Power Control Framework for Green Data Centers

Ting Yang, Yucheng Hou, Young Choon Lee, Hao Ji, Albert Y. Zomaya

Abstract—In recent years, renewable energy, such as wind and photovoltaic electric power has been increasingly integrated into data center power provisioning systems to address high energy consumption of data centers. However, in reality, the intermittency and randomness of renewable energy (power supply fluctuation) is detrimental to the reliable operation of sophisticated IT equipment in those so-called green data centers. In this paper, we address the problem of data center power regulation explicitly taking into account the unreliability and instability of renewable energy sources. To this extent, we design a novel data center power control framework that smoothens the power fluctuation and instability of renewable energy sources. The core of our framework is two power regulation optimization algorithms. In particular, a server workload scheduling algorithm deals with high frequency fluctuations while an Uninterruptable Power Supply (UPS) power regulation algorithm handles low frequency and large extent power fluctuations. These algorithms are also designed to satisfy service level agreement (SLA) and standby power supply capacity. We have conducted an extensive evaluation study using trace data of a real data center of 30000-node cluster with 50 x 250 UPS battery groups and 24-hour power generation data from real wind farm and photovoltaic power station. The experimental results show our framework effectively smoothens fluctuations of data center power supply, more effective use of renewable energy and extend the UPS batteries' lives to reduce the skyrocketed data center operating expenses.

Index Terms—Data center, Power Control Framework, Service Level Agreement, Workloads Scheduling

I. Introduction

With the growing resource demand for cloud computing and big data technologies, data centers are continued to be built. The scale of these data centers is also becoming increasingly large particularly with low hardware prices. In the meantime, powering and cooling data centers have become major hindering factors for the sustainability of data centers with skyrocketing energy prices and excessive carbon emission [1],[2],[3].

In attempts to mitigate such sustainability issues with data centers, a number of data centers have been built with the full or partial adoption of renewable energy, such as wind and photovoltaic power, as a form of electric microgrid. For example, Apple has installed a large scale photovoltaic array in its *iCloud* data center park located in Northern California, providing 840 million kWh of clean energy for the park each year [5]. Facebook has built a solar-powered data center in Oregon, and Green House Data has built a new wind-powered data center in Wyoming [6].

There have been several studies on the use of renewable energy for data centers [17], [20]. The focus of these studies lies primarily in the maximization of renewable energy usage for reduction of electricity cost and/or environmental impact (carbon emission) [7], [8]. However, for data centers, as the sensitive power loads, ensuring the quality of power supply (stability and reliability) is more crucial than such cost savings in the context of effective and sustainable use of renewable energy. In particular, the intermittency and randomness of renewable energy threaten the normal operation of data center equipment including sophisticated computing equipment (CPU, GPU, HDD), and cause voltage/current, frequency and power fluctuations in data center microgrid. Moreover, these disadvantages will be exacerbated as the renewable energy's supply rate increases [9]. To ensure normal and stable operation of data centers and reduce the impact on the stability of the main power grid, as well as to further increase the utilization of renewable energy and lower the cost of operation and carbon emissions of data centers, the power regulation in data centers under the context of renewable energy needs urgent study.

In this paper, we address the power regulation for *green* data centers that use renewable energy exhibiting unreliable and unstable power supply. To this end, we design a data center power control framework that smoothens such power fluctuation and instability. At the core of our framework there are two power regulation optimization algorithms: The first server workload scheduling algorithm flattens the high frequency fluctuation taking into account the delay sensitiveness of computing tasks respecting service level agreement (SLA); The second Uninterruptable Power Supply (UPS) regulation algorithm judiciously makes decisions on (dis)charging of UPS battery groups to smoothen low frequency fluctuation (hour power load fluctuation) and meet the standby power supply capacity.

The overarching novelty of our work lies in the holistic approach to mitigating data center power fluctuations. This is different from many previous works focusing on minimizing data center energy costs by maximizing renewable energy use. In particular, our power control framework is distinguished from other works in (1) modelling both server workloads and State of Charge (SoC) of UPS battery groups as controllable power regulation resources, (2) adopting a two-stage low-pass filter that dynamically determines target power levels for server load responses and UPS power load responses, and (3) designing two novel optimization algorithms to smoothen high and low power fluctuations.

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We evaluate the efficiency of our framework with trace data from a real data center of 30000-node cluster with 50x250 UPS battery groups and 24-hour power generation data from real wind farm and photovoltaic power stations. Our experimental results confirm our framework with two optimization algorithms can effectively address data center power fluctuations.

The rest of the paper is organized as follows: Section II reviews related work. Section III describes the data center power management model and models server workloads and UPS power regulation. In Section IV, we formulate the problem of data center power regulation using a two-stage low-pass filter. We present our data center power control framework consisting of two optimization algorithms in Section V. Section VI presents experimental results under different power supply scenarios. We conclude the paper in Section VII.

II. Related Work

In the recent past, renewable energy as a viable power source of data centers has been vigorously sought by both industry practitioners and researchers [10]. For data center operators, soaring energy costs for not only powering, but also cooling data centers is a major driving force of building green data centers. In particular, these costs are increasingly leveling with hardware costs. Renewable energy, such as wind and photovoltaic, has been planted in focused green data centers' infrastructure design. This approach has grown from a whisper to a major theme for many vendors seeking to secure energy availability, lowering environmental impact, and improving brand reputation. Notable examples are data centers of Google [11], Apple [12], Digital Realty [13], Facebook [14], Microsoft [15], and IBM [16].

Studies on the application of renewable energy in data centers can be classified into two categories. The first category is the energy allocation planning of data centers. On the premise of meeting the demand of data centers corresponding energy consumption, many studies make contributions to optimizing the different energy supply combination to minimize the data centers operation overhead and carbon emission. The renewable energy-aware multi-indexed job classification and scheduling scheme proposed in [4] uses container-as-a-service for data centers sustainability to achieve considerable energy savings. The work in [17] focuses on data center backup power supply (UPS) and proposes the RE-UPS control strategy to realize the maximization of renewable energy utilization.

