Second Chance Works Out Better: Saving More for Data Center Operator in Open Energy Market

(Invited Paper)

Peijian Wang[*], Ying Zhang[*], Lei Deng[*], Minghua Chen[*], Xue Liu[†]

[*]Department of Information Engineering, The Chinese University of Hong Kong, Hong Kong
[†]School of Computer Science, McGill University, Canada

Abstract—Geographical load balancing (GLB) is a promising technique to reduce power cost for cloud service providers (CSPs). To fully exploit the potential of GLB, Camacho *et al.* [1] advocate broker-assisted GLB where CSPs first bid in deregulated electricity markets and then balance their workloads accordingly. In this paper, we further explore along this line and propose the idea of Second Chance, which explores the design space in sequential bidding into sequential geographical markets. We formulate the optimal sequential bidding and GLB problem as a Markov Decision Process (MDP) problem. To solve this problem, however, faces the curse of dimensionality commonly encountered in MDP approach. To tackle this challenge, we first establish an optimality criterion for the problem and derive the structure of cost-to-go function. Then we analytically characterize the optimal action. Real-world trace-driven evaluation shows that the electricity cost can be reduced by more than 10% by jointly using GLB and Second Chance.

I. INTRODUCTION

Nowadays, cloud services providers (CSPs) such as Google and Facebook have deployed massive geo-distributed data centers to provision Internet-scale cloud computing. Consequently, data centers consume a significant amount of electricity. According to [2], date centers consume 1.1%-1.5% of total worldwide electricity, exceeding 200 millon MWh per year. Electricity cost inevitably becomes a large portion of data center operating expense [3]. To reduce electricity cost, geographical load balancing (GLB) [4]–[7] has been proposed by moving location-independent workload to data centers at locations with cheaper electricity price. Extensive research has been proposed and can be found in a recent survey [8].

Trace-driven studies show that GLB can reduce 30%-45% electricity cost, depending on the amount of shifted workload [4]. However, such positive result usually relies on the assumption that the electricity prices are known as a prior and will not be affected by GLB. On the negative side, some recent works [9], [10] show that the electricity price will increase remarkably if too much workload is routed to that data center. Camacho et al. [1] demonstrate that GLB can make the electricity supply chain less efficient in the sense that it introduces significant demand uncertainty such that utilities cannot predict demand accurately and therefore will increase the electricity price for data centers. They also show that CSP may end with even *higher* electricity cost after using GLB. To exploit the benefit of GLB realistically, Camacho et al. [1] propose the so-called *broker-assisted GLB*. Broker-assisted GLB suggests that data centers directly participate in wholesale electricity markets, which no longer causes economic inefficiency to utilities. This completely changes

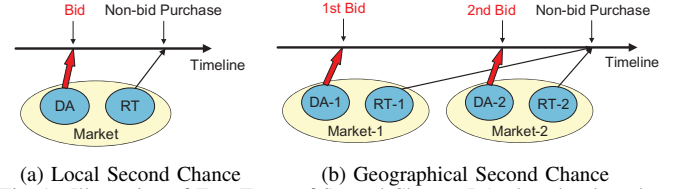(a) Local Second Chance   (b) Geographical Second Chance

Fig. 1. Illustration of Two Types of Second Chance. DA: day-ahead market; RT: real-time market.

CSP's electricity procurement paradigm, introducing new opportunities and also challenges.

Such new paradigm introduces a key challenge that CSPs must directly face market uncertainty themselves. To clarify this challenge, we briefly introduce current wholesale electricity markets. In North America, the electricity markets are regional and there are usually two types of markets in each region: day-ahead market and real-time market. To purchase electricity in the day-ahead market, customers should submit their bids before market close time. The bidding results are usually published several hours before the dispatching day. Real-time market is a pay-as-you-go on-dispatching market that the price is calculated based on actual electricity usage. For both markets, the prices are unknown while making procurement decisions. Thus, CSPs must decide electricity procurement in each market with incomplete information.

On the other hand, there are also new opportunities. An important observation is that different markets are usually operated at different time. Inspired by this observation, we propose the idea of Second Chance, which sequentially makes electricity procurement decisions in different markets. The market uncertainties of earlier markets can be eliminated while making decisions in later markets. On the one hand, after revealing the outcomes of earlier markets, CSPs could adapt their decisions in later markets. On the other hand, later markets also provide a 'second chance' to fulfill unsatisfied demand. This encourages CSPs to aggressively make decisions in earlier markets. Thus, by taking into account Second Chance, CSPs have new design space to explore.

