Coordinated Energy Management for Colocation Data Centers in Smart Grids

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***Abstract*—Colocation data center is an important type of data centers that has some unique challenges in managing its energy consumption. Tenants in a colocation data center usually manage their servers independently without coordination, leading to inefficiency. To address this issue, we propose a formulation of coordinated energy management for colocation data centers. We formulate it as a large-scale optimization problem, and then develop a novel decentralized algorithm to solve it efficiently. Our algorithm is based on the alternating direction method of multipliers (ADMM) which converges to the global optimal solution within tens of iterations and is insensitive to step size. Extensive numerical evaluations based on real-world traces are conducted to show the performance of our algorithm.**

I. Introduction

With the current trend of transforming the century-old power grids into smart grids, the energy issue in one of the largest electricity consumers, data centers, has gained significant attention in recent years. It is estimated in [1] that data centers nowadays account for about 3% of all worldwide electricity usage. Data center operators are eager to reduce their electricity bills since electricity costs account for almost half of their total operating costs.

Most of the existing efforts in data center energy management focus on owner-operated data centers such as Google data centers or Facebook data centers. In this type of data centers, data center operators have full control of both IT equipment and facilities, and can therefore easily optimize their energy utilization through various power management techniques such as DVFS, dynamic capacity provisioning, workload migration, and advanced cooling (see [2] for a survey of these techniques). On the other hand, another important type of data centers, colocation data centers as exemplified by Equinix and TelecityGroup, is largely unexplored. A colocation data center (simply called "colo") rents out spaces for multiple tenants to host their own servers, and the colocation data center operator is mainly responsible for facility support such as power supply, cooling, and security. In practice, most large data centers belong to the latter type.

However, it is challenging to manage the energy usage in these colocation data centers. The data center operator desires reducing its electricity cost but has little control over tenants' servers, while tenants manage their servers independently based on their workload conditions without any coordination with others. Furthermore, tenants in a colocation data center are usually billed for their electricity usage based on their subscribed/reserved peak power at fixed rates no matter how much energy they consume. Therefore, electricity costs in these collocation data centers are usually high.

In this paper, we propose a coordinated energy management scheme for data center operator and tenants in a colocation data center. Our goal is to maximize the total benefits of both the data center operator and tenants obtained through such coordination. Specifically, we formulate the problem as a large-scale optimization problem. Since it is hard for the data center operator to directly control the servers owned by individual tenants, we develop a decentralized algorithm to solve the optimization problem. Our algorithm is based on the alternating direction method of multipliers (ADMM), which is simple but very efficient and has better convergence properties compared with conventional methods such as dual decomposition.

In summary, the major contributions of this work are the following:

- We propose a general formulation of coordinated energy management for colocation data centers. The quality of service for tenants is guaranteed when participating into such coordination. Moreover, various electricity and load curtailment cost functions can be applied into our formulation easily.
- We develop a novel decentralized algorithm to solve the problem efficiently. We show that tenants can solve their local problems in parallel, and then coordinate with the data center operator to find the global optimal solution efficiently. Moreover, the decentralized algorithm provides a natural way for the data center operator to incentivize its tenants to manage their energy consumption.
- We conduct extensive performance evaluations based on real traces. We show that the proposed algorithm converges fast to the optimal solution and can achieve significant cost savings for both tenants and data center operator.

The remainder of this paper is organized as follows. In Section II, we describe the models for both tenants and data center operator in a colocation data center, and formulate an optimization problem to maximize their joint benefits. We then present our decentralized algorithm to solve the optimization problem in Section III. After that, we describe the performance evaluation of our algorithm based on real traces in Section IV. Related work is reviewed in Section V. We conclude our paper in Section VI.

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II. System Modeling and Problem Formulation

We consider a colocation data center with N tenants, operated by a data center operator (DCO). Each tenant $i \in \mathcal{N} = \{1, 2, \cdots, N\}$ manages its own servers and subscribes a certain peak power supply from the DCO based on a long-term contract. The DCO is responsible for managing the data center facility to provide power supply, cooling, and physical security for tenants. In this paper, we focus on the energy management in a single period with the duration ranging from 15 minutes to one hour.