The second category is tasks scheduling in data centers to minimize the energy consumption of server cluster power consumption or maximize the utilization of renewable energy. The genetic simulated annealing algorithm proposed in [18] assigns tasks in data centers with under-floor air supply according to the corresponding air organization, minimizing the inlet temperature and reducing the cooling cost. The task allocation and scheduling methods introduced in [19] dispatch the coming tasks to the active servers by using servers as less as possible and adjust the execution frequencies of relative cores to save energy in data centers. The work in [20] proposed iswitch migrating workloads among racks following the wind power characteristics. The research conducted in [20] introduces a novel Virtual machine Placement and Traffic Configuration Algorithm (VPTCA) scheme to reduce the energy consumption of data center networks (DCN) while still meeting as many network QoS requirements as possible. The proposed scheme focuses on not just migrating large data flows, but also integrating small data flows to improve the utilization rate of the communication links.

The work in this paper differs from previous works in that the focus is smoothening power fluctuation for the stable and reliable electric supply for data centers.

III. Modeling of data center power management

In this section, we first model the power supply and consumption relationship of data center (Fig. 1). Then we model server workload and State of Charge (SoC) of UPS battery groups as controllable power regulation resource to devise our power control framework.

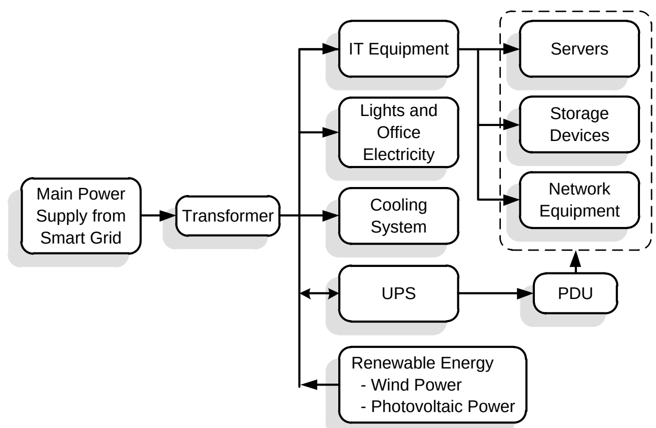

Fig. 1. Typical data center microgrid with renewable energy.

A. Green Data Center Power Supply and Consumption Model

From the perspective of electric power generation and utilization, one can model a data center, renewable energy system and the utility power grid as a microgrid system. The power supply system consists of the utility power grid and distributed renewable energy sources. The data center power load include the server cluster, UPS battery groups [22], refrigeration and lighting system, in which the first two parts are modeled as controllable power load and actually execute the power regulation in this study.

For a given unit time period, i (minute in this paper), the power balance between supply and demand for the date center microgrid is defined as

$$P_{UPG,i} + P_{RE,i} = P_{SC,i} + P_{UL,i} + P_{UPS,i} \tag{1}$$

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where $P_{UPG,i}$ is the external power supply to data centers system from the utility power grid; $P_{RE,i}$ is the renewable energy, such as the wind or photovoltaic power generations set in the data center microgrid; $P_{SC,i}$ is the power consumption by the server cluster; $P_{UL,i}$ is the power consumed by uncontrollable load, such as refrigeration and lighting system; $P_{UPS,i}$ is the UPS battery consumption, in which we assume that the value of charging power is positive and discharging power is negative. It is additional instruction that the renewable energy $P_{RE,i}$ and UPS battery consumption $P_{UPS,i}$ are the results of multiplying the conversion efficiency, that is, the actual power available for data centers.

Based on the relationship shown in Fig. 1 and Eq. (1), the intermittency of renewable energy and the randomness of arrived computing workloads will cause data center electric power fluctuations. With the increase of renewable energy penetration, such fluctuations become more serious.

Furthermore, the power consumption by the server cluster $P_{SVR,i}$ can be expressed as:

$$P_{SC,i} = \sum_{m=1}^{M} P_{SVR,i}^{m} = \sum_{m=1}^{M} [P_{idle} + (P_{max} - P_{idle}) \cdot \gamma_{i}^{m}] \qquad (2)$$

where $P_{SVR,i}$ is the power consumption of one single server and there are M homogeneous servers in the data center, P_{idle} and P_{max} represent for the idle and full-load power consumption of a server, respectively, and γ_i^m is the CPU utilization of the m^{th} server in minute i.

B. The controllable power load model of server workloads

Traditionally, non-real-time or insensitive power load such as electric heater is regarded as controllable load to participate in power regulation, while IT equipment like computing server is too critical to be regulated power. We analyze the operational principle and workload characteristics of data centers and creatively propose that server cluster workload in data center is controllable and can be used as a quick regulating resource.

Mega-load: In response to the growing demand for cloud services, data centers are quickly growing in size, and the dense integration of tens of thousands of server clusters and cooling equipment makes the data center a considerable power load [23]. According to statistics, the peak power load of Microsoft Quincy Data Center in Washington has been up to 48MW, which is equivalent to the sum of 40000 families power load [24], while the mega-datacenter built by US National Security Agency in Utah reaches a high peak power consumption of 70MW [25].

Time-varying load: Huge power consumption of data center is time-varying as the random arrival of computing requests. Overall, the data center power load curve shows a great peak-valley difference. According to the statistics of a small data center of Facebook [26], in the daily working condition, peak-valley difference of workload is equivalent to 80%-87% of its peak load [27].

The characteristics of mega load and huge peak-valley difference of data center's power load make it be possible to participate in power regulation. The virtual machine and task scheduling technologies make the server cluster computing load and the linear corresponding power consumption become flexible and adjustable [21], which is innate as power regulating resource.