For a CSP who operates multiple geo-distributed data centers, there are two types of Second Chance: *local* Second Chance and *geographical* Second Chance. *Local* Second Chance is applied to different markets, i.e. day-ahead and real-time markets, at the same locations. Consider a simple example shown in Fig.1a. Since day-ahead market and real-time market are operated at different time, CSPs could first bid in day-ahead market aggressively, then make decisions in real-time market after revealing the outcomes of day-ahead market.

Geographical Second Chance is applied to different markets at different locations. Consider another example shown in Fig.1b. A CSP has two data centers which should participate in different day-ahead and real-time markets in different regions. Due to time difference, two day-ahead markets are operated at different time. So the CSP can first bid in the earlier day-ahead market. After the bidding results are published, he can adaptively place bids in the second day-ahead market.

It is worth noting that *local* Second Chance is applicable for all customers who can participate in both day-ahead and real-time markets. Similar idea has been studied in some recent works [1], [11]. However, *geographical* Second Chance is impossible to apply to traditional electricity customers. By introducing GLB, CSPs become a new type of users that never appear in electricity supply chain before. They have flexible demand which can be moved across locations, and thereby can apply *geographical* Second Chance. Besides flexible demand, *geographical* Second Chance also requires sequential day-ahead markets in different regions. To justify this, we investigate all deregulated markets in the US, and show the related timeline in Table I. In day-ahead market, customers must submit bids before market close time, and see the results at post time. They can do nothing during this time interval. To apply *geographical* Second Chance, such time intervals in different day-ahead markets should not overlap. As shown in the table, there do exist some markets which satisfy this condition, e.g. NYISO and PJM.

We note that the related sequential decision problems have been studied extensively, by using for example Markov Decision Process (MDP) approach. Unfortunately, such classical strategies do not work well for our Second Chance problem due to the following unique challenges. First, the problem suffers the curse of dimensionality due to the continuous state space. CSPs should sequentially decide how much workload is served by each data center. So the system state is unsatisfied workload, which the set of possible value is a continuous interval. It is highly non-trivial to solve the problem using the classic backward induction approach by enumerating all states. Second, GLB introduces some unique constraints (e.g. data center capacity constraints), and traditional sequential bidding strategy [11] cannot be directly applied to take care of these new constraints.

In this paper, we investigate the problem how CSPs utilize Second Chance to reduce the electricity cost and address above challenges. In particular, we make the following contributions:

▷ We formulate our problem of GLB with both local and geographical Second Chance as an infinite-dimension (continuous state space) finite-horizon MDP problem in Sec. II.

▷ As commonly rooted in the MDP approach, our problem with MDP formulation suffers the curse of dimensionality

where we have an infinite number of states. However, by carefully exploiting our problem structure, we obtain the optimal policy structure in Sec. III. More specifically, we prove that the cost-to-go function is convex and piece-wise linear for any state, the optimal action can be characterized analytically.

▷ In Sec. IV, we use real-world data-trace to show that our algorithm utilizing both *local* and *geographical* Second Chance can reduce electricity cost by more than 10%.

II. SYSTEM MODEL AND MDP FORMULATION

A. CSP and Electricity Price

Consider a cloud provider, e.g. Google or Facebook, operates N data centers located in different regions, and indexed from 1 to N. Users submit requests to a front-end portal, and the requests should be forwarded to some data centers to be processed. For simplicity, we do not consider the network cost in this paper and we assume that any user request can be delivered to any data center freely.

We assume that all users' requests incur $D > 0$ amounts of electricity demand and data center i has a maximum capacity C_i. To serve users' requests, each data center $i \in [1, N]$ needs to buy electricity from its own local electricity markets. The total amount of electricity purchased from all local markets should not exceed the capacity C_i. As discussed in Sec. I, we consider two types of local electricity markets, day-ahead market and real-time market. Denote the electricity prices in day-ahead and real-time markets at location i by random variables P_i and P_i^b, respectively. We assume that the stochastic information of prices can be obtained from historical data. Denote the probability density functions (PDF) for P_i and P_i^b by $f_i(\cdot)$ and $f_i^b(\cdot)$, respectively. Also, we assume all P_i's and P_i^b's are mutually independent.

Without loss of generality, we assume that the close time of bid submission for data center $i + 1$ is later than the post time of auction result for data center i such that all data centers can make decisions based on the auction results of previous day-ahead markets.

B. Bidding Strategy

Suppose that a data center submits K bids $\{< b_k, q_k >: k = 1, 2, \cdots, K\}$ to ISO. If the market clear price (MCP) in day-ahead market is p, all bids with bidding price $b_k \geq p$ could succeed and the successful procurement from day-ahead market would be $q(p) = \sum_{k: b_k \geq p} q_k$. This function $q(p)$ captures the relationship between the actual electricity procurement and MCP in day-ahead market. We call it *bidding curve* since it can be realized by submitting multiple bids. In the following, we will use bidding curves to denote the strategy of procuring electricity from day-ahead market for each data center. In this paper, we do not restrict the number of bids K and we will assume that a data center can submit a bidding curve $q(\cdot)$ as long as $q(\cdot)$ is a nonincreasing function over $\mathbb{R}$ with $q(+\infty) = 0$. Note that our model is general enough to capture the negative price, which occurs in real world. Thus the total/aggregate bidding quantity in a bidding curve $q(\cdot)$ is $q(-\infty) \triangleq \lim_{p \to -\infty} q(p)$.