A. Tenants

Without loss of generality, we assume that each tenant $i \in \mathcal{N}$ owns M_i homogeneous servers. The power consumption of a server associated with tenant i is often described by a linear function [3]:

$$p_i(u) = \alpha_i^0 + (\alpha_i^1 - \alpha_i^0)u, \tag{1}$$

where α_i^0 is its power consumption at idle status, α_i^1 is its power consumption at fully utilized status, and u denotes its average CPU utilization level. Using the above model, the total power consumption for tenant i can be calculated as

$$\begin{aligned} e_i(n) &= n\left(\alpha_i^0 + \left(\alpha_i^1 - \alpha_i^0\right)\frac{\lambda_i}{n\mu_i}\right) \\ &= n\alpha_i^0 + (\alpha_i^1 - \alpha_i^0)\frac{\lambda_i}{\mu_i}, \end{aligned} \tag{2}$$

where λ_i is the mean workload arrival rate, μ_i is the mean service rate of a server, and n is the number of active servers.

Various power management techniques exist for reducing tenants' server energy consumption such as DVFS and geographical load balancing. Here, without loss of generality, we assume that tenant i coordinates its energy consumption by turning off some unused servers. To calculate the load curtailment, a baseline case where tenants do not actively manage their energy consumption is needed. As explained in [4], tenant i will turn on all M_i servers in the baseline case because it does not have any incentive to turn off any of them. When tenant i turns off m_i servers, its load curtailment s_i can be calculated as

$$s_i(m_i) = e_i(M_i) - e_i(M_i - m_i) = \alpha_i^0 m_i. \tag{3}$$

However, turning off servers may result in cost and performance degradation. Let $U_i(m_i)$ denote the cost incurred when turning off m_i servers for tenant i. The load curtailment cost function $U_i(\cdot)$ can take various forms depending on different goals of tenant i. For instance, it may include switching cost and delay cost [4]. Here, we only assume that the cost function $U_i(\cdot)$ is non-negative, increasing, convex, and has $U_i(0) = 0$.

To characterize the performance degradation by turning off servers, we adopt the M/G/1/PS queueing model to analyze the workload serving process. Tenant i needs to ensure that the average delay for tenant i's workload can still meet the service level agreement (SLA) after turning off m_i servers. Therefore, we have

$$\frac{1}{\mu_i - \lambda_i/(M_i - m_i)} \le \overline{d}_i, \tag{4}$$

where $\overline{d}_i$ is the response time requirement as prescribed by the SLA for tenant i.

B. Colocation Data Center Operator

The DCO is responsible for providing reliable power supply and cooling to tenants' servers hosted in the colocation data center. The electricity may be generated by on-site generation, purchased from electricity market, or both. We capture the electricity cost of the DCO through a generic function $C(\cdot)$. We assume that this electricity cost function $C(\cdot)$ is convex, non-negative, and non-decreasing with respect to the power consumption. Typical examples include quadratic or piece-wise linear forms.

In a colocation data center, the power consumption mainly consists of two parts: IT power and non-IT power. The IT power is the sum of the power consumed by the servers of all tenants. Given the model in the previous section, the total IT power is $\sum_{i=1}^N e_i(M_i - m_i)$ when tenants coordinate their energy consumption. On the other hand, data centers have many non-IT power usage such as cooling, power distribution, etc. To capture this aspect, we use the power usage effectivenss (PUE) factor β which is defined as the ratio of the total power to the IT power consumed by the data center facility. In practice, β ranges from 1.1 to 2.0, depending on factors such as outside temperature and cooling technology in use. Therefore, the total power consumption for the data center is $\beta \sum_{i=1}^N e_i(M_i - m_i)$.

C. Social Cost Minimization

In this paper, we consider the setting that the DCO wishes to offer some incentives (e.g., economic rewards) to its tenants so that tenants can reduce their energy consumption to help DCO reducing its electricity cost. The objective of DCO here is to induce tenants' load curtailment in a way that minimizes the social cost defined as the sum of the total tenant costs due to load curtailment and the DCO's electricity cost. Hence the DCO aims to solve:

$$\min_{m} \quad \sum_{i=1}^N U_i(m_i) + C\left(\beta \sum_{i=1}^N e_i(M_i - m_i)\right) \tag{5a}$$

$$\text{s.t.} \quad 0 \le m_i \le M_i - \lambda_i/(\mu_i - 1/\overline{d}_i), \forall i \tag{5b}$$

where the upper bound in (5b) is obtained by rearranging (4). Note that in the above problem formulation, we make a simplification that m_i does not need to be integer-valued, which is acceptable since the number of servers in a typical data center is large.