According to the Service-Level Agreement (SLA), user's computing requests can be divided into delay-sensitive ones and delay-tolerant ones. Delay-sensitive requests, such as instant messaging, real-time transactions and video decoding [28], require to be processed immediately by data centers without being delayed. Delay-tolerant tasks, including non-real-time scientific calculations [29], should just be processed before the deadline and do not violate SLA [30]. In this study, we are particularly interested in delay tolerant tasks as their placement and execution can be more flexibly regulated in term of both space–server and VM placement/migration–and time. Such flexibility in data centers plays a crucial role in power regulation.

For a delay-tolerant basic task unit, the SLA conformance level is defined as

$$\begin{aligned} & s = 1 - \frac{T_{dly}}{\Delta T_{\max\_dly}} = 1 - \frac{t_{fnl} - (t_{arr} + T_{exe})}{\Delta T_{\max\_dly}} \\ & s.t.\ T_{dly} \le \Delta T_{\max\_dly} \end{aligned} \qquad (3)$$

where T_{dly} is the actual delay, ΔT_{max_dly} is the maximum allowed delay (based on the deadline), t_{fnl} is the finish time, t_{arr} is the arrival time and T_{exe} is the duration of task execution.

Although Eq. (3) ensures SLA conformance, the degree of user experience/satisfaction differs with respect to SLA conformance levels. For a particular time period, the average user satisfaction level, S_i can be classified as one of four ranges: (S_{high}, 1], (S_{low}, S_{high}], (S_{LL},S_{low}] and [0, S_{LL}]. Clearly, the higher user satisfaction level the more flexible for regulating delay-tolerant tasks (more precisely, task/VM migration). The distribution interval of S_i is shown in Fig. 2.

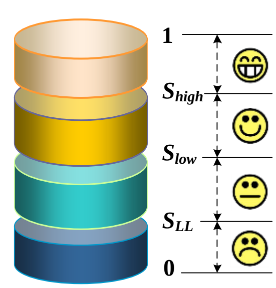

Fig. 2. The distribution interval of user satisfaction status.

If S_i locates in interval (S_{high}, 1], there is enough space to migrate delay-tolerant tasks to later periods, and users are not sensitive enough to this scheduling. The decline of user satisfaction also does not produce much negative effect on user experience. So the server cluster consumption gets a larger regulatory range and data center can participate in the demand side response better. On the other condition that S_i locates in interval (S_{LL}, S_{low}], users become sensitive to the change of QoS, the decline of user satisfaction will recruit enough negative effect on user experience, resulting in a weaker control ability of the tasks in the control period and a smaller regulatory range of server cluster consumption, which is also an effective protective measure to prevent system performance from being destroyed. The data center, of course, has less ability to participate in the optimization strategy. S_{LL} is the lowest limit of user satisfaction status, S_i of any control period must be required to be beyond S_{LL} and maintain system performance.

C. The controllable power regulation model of UPS battery groups

To improve the operational reliability, data centers normally equip high capacity UPS, such as following *Tier4* standards with dual system backup, to form a parallel redundant power system [38]. Amazon data center adopts the (*N*+*R*) power supply architecture, one of the higher reliability designs, to ensure the reliability of power supply, in which N=1 and R≥1 [39]. Under the premise of ensuring the reliable power supply to data centers, the redundant UPS battery groups can be dynamically controlled with (dis)charging status to participate the power regulation.

The remaining electric power of UPS can be measured by its SoC. In this paper, using the Kinetic Battery Model (KiBaM) [31] to measure and describe SoC of UPS battery groups' remaining electric power, The UPS energy storage model is established as follows:

$$P_{UPS,i} = \begin{cases} [\varphi \cdot (SoC_{i+1} - SoC_i)] \cdot \psi_c, \text{ battery-charging} \\ [\varphi \cdot (SoC_{i+1} - SoC_i)] / \psi_d, \text{ battery-discharging} \end{cases} \quad (4)$$

where SoC_i is the UPS battery's SoC in minute i. ψ_c and ψ_d are the charging coefficient and discharging coefficient, respectively. φ is the power factor of UPS, which can be calculated as

$$\varphi = \frac{N_s N_n U_r C_{UPS}}{\Delta T} \quad (5)$$

where, N_s is the number of string batteries, and N_n is the number of parallel batteries. U_r is the rated voltage of each battery. C_{UPS} is the capacity of a single UPS battery (A·h). ΔT is 1 minute.

IV. Problem Formulation

In this section, we formulate the problem of data center power regulation. In particular, we use a two-stage low-pass filter (Fig. 3) to address the high and low frequency fluctuations by regulating server workloads and UPS power load, respectively. The actual formulation of these two optimization problems is then presented.

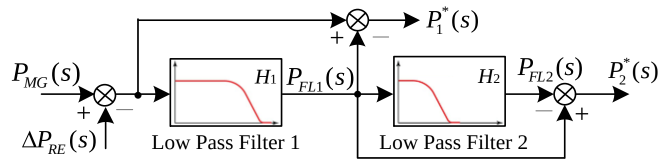

Fig. 3. The overview of data center power control framework based on a two-stage low-pass filter.

A. Two-state low-pass filter to address the high and low frequency

As the flow chart of the control strategy shown in Fig. 3, the input variable is the data center power consumption P_{MG}=P_{SC}+P_{UL}. The fluctuation of renewable energy output ΔP_{RE}=P_W+P_V is regarded as the disturbance, due to its intermittence. The first stage of low pass filter $H_1(s)$ removes high frequency fluctuation and the output is P_{FL1}. We also obtain the target power P_1*=P_{MG}−ΔP_{RE}−P_{FL1}, to which the server cluster responds by migrating delay-tolerant tasks. Then the processed power signal P_{FL1} through the second stage of low-pass filter $H_2(s)$ and the final power curve as P_{FL2}. The target power of UPS power load regulation P_2*= P_{FL1}−P_{FL2}.

Not only smoothen the power fluctuations, we also seek higher user satisfaction and better UPS batteries' SoC in the data center power controlling process. Therefore, we optimize variable time constants T_L to dynamically adjust the two-stage low pass filter, where T_L is time constant in the Butterworth low-pass filter's transfer function $H(s)$=1/(1+sT_L).