On the other hand, data centers cannot guarantee to win bids and buy electricity from the uncontrollable day-ahead market. For business purpose, ensuring user experience is

more important than saving cost. We thus require that the CSP should satisfy all demand D for surely. However, due to individual capacity constraint C_i for each data center i, the CSP cannot move demand arbitrarily to some data centers. In this paper, we thus require that a fixed amount of demand is guaranteed to be served by each data center sequentially.

Specifically, data center i submits two bidding curves $q_{i,1}(\cdot)$ and $q_{i,2}(\cdot)$ to its day-ahead market. They are both non-increasing functions of the MCP of day-ahead market i, and capture *geographical* Second Chance and *local* Second Chance, respectively. When the MCP is $P_i = p$, the successful bidding quantity in $q_{i,1}(\cdot)$ (resp. $q_{i,2}(\cdot)$) is $q_{i,1}(p)$ (resp. $q_{i,2}(p)$). For *geographical* Second Chance, the unsuccessful bids ($q_{i,1}(-\infty) - q_{i,1}(p)$) will be served by later data centers (from $i+1$ onward). In contrast, the unsuccessful bids for *local* Second Chance ($q_{i,2}(-\infty) - q_{i,2}(p)$) should be purchased in local real-time market i. Thus, the aggregate bidding quantity $q_{i,2}(-\infty)$ is guaranteed to be served locally in data center i.

Before formulating our problem, we summarize key notations in Tab. II.

TABLE II
KEY NOTATIONS

Notation	Definition
N	Number of data centers
i	Location/Data center/Day-ahead market/Real-time market i
D	Total demand
C_i	Capacity of data center i
P_i	Market clearing price in day-ahead market i
P_i^b	Price in real-time market i
$\bar{P}_i^b$	Expected price in real-time market i, i.e., $\bar{P}_i^b \triangleq \mathsf{E}\left[P_i^b\right]$
$f_i(\cdot)$	Probability density function (PDF) of P_i
$f_i^b(\cdot)$	Probability density function (PDF) of P_i^b
$q_{i,1}(\cdot)$	First bidding curve in day-ahead market i
$q_{i,2}(\cdot)$	Second bidding curve in day-ahead market i
$q_{i,1}(-\infty)$	Defined as $q_{i,1}(-\infty) \triangleq \lim_{p \to -\infty} q_{i,1}(p)$
$q_{i,2}(-\infty)$	Defined as $q_{i,2}(-\infty) \triangleq \lim_{p \to -\infty} q_{i,2}(p)$

C. MDP Formulation

Our goal is to minimize the total (expected) cost of all N data centers while satisfying all demand D. The design space is data centers' bidding strategy. It is a stochastic optimization problem due to the randomness of day-ahead market price P_i and real-time market price P_i^b. Since data centers make decisions sequentially, it is natural to use MDP to formulate our problem. This subsection explains how to cast it to a (continuous-state-space) finite-horizon MDP problem.

Similar to classic MDP definition [12], our MDP problem can be described by a tuple $(\mathcal{T}, \mathcal{S}, \mathcal{A}_{i,s}, g_i(s'|s,a), c_i(s,a))$ where $\mathcal{T}$ is the set of decision epochs, $\mathcal{S}$ is the state space which is continuous in our problem, $\mathcal{A}_{i,s}$ is the set of all possible actions when the state is $S_i = s \in \mathcal{S}$ at decision epoch i, $g_i(s'|s,a)$ is the conditional PDF transiting from state $S_i = s \in \mathcal{S}$ at decision epoch i to state $S_{i+1} = s' \in \mathcal{S}$ at decision epoch $i + 1$ when the action is $A_i = a \in \mathcal{A}_{i,s}$ at decision epoch i, and $c_i(s,a)$ is the cost at decision epoch i of taking action $A_i = a$ under state $S_i = s$. We now describe the tuple in details.

Definition of the decision epochs: In our problem, all data centers take decisions sequentially from 1 to N. Thus, the set of all decision epochs is naturally defined as $\mathcal{T} \triangleq \{1, 2, \cdots, \mathsf{N}\}$. Based on this, in the rest of this paper, we will use decision epoch i and data center i interchangeably.