By assumption, both the objective function and the feasible set in the above problem are convex, and hence the optimal solution can be efficiently computed by the DCO using the interior-point method [5]. However, it requires the DCO to know all the tenant cost functions and all the constraints, which may be impractical since they may contain some private information. Moreover, scalability is a concern if the number of tenants is very large. This motivates us to develop a decentralized algorithm that is scalable and does not need the private information from tenants.

III. Decentralized Algorithm

A common approach to developing distributed algorithms is through dual decomposition with subgradient dual update. However, this approach requires the functions $U_i(\cdot)$ and $C(\cdot)$ to be strictly convex and is often slow. In our setting, it is common for these functions to be in affine forms. Moreover, it is not easy to choose a right step size in subgradient methods. In the following, we develop a decentralized algorithm based on the alternating direction method of multipliers (ADMM) [6], which does not suffer from the aforementioned drawbacks.

A. Background on ADMM

The ADMM is a simple but powerful algorithm that is well suited to distributed convex optimization and has been widely used in applied statistics and machine learning [6]. The algorithm solves problems in the following form:

$$\begin{aligned} \min \quad & f(x) + g(z) \\ \text{s.t.} \quad & Ax + Bz = c \end{aligned} \tag{6}$$

with variables $x \in \mathbf{R}^n$ and $z \in \mathbf{R}^m$, where $A \in \mathbf{R}^{p\times n}$, $B \in \mathbf{R}^{p\times m}$, $c \in \mathbf{R}^p$, and $f : \mathbf{R}^n \to \mathbf{R}$ and $g : \mathbf{R}^m \to \mathbf{R}$ are convex. Here, the objective function is separable over two sets of variables x and y.

As with the method of multipliers, we can form the augmented Lagrangian

$$\begin{aligned} L_\rho(x,z,y) =& f(x) + g(z) + y^T(Ax + Bz - c) \\ &+ (\rho/2)\left\|Ax + Bz - c\right\|_2^2, \end{aligned} \tag{7}$$

where $\rho > 0$ is the penalty parameter and y is the dual variable corresponding to the constraint $Ax + Bz = c$. This augmented Lagrangian can be viewed as the unaugmented Lagrangian associated with the problem

$$\begin{aligned} \min \quad & f(x) + g(z) + (\rho/2)\left\|Ax + Bz - c\right\|_2^2 \\ \text{s.t.} \quad & Ax + Bz = c. \end{aligned} \tag{8}$$

Note that the above problem is equivalent to problem (7) since the quadratic penalty term added to the objective function is zero for any feasible solution x and z. The key benefit of including the penalty term is that the dual problem of (8) is differentiable under mild conditions on f and g. This can greatly improve the convergence property when solving the problem using iterative methods.

ADMM consists of the following iterations:

$$x^{k+1} := \operatorname*{argmin}_x L_\rho(x, z^k, y^k) \tag{9}$$

$$z^{k+1} := \operatorname*{argmin}_z L_\rho(x^{k+1}, z, y^k) \tag{10}$$

$$y^{k+1} := y^k + \rho(Ax^{k+1} + Bz^{k+1} - c), \tag{11}$$

where the step size ρ is simply the penalty parameter. Similar to dual ascent algorithm, it consists of x-minimization step (9), z-minimization step (10), and a dual variable update (11). However, in ADMM, x and z are updated in an alternating or sequential fashion, which allows for decomposition when f or g are separable.

The convergence of ADMM can be proved under very mild assumptions, which generally hold in practice [7]. Moreover, ADMM converges to modest accuracy, which is sufficient for many applications, within a few tens of iterations in many cases.