The optimization of the first stage filter's variable time constant $T_{1,i}$ (for server cluster response) is shown in Fig. 4. We first identify a user satisfaction status identification S_i at the beginning of the control period i. The actual optimization proceeds with S_i in three ways to deal with $T_{1,i}$:

(1) If S_i is in the interval (S_{low}, S_{high}], the time constant $T_{1,i}$ of the first stage filter is set to the initial value T_1^0,

(2) If S_i∈(S_{high}, 1], then S_{i-1} of the previous control period (the i-1th one) should be discussed. If S_{i-1}∈(S_{high}, 1] too, then $T_{1,i}$=$T_{1,i-1}$+ΔT_1, where ΔT_1 is the increment. Compared $T_{1,i}$ with the upper limit T_1^{max}, if $T_{1,i}$>T_1^{max}, set $T_{1,i}$=T_1^{max}; If S_{i-1} is not in the interval (S_{high}, 1], $T_{1,i}$=T_1^0+ΔT_1, and

(3) If S_i∈(S_{LL}, S_{low}], and S_{i-1} is also in the interval (S_{LL}, S_{low}], then $T_{1,i}$=$T_{1,i-1}$-ΔT_1. Compared $T_{1,i}$ with lower limit T_1^{min}, if $T_{1,i}$<T_1^{min}, set $T_{1,i}$=T_1^{min}; If S_{i-1} is not in the interval(S_{LL}, S_{low}], $T_{1,i}$=T_1^0-ΔT_1.

The optimization of the second stage filter's variable time constant $T_{2,i}$ (for UPS battery pack response) is shown in Fig. 5. It starts with the identification of SoC_i of UPS battery pack for a given control period i. Similar to those in the optimization in first stage filter, there are three conditions to deal with $T_{2,i}$:

(1) If SoC_i is in the interval (SoC_{low}, SoC_{high}], the time constant $T_{2,i}$ is set to the initial value T_2^0,

(2) If SoC_i∈(SoC_{high}, SoC_{max}], indicating that the UPS battery pack may be over-charged. At this time, the UPS power control signal P_2*(s) should be discussed: If the current actual power is lower than the target power, $\Delta P_{UPS,i}$≥0, it

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means that UPS battery pack needs to charge in the control period i, then $T_{2,i-1}$ of the previous control period (the i-1th one) should be discussed as well, if $T_{2,i-1}<T_2^0$, $T_{2,i}=T_{2,i-1}-\Delta T_2$, where ΔT_1 is the increment. Compared $T_{2,i}$ with the lower limit T_2^{min}, if $T_{2,i}<T_2^{min}$, set $T_{2,i}=T_2^{min}$; else If $T_{2,i-1}>T_2^0$, set $T_{2,i}=T_2^0-\Delta T_2$; If the current actual power is higher than the target power, $\Delta P_{UPS,i}<0$, it means that UPS battery pack needs to discharge in the control period i, then $T_{2,i-1}$ should also be discussed. If $T_{2,i-1}>T_2^0$, then $T_{2,i}=T_{2,i-1}+\Delta T_2$. Compared $T_{2,i}$ with the upper limit T_2^{max}, if $T_{2,i}>T_2^{max}$, set $T_{2,i}=T_2^{max}$; else If $T_{2,i-1}<T_2^0$, then $T_{2,i}=T_2^0+\Delta T_2$, and

(3) If $SoC_i \in (SoC_{min}, SoC_{low}]$, indicating that the UPS battery pack may be over-discharged. At this time the UPS control signal $\Delta P^*_{UPS,i}$ of current period should be discussed: If $\Delta P_{UPS,i} \geq 0$, it means that the UPS battery pack needs to charging in the control period i, then $T_{2,i-1}$ should be discussed as well. If $T_{2,i-1}>T_2^0$, then $T_{2,i}= T_{2,i-1}+\Delta T_2$. Compare $T_{2,i}$ with T_2^{max}, if $T_{2,i}>T_2^{max}$, set $T_{2,i}=T_2^{max}$; else if $T_{2,i}<T_2^0$, set $T_{2,i}=T_2^0+\Delta T_2$; If $\Delta P_{UPS,i}<0$, it means that UPS battery pack needs to discharge in the control period i, then $T_{2,i-1}$ should be discussed. If $T_{2,i-1}<T_2^0$, then $T_{2,i}=T_{2,i-1}-\Delta T_2$. Compared $T_{2,i}$ with T_2^{min}, if the $T_{2,i}<T_2^{min}$, set $T_{2,i}=T_2^{min}$; else if $T_{2,i-1}>T_2^0$, set $T_{2,i}=T_2^0-\Delta T_2$.

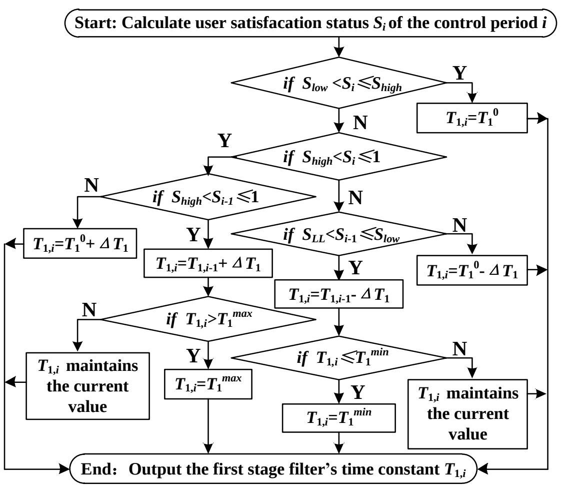

Fig. 4. Regulation process of the first stage filter's time constant T_1.

