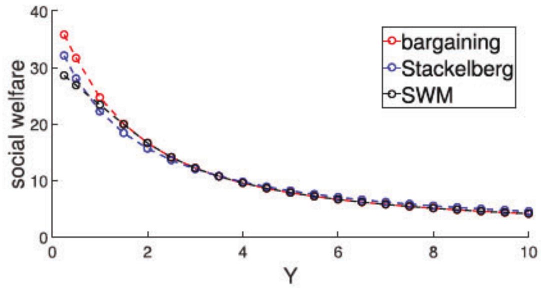

Fig. 9. Comparison of social welfare when the load reduction cost of the data center is linear in Y.

TABLE II
COMPARISON BETWEEN THE THREE SCHEMES

Criteria \ Schemes	Bargaining	Stackelberg game	SWM
Unit price	High	Low	Medium
Load reduction for small X	High	Low	Medium
Utility of the LSE	Low	High	Medium
Utility of the data center	High	Low	Medium
Social welfare for small X	High	Low	Medium
Utility product	High	Low	Medium

for different values of Y, where $\underline{y} = 0.25$ and $\overline{y} = 10$. We observe that, the bargaining approach still outperforms the SWM and Stackelberg game schemes when Y is small. The reason is similar to that of the original model. When Y is small, the supply function of the data center $\frac{p}{Y}$ decreases dramatically with Y and deviates significantly from its mean value for random Y. In such a case, the information about Y is very valuable, which is fully utilized by the bargaining approach.

Finally, we compare the product of the utilities of the LSE and the data center in Fig. 8-(f). The utility product of the bargaining mechanism is the highest, especially when X is small. This again highlights the proportional fairness of the bargaining approach established theoretically in Theorem 2. Besides, unsurprisingly, the Stackelberg game yields the lowest utility product because it is the least fair scheme (the LSE has a remarkable leader's advantage, c.f. Fig. 8-(d)).

The numerical comparison between the proposed bargaining, the Stackelberg game, and the SWM schemes is summarized in Table II. From the table, it is clear that the bargaining approach favors the data center the most, while the Stackelberg game favors LSE the most. The effect of the SWM scheme is between that of bargaining and the Stackelberg game. The performance of the bargaining approach manifests the significant market power of the price-negotiating data center.

V. CONCLUSION

In this paper, we have proposed an iterative bargaining algorithm for pricing data center demand response with on-site renewable generation, where the data center has significant market power in affecting the price. Computationally efficient methods of implementing the best response updates in the bargaining have been presented by making use of the log-concavity of the (expected) utility functions. Furthermore, we have shown analytically that the bid sequences of the LSE and the data center are convergent and the final price clinched by the bargaining coincides with the NBS, a proportionally fair outcome. In addition, the breakdown probability of the bargaining can be made arbitrarily small by parameter tuning. Two other demand response schemes, namely SWM and Stackelberg game schemes, have also been considered for comparison purposes. Extensive numerical results have been presented to corroborate the effectiveness of the proposed bargaining approach. The impact of system parameters and comparison with other demand response schemes have been studied to provide insight into the design of data center demand response.

Assuming linear pricing for the demand response products, this paper has focused on a bargaining solution that can efficiently utilize renewable resources and distributed demand response products in concert with traditional grid resources. There are more sophisticated pricing schemes, including tiered piecewise linear pricing and nonlinear pricing. It is of great interest to study data center demand response under these pricing mechanisms in the future.

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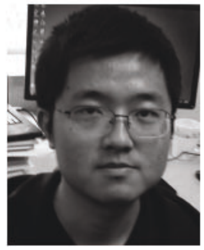

Xuanyu Cao received the B.E. degree in electrical engineering from Shanghai Jiao Tong University, Shanghai, in 2013, and the M.S. and the Ph.D. degrees in electrical engineering from the University of Maryland, College Park, MD, USA, in 2016 and 2017, respectively. Since 2017, he has been a Post-Doctoral Research Associate with the Department of Electrical Engineering, Princeton University, Princeton, NJ, USA. His research interests lie in the optimization, game theory, signal processing, and probabilistic methods, with applications to information systems and networks.

Junshan Zhang (S'98–M'00–SM'06–F'12) received the Ph.D. degree from the School of ECE, Purdue University in 2000. He joined the School of ECEE at Arizona State University in August 2000, where he has been Fulton Chair Professor since 2015. His research interests fall in the general field of information networks and data science, including communication networks, Internet of Things (IoT), Fog Computing, social networks, and smart grid. His current research focuses on fundamental problems in information networks and data science, including Fog Computing and its applications in IoT and 5G, IoT data privacy/security, optimization/control of mobile social networks, information theory, stochastic modeling and control for smart grid.

He received the ONR Young Investigator Award in 2005, the NSF CAREER Award in 2003, and the IEEE Wireless Communication Technical Committee Recognition Award in 2016. His papers have won a few awards, including the Best Student Paper award at WiOPT 2018, the Kenneth C. Sevcik Outstanding Student Paper Award of ACM SIGMETRICS/IFIP Performance 2016, the Best Paper Runner-up Award of IEEE INFOCOM 2009 and IEEE INFOCOM 2014, and the Best Paper Award at IEEE ICC 2008 and ICC 2017. Building on his research findings, he co-founded Smartiply Inc., a Fog Computing startup company delivering boosted network connectivity and embedded artificial intelligence.

Prof. Zhang was TPC Co-Chair for a number of major conferences in communication networks, including IEEE INFOCOM 2012 and ACM MOBIHOC 2015. He was the General Chair for ACM/IEEE SEC 2017, WiOPT 2016, and IEEE Communication Theory Workshop 2007. He was a Distinguished Lecturer of the IEEE Communications Society. He was an Associate Editor for the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS and an Editor for the *Computer Network* journal and *IEEE Wireless Communication Magazine*. He is currently serving as an Editor-at-Large for IEEE/ACM TRANSACTIONS ON NETWORKING and an editor for *IEEE Network Magazine*.

H. Vincent Poor (S'72–M'77–SM'82–F'87) received the Ph.D. degree in EECS from Princeton University in 1977. From 1977 to 1990, he was on the faculty of the University of Illinois at Urbana–Champaign. Since 1990, he has been on the faculty at Princeton, where he is currently the Michael Henry Strater University Professor of Electrical Engineering. From 2006 to 2016, he served as the Dean of Princeton's School of Engineering and Applied Science. He has also held visiting appointments at several other universities, including most recently at Berkeley and Cambridge. His research interests are in the areas of information theory and signal processing, and their applications in wireless networks, energy systems, and related fields. Among his publications in these areas is the recent book *Information Theoretic Security and Privacy of Information Systems* (Cambridge University Press, 2017).

Dr. Poor is a member of the National Academy of Engineering and the National Academy of Sciences, and a foreign member of the Chinese Academy of Sciences, the Royal Society, and other national and international academies. He received the Marconi and Armstrong Awards of the IEEE Communications Society in 2007 and 2009, respectively. Recent recognition of his work includes the 2017 IEEE Alexander Graham Bell Medal, Honorary Professorships at Peking University and Tsinghua University, both conferred in 2017, and a D.Sc. *honoris causa* from Syracuse University in 2017.