B. Our Algorithm

The problem (5) cannot be readily solved by ADMM since the variables are coupled together in the objective function. To solve it using ADMM, we first reformulate the problem into the following form:

$$\min_{m,s} \quad \sum_{i=1}^N U_i\left(m_i\right) + C\left(E - \beta\sum_{i=1}^N s_i\right) \tag{12a}$$

$$\text{s.t.} \quad 0 \le m_i \le M_i - \lambda_i/(\mu_i - 1/\bar{d}_i), \forall i \tag{12b}$$

$$\alpha_i^0 m_i = s_i, \forall i, \tag{12c}$$

where we substitute (2) into the objective function and denote $E := \beta\sum_{i=1}^N \left(M_i\alpha_i^0 + (\alpha_i^1 - \alpha_i^0)(\lambda_i/\mu_i)\right)$. This new problem (12) is obviously equivalent to the original problem (5). We observe that the objective function in the new problem is now separable over two sets of variables m and s, and (12c) are the only coupling constraints, which matches the ADMM form. By relaxing the coupling constraints (12c), we formulate the augmented Lagrangian of (12) as

$$\begin{aligned} L_\rho(m,s,u) =& \sum_{i=1}^N U_i\left(m_i\right) + C\left(E - \beta\sum_{i=1}^N s_i\right) \\ &+ \sum_{i=1}^N \left(u_i(s_i - \alpha_i^0 m_i) + \frac{\rho}{2}(s_i - \alpha_i^0 m_i)^2\right), \end{aligned} \tag{13}$$

where $\rho > 0$ is the augmented Lagrangian parameter and $\{u_i, i \in \mathcal{N}\}$ are the dual variables corresponding to constraints (12c).

The problem is then solved by updating m, s, and u sequentially. Specifically, at the $(k+1)$-th iteration, the m-minimization step involves solving the following problem:

$$\min_{m\in\mathcal{M}} \quad \sum_{i=1}^N \left(U_i(m_i) - u_i^k\alpha_i^0 m_i + \frac{\rho}{2}\alpha_i^0 m_i\left(\alpha_i^0 m_i - 2s_i^k\right)\right), \tag{14}$$

where $\mathcal{M} := \prod_{i=1}^N \mathcal{M}_i$ and $\mathcal{M}_i = \{0 \le m_i \le M_i - \lambda_i/(\mu_i - 1/\bar{d}_i)\}$. This problem can be decomposable over tenants because both the objective function and the constraints are separable over i. In some cases, we can provide a closed-form solution to the above problem depending on the specific form of the cost function $U_i(\cdot)$.

After obtaining m^{k+1} from the m-minimization step, the s-minimization step involves solving the following problem:

$$\min_s C\left(E - \beta\sum_{i=1}^N s_i\right) + \sum_{i=1}^N s_i\left(u_i^k + \frac{\rho}{2}(s_i - 2\alpha_i^0 m_i^{k+1})\right). \tag{15}$$

Then, with the optimal m^{k+1} and s^{k+1}, the final step is to update the dual variables:

$$u_i^{k+1} := u_i^k + \rho\left(s_i^{k+1} - \alpha_i^0 m_i^{k+1}\right). \tag{16}$$

Note that both the m-minimization step and the dual update step can be carried out independently in parallel for each $i \in \mathcal{N}$. The s-minimization step needs to solve an optimization problem with N variables. In the following, we show that we can simplify this step by solving an optimization problem with a single variable.

Firstly, let $\overline{s}$ denote the average of s_i across all $i \in \mathcal{N}$. Problem (15) can be rewritten as

$$\min_{s,\overline{s}} \ C\left(E - \beta N \overline{s}\right) + \sum_{i=1}^{N} s_i \left(u_i^k + \frac{\rho}{2}(s_i - 2\alpha_i^0 m_i^{k+1}) \right)$$

$$\text{s.t. } \overline{s} = (1/N) \sum_{i=1}^{N} s_i. \tag{17}$$

Note that minimizing over $s_i, \forall i$ with $\overline{s}$ fixed has the solution

$$s_i = \alpha_i^0 m_i^{k+1} - u_i^k/\rho + \overline{s} + (1/N) \sum_{i=1}^{N} \left(u_i^k/\rho - \alpha_i^0 m_i^{k+1} \right). \tag{18}$$

Therefore, the above problem can be computed by solving the following unconstrained optimization problem:

$$\min_{\overline{s}} C\left(E - \beta N \overline{s}\right) + (\rho N/2)\overline{s}^2 + \rho \overline{s} \sum_{i=1}^{N} \left(u_i^k/\rho - \alpha_i^0 m_i^{k+1} \right) \tag{19}$$

and then applying (18). Note that the problem (19) only contains a single variable and is easy to solve.