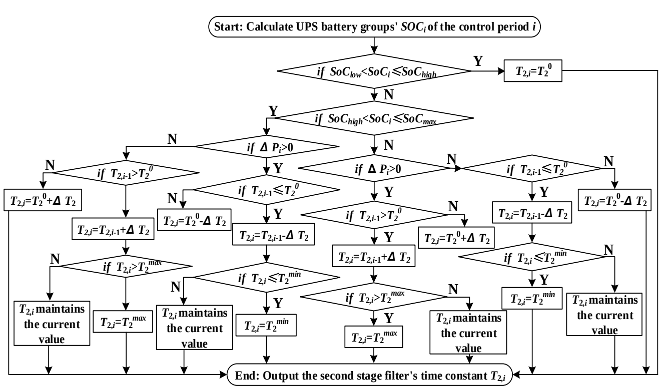

Fig. 5. Regulation process of the second stage filter's time constant T_2.

B. Establishing the Optimization Models

The actual smoothening of data center power fluctuation is addressed by solving two optimization problems using server workload scheduling algorithm and UPS power regulation algorithm, respectively. The objective of former workload scheduling algorithm is to minimize the difference value between the target power P_1* and the adjusted actual power P_{act}. The mathematic model is shown as:

$$\begin{aligned}
&\min \sum_{i=1}^{T} (P_{1,i}^* - P_{act,i})^2 \\
&\text{s.t. } \bar{\gamma}_i^{\min} \le \bar{\gamma}_i \le \bar{\gamma}_i^{\max} \\
&\begin{cases} n_{1,i} + n_{1,i}^{im} - n_{1,i}^{em} \le \gamma_{1,i} \cdot n_{\max} \\ n_{2,i} + n_{2,i}^{im} - n_{2,i}^{em} \le \gamma_{2,i} \cdot n_{\max} \\ \cdots\cdots \\ n_{k,i} + n_{k,i}^{im} - n_{k,i}^{em} \le \gamma_{k,i} \cdot n_{\max} \end{cases} \\
&0 \le n_{k,i}^{im},\ 0 \le n_{k,i}^{em} \le n_{k,i}
\end{aligned} \tag{6}$$

where $\bar{\gamma}_i^{\min}$ and $\bar{\gamma}_i^{\max}$ are the upper and lower limits of the average resource utilization of server cluster. The second group of constraints indicates that to ensure SLA the number of tasks being processed at any minute should not exceed computing capacity of server cluster. The constraints also specify the number of tasks to be moved in ($0 \le n_{k,i}^{im}$) and the number of tasks to be moved out ($0 \le n_{k,i}^{em} \le n_{k,i}$) during control periods.

The objective of UPS power regulation optimization algorithm is defined as:

$$\min \begin{cases} \sum_{i=1}^{T} (P_{2,i}^* - P_{act,i})^2 \\ \sum_{i=1}^{T} sw_i \end{cases} \tag{7}$$

$$\text{s.t. } \underline{SoC} \le SoC_i \le \overline{SoC}$$

In the object function, sw_i is the number of UPS charging and discharging times, which is counted as:

$$sw_i = \begin{cases} 1, & (P_{UPS,i-1} \cdot P_{UPS,i}) < 0 \\ 0, & (P_{UPS,i-1} \cdot P_{UPS,i}) > 0 \end{cases} \tag{8}$$

When the result of multiplying two UPS power in the two adjacent periods (i-1 and i) is negative, the value of sw_i is 1, otherwise sw_i is 0. In this paper we define that $P_{UPS,i} > 0$ while being charged and $P_{UPS,i} < 0$ while being discharged.

The constraint in Eq. (7) defines the range of SoC to prevent excessive charging and discharging, so as to ensure adequate backup power of the UPS and ensure the reliability of data center power supply.

We can determine the way how to migrate tasks as well as UPS charge/discharge mode by solving sub-problems (Eqs. (6) and (7)), achieving the optimal tracking of target power.

V. Data Center Power Control Framework

In this section, we present the core components of our power control framework, server workload scheduling

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algorithm and UPS power regulation algorithm as power regulation optimization algorithms.

The mathematical models of two optimization problems are all multi-variable nonlinear scheduling problems, as both of their objective functions are nonlinear. Their optimization decisions are primarily guided by control signals generated by the two-stage filter presented in Section IV.

A. Server workloads scheduling algorithm

The server workloads scheduling algorithm (Algorithm 1) migrates delay tolerant tasks without violating SLA to reduce or increase the server power consumption. The algorithm sorts task units, waiting to be processed within the control period (minute i), in descending order of user satisfaction level. Tasks with the same user satisfaction level are then sorted in descending order according to their current maximum tolerable delay $\Delta T'_{max\_dly}$. $\Delta T'_{max\_dly}$ is the remaining tolerable delay of a task, which task has probably been migrated before. Finally we get the sequence of task units $TK=\{s^1_i, s^2_i,\ldots, s^n_i\}$.

We now calculate $\Delta P_{1,i} = P^*_{1,i} - P_{act,i}$, as the power to be regulated by controllable server cluster workloads during minute i. Based on the server cluster energy consumption model, we can calculate the number of basic task units that should be migrated ($n^*_{tk,i}$). The front $n^*_{tk,i}$ tasks located in sequence $\{TK\}$ are migrated. Since the current maximum tolerable delay $\Delta T'_{max\_dly}$ for these tasks is different, the target periods of migration vary significantly, corresponding to different migration schemes. The algorithm measures the deviations from the target power under different schemes and chooses the scheme with the minimum deviation. For one of tasks in $\{TK\}$, Algorithm 1 goes through all of the migratable time periods. Firstly, it ensures CPU utilization not to be over upper limit when task migrates in minute j (line 9). We calculate the new value of power $P_{act,j}$ during minute j (line 10) and count the difference $\Delta P[j]= P^*_{1,j} - P_{act,j}$ (line 11). Then the j with the minimum $\Delta P[j]$ is selected as the migration destination time period (line 13).