Definition of the state: We define the remaining demand as the state at each data center. Thus, the state space is a continuous interval, defined as $\mathcal{S} \triangleq [0, \mathsf{D}]$. We use random variable S_i as the state at data center i, which is the remanning demand that must be satisfied by data centers $i, i+1, \cdots, \mathsf{N}$.

Definition of the action: When data center i observers state $S_i = s$, its action A_i is to submit two bidding curves $q_{i,1}(\cdot)$ and $q_{i,2}(\cdot)$ to its day-ahead market. Bidding curves $q_{i,1}(\cdot)$ and $q_{i,2}(\cdot)$ should satisfy the following constraints,

$$q_{i,1}(p) \geq q_{i,2}(p'), q_{i,2}(p) \geq q_{i,2}(p'), \quad \forall p < p', \qquad (1a)$$

$$q_{i,1}(-\infty) + q_{i,2}(-\infty) \leq \min\{s, \mathsf{C}_i\}, \qquad (1b)$$

$$s - q_{i,2}(-\infty) \leq \sum_{j=i+1}^{\mathsf{N}} \mathsf{C}_j. \qquad (1c)$$

Constraint (1a) restricts biding curves to be non-increasing. Constraint (1b) restrict that the total bidding quantities should not exceed the remaining demand s and data center capacity C_i. In addition, to make sure that all demand D can be satisfied, we restrict that after data center i, the remaining demand cannot exceed the total capacities of the remaining data centers. However, in the worse case, all bids in day-ahead market i could fail, under which data center should buy at least $q_{i,2}(-\infty) = s - \sum_{j=i+1}^{\mathsf{N}} \mathsf{C}_j$ amounts of electricity from its real-time market. This is constraint (1c).

We refer $(q_{i,1}(\cdot), q_{i,2}(\cdot))$ as the action at data center i. The action set is thus defined as $\mathcal{A}_{i,s} \triangleq \{(q_{i,1}(\cdot), q_{i,2}(\cdot)) : q_{i,1}(\cdot)$ and $q_{i,2}(\cdot)$ satisfy $(1a) - (1c)\}$.

The outcome after bidding: Before we give definitions of the transition probabilities and the cost, we first need to analyze the bidding outcome. Suppose that at data center i, its state is $S_i = s$ and its action is $A_i = (q_{i,1}(\cdot), q_{i,2}(\cdot))$. Clearly, $q_{i,1}(P_i) + q_{i,2}(P_i)$ amounts of electricity are purchased in day-ahead market with price P_i. The failed bids with amount $(q_{i,2}(-\infty) - q_{i,2}(P_i))$ for *local* Second Chance will be purchased in real-time market with real-time market P_i^b. Therefore, the state of data center $i + 1$ comes to

$$\begin{aligned} S_{i+1} &= s - (q_{i,1}(P_i) + q_{i,2}(P_i)) - (q_{i,2}(-\infty) - q_{i,2}(P_i)) \\ &= s - q_{i,1}(P_i) - q_{i,2}(-\infty). \end{aligned} \qquad (2)$$

Definition of the transition probabilities: Since the state in our problem is a continuous random variable, we capture the transitions by a conditional PDF $g_i(s'|s,a)$. According to (2), in order to reach state $S_{i+1} = s'$ from state $S_i = s$, we must have $q_{i,1}(P_i) = s - s' - q_{i,2}(-\infty)$, which together with $f_i(\cdot)$ and $q_{i,1}(\cdot)$ can completely characterize $g_i(s'|s,a)$. However, we should differentiate non-increasing-staircase bidding curve and strictly-decreasing bidding curve, which respectively incur discrete s' such that $g_i(s'|s,a)$ is a distribution function and continuous s' such that $g_i(s'|s,a)$ is a density function. Both cases can be written in a unified way where $g_i(s'|s,a)$ is a density function. Our solution works for both cases. Due to space limitation, we omit such unified characterization for $g_i(s'|s,a)$.

Definition of the cost: According to the bidding outcome, if the state and the action of data center i are $S_i = s$ and $A_i =$

$(q_{i,1}(\cdot), q_{i,2}(\cdot))$, the cost of data center i includes day-ahead market cost and real-time market cost, and is thus defined as

$$
\begin{aligned}
&c_i(s, (q_{i,1}(\cdot), q_{i,2}(\cdot))) \\
&\triangleq \mathsf{E}_{P_i, P_i^b} \left[P_i(q_{i,1}(P_i) + q_{i,2}(P_i)) + P_i^b (q_{i,2}(-\infty) - q_{i,2}(P_i)) \right] \\
&= \mathsf{E}_{P_i} \left[P_i(q_{i,1}(P_i) + q_{i,2}(P_i)) + \bar{P}_i^b (q_{i,2}(-\infty) - q_{i2}(P_i)) \right] \\
&= \int_{-\infty}^{+\infty} \left[p(q_{i,1}(p) + q_{i,2}(p)) + \bar{P}_i^b (q_{i,2}(-\infty) - q_{i,2}(p)) \right] f_i(p) dp \\
&= \bar{P}_i^b q_{i,2}(-\infty) + \int_{-\infty}^{+\infty} \left[p(q_{i,1}(p) + q_{i,2}(p)) - \bar{P}_i^b q_{i,2}(p) \right] f_i(p) dp.
\end{aligned}
$$