Moreover, substituting (18) for s_i^{k+1} in the dual update equation (16) gives

$$u_i^{k+1} := \rho \left(\overline{s}^{k+1} + (1/N) \sum_{i=1}^{N} \left(u_i^k/\rho - \alpha_i^0 m_i^{k+1} \right) \right), \tag{20}$$

which does not depend on i. Therefore, the dual variables $u_i^{k+1}, i \in \mathcal{N}$ are all equal and can be replaced by a single dual variable u^{k+1}.

In summary, by substituting u and (18) in the expressions for m-minimization (14), $\overline{s}$-minimization (19), and dual variable update (20), our final algorithm consists of the following iterations

$$m_i^{k+1} := \operatorname*{argmin}_{m_i \in \mathcal{M}_i} \Bigg(U_i(m_i) - u^k \alpha_i^0 m_i + \frac{\rho}{2}(\alpha_i^0 m_i)^2 \tag{21}$$

$$- \rho \alpha_i^0 m_i \big(\alpha_i^0 m_i^k + \overline{s}^k - (1/N) \sum_{i=1}^{N} \alpha_i^0 m_i^k \big) \Bigg),$$

$$\overline{s}^{k+1} := \operatorname*{argmin}_{\overline{s}} \Bigg(C\left(E - \beta N \overline{s}\right) + u^k N \overline{s} + \frac{\rho}{2} N \overline{s}^2$$

$$- \rho \overline{s} \sum_{i=1}^{N} \alpha_i^0 m_i^{k+1} \Bigg), \tag{22}$$

$$u^{k+1} := u^k + \rho \left(\overline{s}^{k+1} - (1/N) \sum_{i=1}^{N} \alpha_i^0 m_i^{k+1} \right). \tag{23}$$

Algorithm 1 describes the entire procedures of solving our problem using the ADMM method.

Intuitively, our algorithm works in the following way. The dual variable u^k acts as the reward price [5] the DCO offers to tenants for load curtailment. Our algorithm first optimizes load curtailment m for tenants given the reward price u^k. It then optimizes the average load curtailment $\overline{s}$ from all tenants given the previously computed curtailment m^{k+1}. The dual update chooses the reward price u^{k+1} to ensure that these two sets of variables converge to the same optimal load curtailment decision.

Algorithm 1 Decentralized Algorithm to Solve (5)

The DCO initializes $(1/N)\sum_{i=1}^{N} \alpha_i^0 m_i^k \leftarrow 0$, $\overline{s}^0 \leftarrow 0$, $u^0 \leftarrow 0$ and broadcasts them to all tenants.
repeat
    After receiving $(1/N)\sum_{i=1}^{N} \alpha_i^0 m_i^k$, $\overline{s}^k$, u^k, each tenant i solves the problem (21), and sends the optimal solution $\alpha_i^0 m_i^{k+1}$ back to the DCO.
    After collecting $\alpha_i^0 m_i^{k+1}$ from all tenants $i \in \mathcal{N}$ and summing them together to get $(1/N)\sum_{i=1}^{N} \alpha_i^0 m_i^{k+1}$, the DCO solves the problem (22) to obtain $\overline{s}^{k+1}$. Next, the DCO updates the dual variable u^{k+1} according to (23). It then broadcasts $(1/N)\sum_{i=1}^{N} \alpha_i^0 m_i^{k+1}$, $\overline{s}^{k+1}$, u^{k+1} to all tenants.
    $k \leftarrow k + 1$
until Convergence criteria is met

C. Case Study

In this section, we provide a case study of the coordinated energy management problem with cost functions proposed in the literature.