Algorithm 1: Server Workloads Scheduling Algorithm

```
1    Input : i: control period (minute i)
2        TK={s_i^1, s_i^2,..., s_i^n}
3        P*_{1,i}: the target power;
4        P_{act,i}: the adjusted actual power after;
5        n*_{tk,i}: number of basic task units to be migrated;
6    u=1
7    While u<= n*_{tk,i} do
8        While j<=ΔT'_{max_dly, u} do
9            If γ̄_j^min ≤ γ̄_j ≤ γ̄_j^max
10               Calculate P_{act,j}
11               ΔP[j]=| P*_{1,j}–P_{act,j} |
12           end if
13           j=min{ΔP[ ]}
14       end while
15       Migrate TK_u to minute j
16       u=u+1
17   end while
```

The algorithm firstly sorts the delay-tolerant tasks in descending orders according to their user satisfaction and current maximum tolerable delay $\Delta T'_{max\_dly}$. The time complexity of using Merge-sort method is $O(n\log_2 n)$. The algorithm then determines the best migration periods of the $n^*_{tk,i}$ tasks to be migrated and the time complexity of this section appears to be $O(n^*_{tk,i} \cdot T)$, which can be regarded as $O(nT)$ since $n^*_{tk,i} < n$. Overall, the time complexity of the whole algorithm is $\max\{O(n\log_2 n), O(nT)\}$.

B. UPS power regulation algorithm

UPS units of existing data centers are equipped with hardware for each battery group to accurately sense the SoC. Algorithm 2 shows how to regulate SoC of UPS battery groups to smoothen the low frequency power fluctuation in data centers. Sorting the battery groups in ascending orders according to their SoC and then we obtain the sequence $BT=\{SoC^1_i, SoC^2_i,\ldots, SoC^m_i\}$

The algorithm determines that UPS battery groups need to be charged (if $\Delta P_{2,i} = P^*_{2,i} - P_{act,i} > 0$, line 6) and starts charging from SoC^1_i, the first unit of {BT} (line 7). ΔP is used to indicate the required power to charge the current battery group to the full electricity capacity during the control period i. If $\Delta P \leq \Delta P_{2,i}$, the current battery group is supposed to be full charged with ΔP and $\Delta P_{2,i}$ should be updated to $\Delta P_{2,i} - \Delta P$ (the *if* statement in lines 9-11). Then the algorithm begins to consider the charging of the next battery group, updating ΔP and comparing ΔP with $\Delta P_{2,i}$ again. Otherwise, once the algorithm detects $\Delta P > \Delta P_{2,i}$, the charging power of the current battery group is set to $\Delta P_{2,i}$. The UPS battery groups charge implement can satisfy the response requirement in minute i (lines 12-16).

If UPS battery groups are to be discharged (i.e., $\Delta P_{2,i} < 0$ in the else block in lines 18-31), the algorithm starts the discharging from SoC^m_i, the last unit of $\{BT\}$ (line 19). In this case, we also use ΔP to indicate the required power to discharge the current battery group to the lower limit of electricity capacity during the control period i. If the power of current battery group is over the required power $|\Delta P|$, the current battery group is supposed to be discharged with ΔP (line 21). $\Delta P_{2,i}$ is updated to $\Delta P_{2,i} + |\Delta P|$ (line 22). Then the algorithm begins to consider the discharging of the previous battery group, updating ΔP and comparing $|\Delta P|$ with $|\Delta P_{2,i}|$ again. Otherwise, once the algorithm detects $|\Delta P| > |\Delta P_{2,i}|$, the discharging power of the current battery group is set to $\Delta P_{2,i}$, and then the UPS battery groups implement can satisfy the response requirement the response during minute i (lines 26-27).

Analyze the time complexity of the SoC-awareness demand-side response algorithm of UPS. The algorithm firstly sorts the battery groups in ascending orders according to their state of charge. The time complexity of using Merge-sort method is $O(m\log_2 m)$. The algorithm then determines the charging and discharging status of battery groups, as well as the power. The time complexity of this section appears to

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be $O(m)$. Overall, the time complexity of the whole algorithm is $O(m\log_2 m)$.

Algorithm 2: UPS Power Regulation Algorithm

Input : i: control period (minute i);
$BT=\{SoC^1_i, SoC^2_i, \ldots, SoC^m_i\}$: sorted list of m battery groups in asc. order by SoC
$P^1_{TL,i}$: tie-line power after first stage filter
$P^*_{TL,i}$: tie-line power after second stage filter

$\Delta P^2_{TL,i} = P^*_{TL,i} - P^1_{TL,i}$
If $\Delta P^2_{TL,i} > 0$ then
  k=1
  While k<=m do
    If $|\Delta P_k| \leq |\Delta P^2_{TL,i}|$ then
      $\Delta P^2_{TL,i} = \Delta P^2_{TL,i} - \Delta P$
      k=k+1
    else
      charge battery group k with $\Delta P^2_{TL,i}$
      $\Delta P^2_{TL,i} = 0$
      break
    end if
  end while
else
  k=m
  While k>=1 do
    if $|\Delta P| \leq |\Delta P^2_{TL,i}|$ then
      discharge battery group k to a lower capacity limit
      $\Delta P^2_{TL,i} = \Delta P^2_{TL,i} + |\Delta P|$
      k=k-1
    else
      charge battery group k with $\Delta P^2_{TL,i}$
      $|\Delta P^2_{TL,i}| = 0$
      break
    end if
  end while
end if

VI. Experiments and Performance Evaluation

The evaluation of the effectiveness of our power control framework including the regulation algorithms is conducted in a simulated environment with data from real data center and renewable energy projects.

Experimental results are presented primarily in degree of power fluctuation smoothening and power change rate, defined as Eq. (9). The compliance of SLA is also presented.

$$\Delta P_{TL,i} = \frac{dP_{TL,i}}{dt} = \frac{P_{TL,i} - P_{TL,i\text{-}1}}{\Delta T} \tag{9}$$

Results presented here are averages of 100 independent experiments.

A. Experimental Setup

We set up a composite power system for our evaluation study. The power system is based on data center microgrid with wind power and photovoltaic power generation as renewable energy, UPS battery groups as energy storage units, and connection with utility power grids.