The overall MDP-based optimization: Based on such definitions, our problem is formulated as the following finite-horizon MDP problem:

$$
\min_{\pi \in \Pi} \sum_{i=1}^{N} \mathsf{E}^{\pi} \left[c_i(S_i, A_i) \right],
$$

where Π is the set of all possible policies.

III. Optimal Solution

We have shown that our problem is fundamentally a MDP problem. However, as rooted in the MDP solution itself, our problem suffers the curse of dimensionality. As we can see, our state space $\mathcal{S} = [0, D]$ is a continuous interval and thus has infinite number of states. It is non-trivial to solve the finite-horizon MDP using the classic backward induction approach [12, Ch. 4] by enumerating all infinite number of states.

The reason is that MDP is a general framework with powerful modeling capability, but cannot exploit problem-dependent structures. In this section, we address the curse of dimensionality by analyzing the structure of our problem. More specifically, we show that the cost-to-go function is convex and piece-wise linear which enables us to characterize the optimal action for any state analytically. It turns out that the optimal action can be realized by submitting a finite number of bids.

A. Optimality Criterion

In this section, we develop an optimality criterion for the MDP problem. We use cost-to-go functions $\text{Cost}_i^*(s)$ to represent the minimal expected total cost from data center i onward, given the remaining demand s. Then we can have the **optimality condition** by

$$
\begin{aligned}
&\text{Cost}_i^*(s) \\
&= \min \int_{-\infty}^{\infty} \Big\{ p(q_{i,1}(p) + q_{i,2}(p)) + \bar{P}_i^b(q_{i,2}(-\infty) - q_{i,2}(p)) \\
&\quad + \text{Cost}_{i+1}^*(s - q_{i,1}(p) - q_{i,2}(-\infty)) \Big\} f_i(p) dp,
\end{aligned} \quad (3)
$$

for $i = 1, \ldots, N-1$. For the last data center, we have

$$
\begin{aligned}
&\text{Cost}_N^*(s) \\
&= \min \int_{-\infty}^{\infty} \Big\{ pq_{N,2}(p) + \bar{P}_N^b(s - q_{N,2}(p)) \Big\} f_N(p) dp.
\end{aligned} \quad (4)
$$

Note that data center N only needs 1 bidding curve $q_{N,2}(p)$ and all remaining demand s must be served. The following theorem shows the structure of cost-to-go functions:

Theorem 1: For each data center $i \in [1, N]$, the cost-to-go function satisfies the following properties:

1) Function $\text{Cost}_i^*(s)$ is a piece-wise linear function of s. Thus, it can be written as,

$$
\text{Cost}_i^*(s) = \begin{cases} \alpha_{i1}s + \beta_{i1}, & \gamma_{i0} \le s \le \gamma_{i1} \\ \vdots & \vdots \\ \alpha_{iK_i}s + \beta_{iK_i}, & \gamma_{i,K_i-1} < s \le \gamma_{iK_i} \end{cases}, \quad (5)
$$

where K_i is the number of pieces, $0 \le \gamma_{i0} < \gamma_{i1} < \ldots < \gamma_{iK_i} \le \sum_{j=i}^{N} C_j$, α_{ik}, β_{ik} and $\gamma_{ik}, k = 1, 2, \ldots K_i$ are all constants.

2) Function $\text{Cost}_i^*(s)$ is a convex function in s. In another word, we have $\alpha_{ik} < \alpha_{i,k+1}$ for any $1 \le k < K_i$.

3) The number of pieces K_i is upper bounded by $2^{N-i+1}-1$.

4) The endpoints of intervals γ_{ik} must be the summation of some of data center capacities.

The proofs and calculation of α_{ik}, β_{ik} and γ_{ik} are omitted due to space limitation. Here we briefly analyze the intuition revealed by the above theorem. Firstly, the cost-to-go function should be always linear if there is no capacity constraint. This is easy to understand. Without capacity constraints, CSPs can always choose the cheapest market to purchase electricity. The marginal cost will be a constant for one data center and the total cost will be a linear function of demand. However, capacity constraints are the sources of changing marginal cost and introducing piece-wise into the cost-to-go function. They also make the cost-to-go function hard to derive. Secondly, the convexity of cost-to-go function infers that the marginal cost keeps increasing. This also confirms the intuition. Since the CSP always chooses the cheapest market first, the marginal cost will increase when the demand increase cross the boundaries of capacities. Finally, the endpoints of intervals are summation of data center capacities. So the maximum number of combinations is 2^{N-i+1} for data center i. The number of pieces is the number of endpoints minus one.