A widely-used electricity cost function for data centers is in the form of demand-responsive electricity price [8], [9], i.e., the electricity price charged to a data center is given as

$$\pi\left(e_d\right) = \begin{cases} a_1(e_d + e_r) + b_1, & \text{if } e_d + e_r \le e_0 \\ a_2(e_d + e_r) + b_2, & \text{if } e_d + e_r > e_0 \end{cases} \tag{24}$$

where $a_2 > a_1 \ge 0$, b_1, b_2, e_0 are parameters for demand-responsive pricing, e_d denotes the energy consumed by our colocation data center, and e_r denotes the energy usage of all other consumers in the local electricity market. Also, this piecewise function is smooth, i.e., $a_1 e_0 + b_1 = a_2 e_0 + b_2$. Note that when the total demand in this local market exceeds a threshold e_0, the electricity price would increase much faster with respect to the total demand. With this cost function, the $\overline{s}$-minimization problem (22) can be transformed into the following form:

$$\begin{aligned} \min_{\theta,\overline{s}} \quad & \theta + u^k N \overline{s} + (\rho/2) N \overline{s}^2 - \rho \overline{s} \sum_{i=1}^{N} \alpha_i^0 m_i^{k+1} \\ \text{s.t.} \quad & \theta \ge \left(a_1(E - \beta N \overline{s} + e_r) + b_1\right)\left(E - \beta N \overline{s}\right), \\ & \theta \ge \left(a_2(E - \beta N \overline{s} + e_r) + b_2\right)\left(E - \beta N \overline{s}\right), \end{aligned}$$

where θ is an auxiliary variable. Note that the above problem can be readily solved by softwares such as CVX package [10] in MATLAB.

When only considering the switching cost, the load curtailment cost function $U_i(\cdot)$ takes the following linear form [11]:

$$U_i(m_i) = \gamma_i m_i, \tag{25}$$

where $\gamma_i > 0$ is a cost parameter (\$/server) to model the wear-and-tear cost of turning off servers. With this linear cost function, the $\overline{m}$-minimization step (21) becomes a quadratic program, and its optimal solution can be derived in an analytical form through KKT conditions as

$$m_i^{k+1} = \Big[m_i^k + \overline{s}^k/\alpha_i^0 - (1/\alpha_i^0 N) \sum_{i=1}^{N} \alpha_i^0 m_i^k + (u^k \alpha_i^0 - \gamma_i)/\rho(\alpha_i^0)^2 \Big]^{\mathcal{M}_i}, \quad (26)$$

where $[\cdot]^{\mathcal{M}_i}$ denotes the projection onto the set $\mathcal{M}_i$ specified by constraints (12b).

Therefore, in these practical settings all iterations in our algorithm are particularly easy to solve.

IV. Performance Evaluation

In this section, we conduct trace-based simulations to evaluate the performance of our algorithm in a realistic scenario.

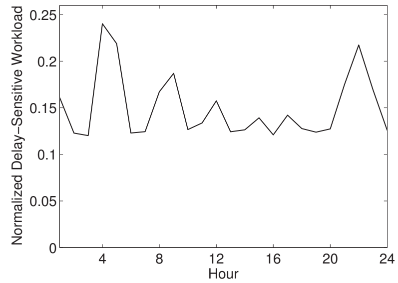
A. Simulation Setup

Colocation data center setup. We consider a colocation data center located in Mountain View, California, which consists of ten tenants. Each tenant has 2,000 servers with each server having an idle and peak power of 150 W and 250 W, respectively. The average PUE of the colo is set to 1.5, i.e., whenever a tenant consumes 1 kWh energy, the total energy consumption at the colo level is 1.5 kWh. Therefore, the peak power consumption of the colo is 7.5 MW.

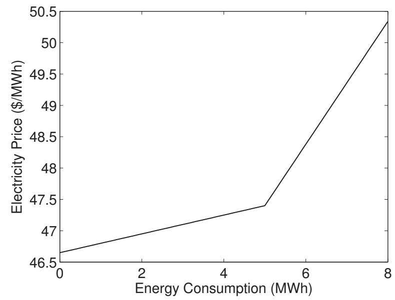
Electricity cost function. As shown in [9], by applying mean square error data fitting to the hourly energy demand and electricity price data from January to June, 2012 at this location, the following parameters for demand-responsive electricity price model (24) are obtained: $a_1 = 0.15$ \$/MWh, $b_1 = -15.6$ \$/MWh, $a_2 = 0.98$ \$/MWh, $b_2 = -364.2$ \$/MWh, $e_0 = 420$ MWh. A snapshot of the resulting demand responsive electricity price charged to the colo when other consumers in the electricity market use 415 MWh energy is depicted in Fig. 1b.