The parameters of data center in our experiments come from one of real data center located in Tianjin, which consists of a 30000-node server cluster and 50x250 UPS battery groups with a single battery capacity of 80Ah. The power consumption of each server ranges from 0.14kW at idle operation state to 0.2kW at maximum operation state.

We have used the 24-hour real renewable energy generation data from Tianjin Avenue Photovoltaic Power and Shajingzi wind farm [32] in the experiments. Renewable energy penetration in the data center micro-grid is set to 20% unless stated otherwise. The experiment lasts for 24 hours (from 6am to the next morning 6am, 1440 minutes in total). Time control interval is set to be 1 minute. Detailed experimental parameters, including UPS units and filter settings, are shown in Table I.

The proportion of delay-tolerant tasks is set to 80% (base experiment) unless stated otherwise. Delay-tolerant task units can be divided into three types: 15min delay upper limit with 20% CPU utilization, 10min delay with 10% CPU utilization, and 5min delay with 5% CPU utilization, accounting for 40%, 30% and 30% of the total delay-tolerant task units, respectively. The other 20% workloads are delay-sensitive tasks with zero tolerance delay and 1% CPU utilization. User satisfaction levels are set to 0.8, 0.5 and 0.3 for S_{high}, S_{low} and S_{LL} , respectively.

TABLE I: SETTINGS OF EXPERIMENT PARAMETERS

	Parameter	Value
Server cluster	Number of servers M	30000
	Idle power of single server P_{idle} (kW)	0.14
	Max power of single server P_{max} (kW)	0.2
Renewable energy	Total capacity of solar power (kW)	500
	Total capacity of wind power (kW)	1000
UPS units	Number of batteries in series N_n	50
	Number of batteries in parallel N_s	250
	Rated voltage U_{rated} (V)	9
	Single battery capacity Q_{ups} (A·h)	80
	Charging coefficient of battery Ψ_c	0.95
	Discharging coefficient of battery Ψ_d	1.05
	Initial SoC S_0	0.8
	Lower limit of SoC S_{min}	0.6
	Upper limit of SoC S_{max}	0.75
	Max charging and discharging times Ω_{max}	50
Filter settings	The first time constant T_1 (min)	10
	Time constant Range of the first stage filter [Tmin1,Tmax1]	[5,20]
	Time constant control step of the first stage filter ΔT_1 (min)	1
	The second time constant T_2 (min)	120
	Time constant Range of the second stage filter [$Tmin_2$,$Tmax_2$]	[60,180]
	Time constant control step of the second stage filter ΔT_2 (min)	2
Simulation time	Simulation step ΔT (min)	1
	Total simulation time T_d (min)	1440

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B. Experiment Results

We present results with respect to the base case with a fixed rate of renewable energy usage (20%), different time constants, SLA compliance, different renewable energy penetration rates and varying proportions of delay-tolerant tasks.

1) *Base case:* Fig. 6 shows the smoothen progress of data center microgrid power through two-stage regulation of server cluster and UPS battery groups in our power control framework.

Due to time-varying computing loads of the data center and intermittent of renewable energy output, the initial power fluctuates (blue curve) significantly with a maximum peak-to-valley difference of 14.5%. Under the premise of the first-stage low pass filter, the target power P_1* can be obtained, shown as the orange curve in Fig. 6. Operating the server workloads scheduling algorithm, the actual power curve shown as green one follows the target orange curve really well. In other words, the proposed server workloads scheduling algorithm can effectively restrain the high-frequency fluctuation parts.

The gray curve in Fig. 6 depicts the target power of UPS power load regulation P_2*. The resultant power (red curve) clearly shows the UPS battery charging and discharging to pursue the target power (gray curve). After this two stages Butterworth low-pass filter, the standard deviation of the power curves is reduced from 0.182MW (blue curve) to 0.123MW (red curve).

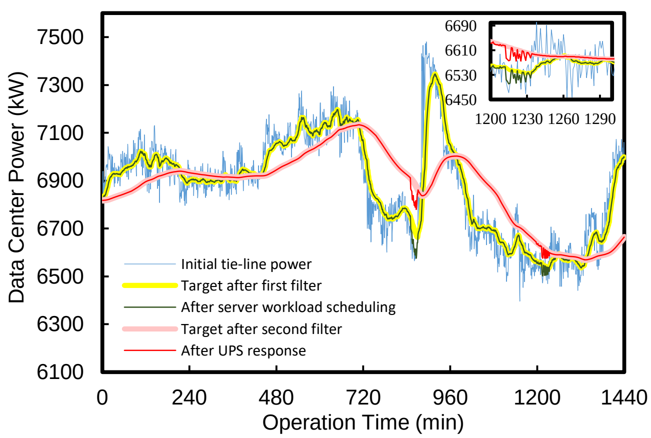

Fig. 6. Data center power curve after regulation by server clusters and UPS.

The probability distribution of power fluctuation is shown in Fig. 7. It shows the proposed regulation algorithms in our framework significantly reduce power fluctuation with high probabilities around the average power. We also calculated the mean absolute error (MAE) of the relative deviation between the actual data center consumption power curve after smoothing and the target power curve, MAE=0.018%, which is much smaller than FLODO algorithm. As the benchmark, reference [33] presented the FLODO algorithm's smoothing effect is MAE=2.71% between the data center consumption and the target load curve. The Calculation formula of MAE is:

$$MAE = \frac{1}{T \cdot \overline{P}_{act}} \sum_{i=1}^{T} \left| P_i^* - P_{act,i} \right| \tag{10}$$

where P_i* is the target power in the *i*th control period. $P_{act,i}$ is the adjusted actual power. $\overline{P}_{act}$ is the average of actual power. T is the number of control periods, where T=1440.