B. Optimal Bidding Strategy

While deriving the cost-to-go function, the optimal bidding strategy is also obtained. Here we just provide brief analysis of the basic idea. To solve problem (3), we can decompose the problem into infinite number of subproblems: minimizing the inner of the integral for each day-ahead price. The objective function is piece-wise linear. So $\alpha_{i+1,k}$ and $\bar{P}_i^b$ divide the feasible region of P_i into several intervals. In each interval, the solutions of all subproblems are the same. Since the number of $\alpha_{i+1,k}$ is upper bounded, we can derive the structure of the solution which is shown in the following theorem:

Theorem 2: Each bidding curve is a non-increasing step function. Thus, each step represents a bid. The height is bidding price and the width is bidding quantity. Specifically, the bids of ith data center has the following properties,

1) If the cost-to-go function $\text{Cost}_{i+1}^*(s)$ is expressed by (5), then the bidding prices must be among $\bar{P}_i^b$ and $\alpha_{i+1,k}, k = 1, 2, \ldots K_{i+1}$.

2) All bidding prices are less than or equal to $\bar{P}_i^b$.

3) The bidding quantity is $\gamma_k - \gamma_{k-1}$.

Note that $\bar{P}_i^b$ is the expected marginal cost of real-time market i. Indeed, $\alpha_{i+1,k}$ is the expected marginal cost from data center $i+1$ onward. So the theorem tells us the CSP will always set the bidding price as the expected marginal cost of the backup market. This shows the features of the optimal

solution: it utilizes Second Chance to seek the cheapest electricity through bidding. Indeed, $\bar{P}_i^b$ can be viewed as the price of utilizing *local* Second Chance. Similarly, $\alpha_{i+1,k}$ is the price of utilizing *geographical* Second Chance. Therefore, the CSP can always compare the day-ahead price with prices of *local* and *geographical* Second Chance, and then choose the cheapest one to serve demand. This also explain why all bidding prices are lese than or equal to $\bar{P}_i^b$. Every data center has *local* Second Chance. If the day-ahead price is higher than the real-time price, the CSP will not purchase any electricity in day-ahead market.

Now, we show how to place bids according to Theorem 2. The procedure is summarized in Algorithm 1. As mentioned, all bidding prices are less than or equal to the local expected real-time price. The codes in Line 3-12 construct the bids for *local* Second Chance. The bids for *geographical* Second Chance are calculated in line 13-22.

Algorithm 1 Optimal Bidding Strategy

Input: $S_i = s$, $\alpha_{i+1,k}$, $\beta_{i+1,k}$, $\gamma_{i+1,k}$;
**Output:** Bidding strategy B_i;

1: $B_i = \emptyset$
2: $K_u = \max\{k : \alpha_{i+1,k} < \bar{P}_i^b\}$;
3: **if** $s > \gamma_{i+1,Ku}$ **then**
4: $\quad q = s - \gamma_{i+1,Ku}$;
5: $\quad$ **if** $C_i > q$ **then**
6: $\quad\quad$ add a new bid $\langle \bar{P}_i^b, q \rangle$ into B_i;
7: $\quad\quad c = \min[C_i, s] - q$;
8: $\quad$ **else**
9: $\quad\quad$ add a new bid $\langle \bar{P}_i^b, C_i \rangle$ into B_i;
10: $\quad\quad c = 0$;
11: $\quad$ **end if**
12: **end if**
13: **while** $c > 0$ **do**
14: $\quad q = \gamma_{i,k} - \gamma_{i,k-1}$;
15: $\quad$ **if** $c \leq q$ **then**
16: $\quad\quad$ add a new bid $\langle \alpha_{i,k}, c \rangle$ into B_i;
17: $\quad\quad$ break;
18: $\quad$ **else**
19: $\quad\quad$ add a new bid $\langle \alpha_{i,k}, q \rangle$ into B_i;
20: $\quad\quad c = c - q$;
21: $\quad$ **end if**
22: **end while**

IV. PERFORMANCE EVALUATION

In this part, we use real-world data to evaluate how much economic gain can be obtained by seeking the Second Chance.