Tenant workload description. We choose a representative type of delay-sensitive workload data for tenants. The workload data are collected from MSR Cambridge [12]. A snapshot of the data over one day is depicted in Fig. 1a, where the workload is normalized with respect to a tenant's service capacity. Due to limited workload traces, we randomly select one day from the workload data and assign the corresponding workload trace to each tenant as its workload.

The service rate of a server is set to 400 requests per second, and the average utilization for each tenant is 15%. The average delay requirements for all tenants are set to be no longer than 6 ms. When tenants save energy by turning off some unused servers, additional maintenance cost and performance degradation may occur. Here we only consider the switching cost resulting from turning off servers as shown in (25). The cost parameter γ_i is set to be uniformly distributed between 0.69 $\sim$ 0.75 cent per server (i.e., 4.6 $\sim$ 5 cents per kWh). Note that the values of these parameters enable the tenant to cover the power management cost if housing servers in its own data center as explained in [13].



(a)



(b)

Fig. 1. Simulation data. (a) Workload trace. (b) Demand responsive electricity price when $e_r = 415$ MW.

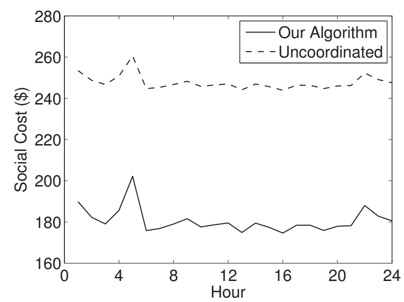


Fig. 2. Comparisons of social cost between our algorithm and the uncoordinated approach.

B. Simulation Results

Our evaluation results are shown below.

Social cost. We first compare the social costs incurred by our algorithm and the current practice without any coordination from tenants, as illustrated in Fig. 2. We execute our algorithm at the beginning of each hour for one day. We observe that our algorithm can always provide cost savings (around 27% in average) compared with the current practice. Therefore, it is important for DCO and tenants to collaborate in reducing the social cost.

Benefits for tenants and DCO. We then show that both the DCO and the tenants can benefit from the coordination. As we mentioned before, the dual variable u^k acts as the reward price offered by the DCO to tenants for load curtailment. Fig. 3a depicts the net profit of tenants (i.e., reward received from DCO minus switching cost). For simplicity, we only present the results for one hour, and results in other hours do not change

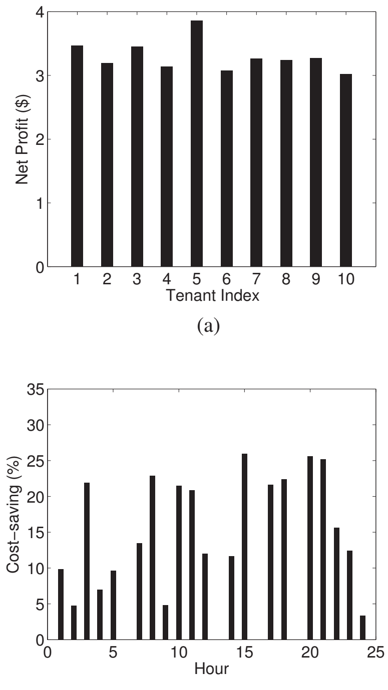


Fig. 3. (a) Tenants' net profits. (b) DCO's cost savings.

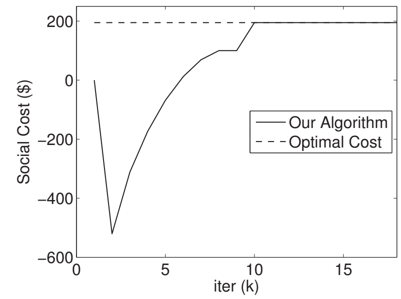


Fig. 4. Convergence of our algorithm.

qualitatively. Note that all tenants receive a positive net profit and therefore, have incentives to collaborate with the DCO. Fig. 3b illustrates the cost savings for the DCO compared to the uncoordinated case at each hour for one day.