A. Experimental Setup

Real-world Electricity Price: In this paper, we leverage the historical electricity price in three electricity markets: NYISO, PJM and Denmark, which satisfy the requirement to exploit *geographical* Second Chance. Note that the operation days of different markets are also different due to time difference. So there are only several hours of a day satisfying the requirement. For simplicity, we ignore this minor issue and assume that *geographical* Second Chance can be applied to all hours for three markets. The price data set spans the
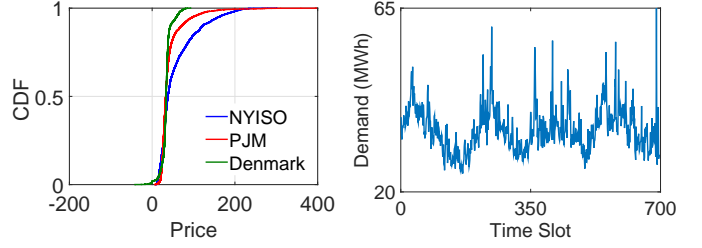
(a) CDFs of Day-Ahead Prices   (b) Workload
Fig. 2. Price and Workload

first 9 months of 2015. It is worth noting that some prices are equal to or even less than zero. Negative price is a unique phenomenon in electricity markets. As mentioned, our framework is general enough to handle negative price. Tab. III shows the expectations of prices in different markets and Fig.2a shows the CDFs of day-ahead prices.

TABLE III
EXPECTATION OF PRICE

| $\bar{P}_1$	$\bar{P}_1^b$	$\bar{P}_2$	$\bar{P}_2^b$	$\bar{P}_3$	$\bar{P}_3^b$
56.80	55.43	41.64	40.61	34.12	33.84

Data center: There are 3 data centers geographically associated with the markets in our experiments. The capacities are 35MW, 20MW and 10MW, respectively.

Workload: Recently, Google published a new sample dataset about workload running on Google compute cells [13]. This trace includes data from a cluster of 11K servers over 29 days. We map the trace into our environment. We split the duration into $24 \times 29 = 696$ slots, with 1 hour per slot. We compute the number of tasks submitted in each slot. We assume that all tasks are immediately served after submission and the power demand is proportional to the number of tasks. Thus, we map the number of tasks to the power demand in each time slot, where the peak of the workload is mapped to the total capacities of three data centers (65MW). Fig. 2b shows the power demand in each time slot.

Scheme for comparison: We compare our algorithm (referred as *SC*) with 3 schemes. The first one only purchases electricity in real-time markets and does GLB among three data centers. However, the CSP does not know the exact real-time prices before making decisions. So the workload is balanced according to the price expectations. We refer this scheme as *RT*. The second scheme directly routs the workload to the data centers proportional to their capacities (no GLB). Then it uses a naive bidding strategy for each data center: place a bid which the bidding price is local expected real-time price and the bidding quantity is the distributed workload. We refer this scheme as *Bid*. The third scheme uses the naive bidding strategy and does GLB jointly. This is the method proposed in [1]. We refer it as *BidGLB*.

B. Behaviour of Second Chance

As shown in Sec. III, the optimality criterion is really interesting: multiple bids and piece-wise linear cost function. Here we inspect the behaviour of our algorithm using real-world traces. Fig.3a shows cost-to-go functions of different data centers. Since there are no data centers with the same
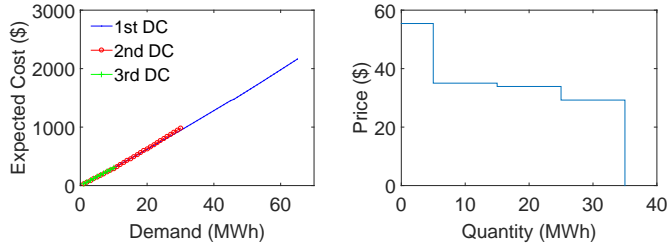
(a) Cost-To-Go Function for Different (b) Bidding Curve of First Data Center Data Centers
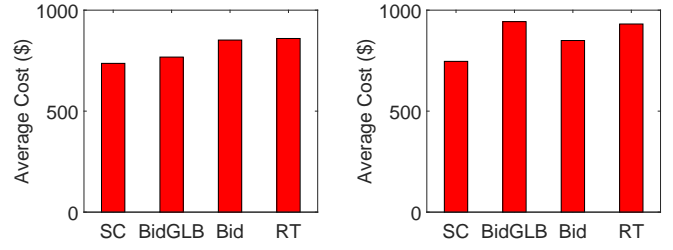
Fig. 3. Expected Cost and Bidding Curve

(a) Experiment 1   (b) Experiment 2

Fig. 4. Comparison of average cost for 4 schemes, (a) use the same part of the trace for both learning distribution and running experiments (b) use different parts, respectively;

capacities, all functions have their maximum number of pieces: 7, 3, 1, respectively. The differences of fragments are not very clear in the figure, since the slop does not increase very much. All three functions nearly coincide with each other (cost with more data centers is a little lower). Note that the first data center has much higher price (Tab. III). By exploiting Second Chance, we can reduce the unit cost to that of the cheapest data center. This is the benefit of Second Chance. Fig.3b shows the bidding curve for the first data center, given the demand as 35MWh. In this case, the CSP will place 4 (maximum number) bids. This is consistent with the analytical results in Sec. III. The earlier data centers have higher real-time prices ($\bar{P}_i^b > \alpha_{i+1,k}$). So the number of bids may achieve its upper bound.