Algorithm convergence. Fig. 4 plots the convergence property of our distributed algorithm when executed at one hour. We observe that our algorithm converges to the optimal solution very fast, usually within 10 iterations, and thus its effectiveness is validated. Note that the social cost achieved by our algorithm can be lower than the optimal cost at the beginning of iterations. The reason is that our algorithm does not yield feasible solutions at all iterations (i.e., constraints in (12c) are not always satisfied). However, after a few iterations, by enforcing the regularization terms for coupling constraints, our algorithm would meet all constraints while optimizing the objective function eventually .

V. Related Work

Data center power management has been investigated by many priori works [3], [8], [9], [11], [14]. However, they have all focused on owner-operated data centers. In contrast, colocation data centers have been explored by a few works recently. Colocation demand response is explored in [4], [13], where the goal is to provide incentives for tenants to reduce their power consumption during emergence demand response events. In [15], an online heuristic algorithm is proposed to optimize the reward for cost savings. Our work focuses on minimizing the data center electricity cost by coordinating tenants' energy usage, and thus is complementary to previous works. Moreover, we propose a new decentralized algorithm which can naturally yield an optimal reward pricing strategy for incentivizing tenants' response.

VI. Conclusion

In this paper, we have considered the problem of coordinated energy management for colocation data centers. We have formulated this problem as a generic convex optimization, and have developed a decentralized algorithm based on ADMM to solve it efficiently. We have shown the effectiveness of the proposed algorithm through numerical evaluations based on real traces. As future work, we plan to investigate the coordinated energy management problem across multiple time periods in colocation data centers.

References

[1] NRDC, "Scaling up energy efficiency across the data center industry: evaluating key drivers and barriers," *Issue Paper*, 2014.

[2] F. Kong and X. Liu, "A survey on green-energy-aware power management for datacenters," *ACM Computing Surveys*, vol. 47, no. 2, pp. 30:1–30:38, November 2015.

[3] Z. Liu, Y. Chen, C. Bash, A. Wierman, D. Gmach, Z. Wang, M. Marwah, and C. Hyser, "Renewable and cooling aware workload management for sustainable data centers," in *ACM Sigmetrics/Performance*, 2012.

[4] S. Ren and M. Islam, "Colocation demand response: Why do I turn off my servers," in *11th International Conference on Autonomic Computing (ICAC 14)*. USENIX Association, 2014.

[5] S. P. Boyd and L. Vandenberghe, *Convex Optimization*. New York: Cambridge University Press, 2004.

[6] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Foundations and Trends® in Machine Learning*, vol. 3, no. 1, pp. 1–122, 2011.

[7] D. P. Bertsekas and J. N. Tsitsiklis, *Parallel and distributed computation: numerical methods*. Prentice hall Englewood Cliffs, NJ, 1989, vol. 23.

[8] P. Wang, L. Rao, X. Liu, and Y. Qi, "D-pro: Dynamic data center operations with demand-responseive," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1743–1754, 2012.

[9] A. H. Mahmud and S. Ren, "Online capacity provisioning for carbon-neutral data center with demand-responsive electricity prices," *ACM SIGMETRICS Performance Evaluation Review*, vol. 41, pp. 26–37, 2013.

[10] M. Grant and S. Boyd, "CVX: Matlab software for disciplined convex programming, version 2.1," http://cvxr.com/cvx, Mar. 2014.

[11] M. Lin, A. Wierman, L. L. H. Andrew, and E. Thereska, "Dynamic right-sizing for power-proportional data centers," *IEEE/ACM Trans. Netw.*, vol. 21, no. 5, pp. 1378–1391, Oct. 2013.

[12] D. Narayanan, A. Donnelly, and A. Rowstron, "Write off-loading: Practical power management for enterprise storage," in *Proc. USENIX Conference on File and Storage Technologies (FAST)*, San Jose, CA, Feb 2008.

[13] L. Zhang, S. Ren, C. Wu, and Z. Li, "A truthful incentive mechanism for emergency demand response in colocation data centers," in *INFOCOM*, 2015.

[14] Y. Guo and Y. Fang, "Electricity cost saving strategy in data centers by using energy storage," *Parallel and Distributed Systems, IEEE Transactions on*, 2012.

[15] M. Islam, H. Mahmud, S. Ren, and X. Wang, "Paying to save: Reducing cost of colocation data center via rewards," in *IEEE HPCA*, 2015.