C. Cost Reduction

In this section we compare our algorithm with 3 baselines. We split the trace of electricity price into two parts: first 5 months and last 4 months. In the first group of experiments, we use one part (latter one) for both learning the price distribution and running the experiments. The results are shown in Fig.4a. As we can see from the figure, our algorithm outperforms all the others. It has more than 10% cost reduction compared to *Bid* and *RT*. But *BidGLB* is very close to our algorithm (only 4% reduction). Since the price distribution can be estimated accurately, the benefit of Second Chance is not obvious. Then we run another group of experiments: we use first part of the trace to estimate the distribution and second part to run the experiments. The results are shown in Fig.4b. Our algorithm still outperforms all the other schemes (12.5% reduction at least). In contrast, *BidGLB* has very bad performance, even worse than two heuristics. This is because that statistic characteristics of two traces are quit different. So *BidGLB* usually makes wrong decisions which lead to higher cost even than doing nothing. For our algorithm, although the statistic estimation is inaccurate, we can still avoid very bad choices by sequential decisions. This shows the robustness of our algorithm to the market uncertainty.

V. CONCLUSION

This paper considers the broker-assisted GLB for data centers and proposes a novel framework for CSP to exploit the diversity of market auction time. In this framework, the data center whose day-ahead market close time is late will serve as a backup, so that CSP can seek cheaper electricity more ambitiously in earlier day-ahead markets. We show that this problem can be formulated as a MDP but classic backward induction fails to produce the optimal policy due to the curse of dimensionality. By carefully examining the structure of its cost-to-go function, we come up with the optimal policy for each data center. The trace-driven simulation shows its great economic potential.

REFERENCES

[1] J. Camacho, Y. Zhang, M. Chen, and D. M. Chiu, "Balance your bids before your bits: The economics of geographic load-balancing," in *Proc. ACM eEnergy*, 2014, pp. 75–85.
[2] J. Koomey, "Growth in data center electricity use 2005 to 2010," *A report by Analytical Press, completed at the request of The New York Times*, p. 9, 2011.
[3] L. A. Barroso and U. Hölzle, "The case for energy-proportional computing," *Computer*, no. 12, pp. 33–37, 2007.
[4] A. Qureshi, R. Weber, H. Balakrishnan, J. Guttag, and B. Maggs, "Cutting the electric bill for internet-scale systems," *ACM SIGCOMM computer communication review*, vol. 39, pp. 123–134, 2009.
[5] L. Rao, X. Liu, L. Xie, and W. Liu, "Minimizing electricity cost: optimization of distributed internet data centers in a multi-electricity-market environment," in *Proc. IEEE INFOCOM*, 2010, pp. 1–9.
[6] Z. Liu, M. Lin, A. Wierman, S. H. Low, and L. L. Andrew, "Greening geographical load balancing," in *Proc. ACM SIGMETRICS*, 2011, pp. 233–244.
[7] P. X. Gao, A. R. Curtis, B. Wong, and S. Keshav, "It's not easy being green," *ACM SIGCOMM Computer Communication Review*, vol. 42, no. 4, pp. 211–222, 2012.
[8] A. Rahman, X. Liu, and F. Kong, "A survey on geographic load balancing based data center power management in the smart grid environment," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 1, pp. 214–233, 2014.
[9] P. Wang, L. Rao, X. Liu, and Y. Qi, "D-pro: dynamic data center operations with demand-responsive electricity prices in smart grid," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1743–1754, 2012.
[10] Y. Zhang, Y. Wang, and X. Wang, "Electricity bill capping for cloud-scale data centers that impact the power markets," in *Proc. ICPP*, 2012, pp. 440–449.
[11] S. Sethi, H. Yan, J. H. Yan, and H. Zhang, "An analysis of staged purchases in deregulated time-sequential electricity markets," *Journal of Industrial and Management Optimization*, vol. 1, no. 4, pp. 443–463, 2005.
[12] M. L. Puterman, *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. John Wiley & Sons, Inc., 1994.
[13] C. Reiss, J. Wilkes, and J. L. Hellerstein, "Google cluster-usage traces: format+ schema," *Google Inc., Mountain View, CA, USA, Technical Report*, 2011.