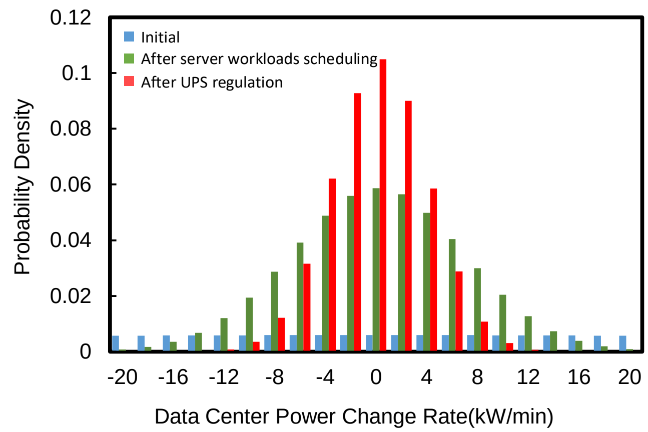

Fig. 7. Probability distribution of data center power change rate.

2) *SLA compliance:* Fig. 8 depicts user satisfaction status (S_i) during 1440 time periods, under variable and fixed time constant strategies. It is obvious that, in both cases, the lowest user satisfaction degree is S_{min}=0.52 in the period of [895min, 960min], but still much higher than S_{LL}=0.3. It means, during the whole operation cycle, the data center's system performance is well maintained. The best cases are the period of [745min, 890min] and [1024min, 1395min], the user satisfaction level S_i remains above 0.98 and closed 1. Another interesting observation is that the variable time constant strategy leads to release more margins to participate in power regulation, shown as the dark green points have a wider Y-axis distribution in Fig. 8.

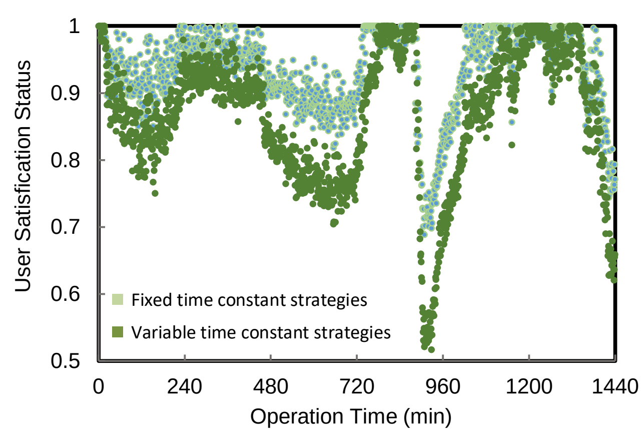

Fig. 8. User satisfaction status.

3) *Different Renewable Energy Usage Scenarios:* Fig. 9 depicts the smoothening effects under different renewable energy penetrations, 20%, 30% and 50%. As the penetrations of

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renewable energy increases, the power fluctuation has become more intense. In particular, the peak-to-valley difference of the red curve (50% of renewable energy penetration) reaches 53.1%, echoing the intermittency and volatility of renewable energy. By performing our power regulation optimization algorithm, the fluctuations can be well restrained to 21.2%, even if under the 50% high penetration of renewable energy. We also calculated the standard deviation of different power curves in different renewable energy penetrations with minute time granularity. The worst case occurs in period of [780min, 1140min] with 50% penetration of renewable energy (red curve), in which the standard deviation reaches 230kW. The best case is the 20% penetration of renewable energy (blue curve), in which, almost all the 24 hours, the actual power can keep the target power curve, and the standard deviation reflected smoothing effect is below to 40kW.

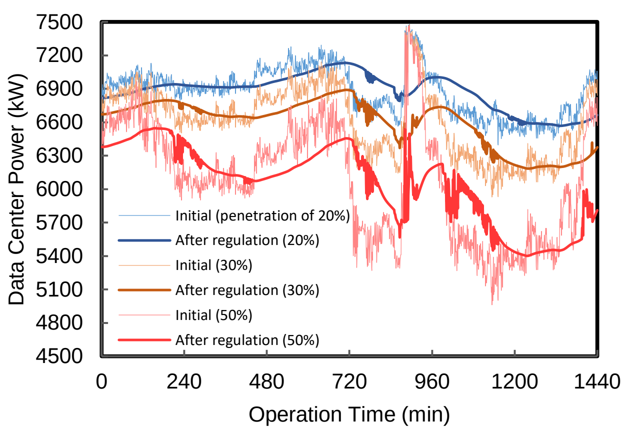
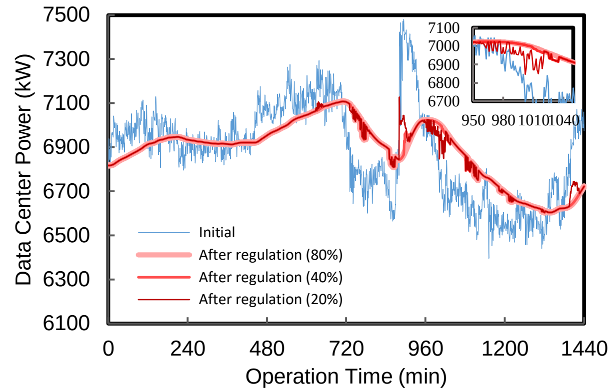
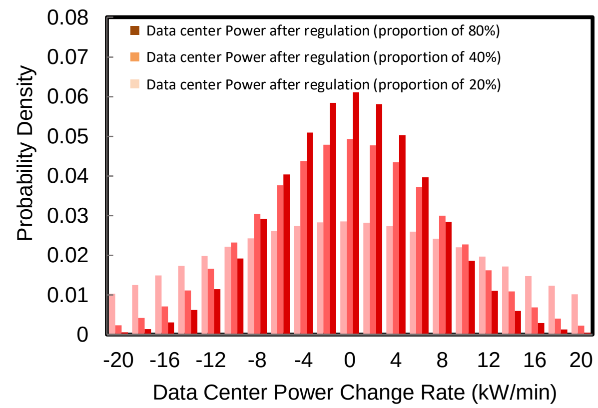


Fig. 9. Data center power with different renewable energy penetrations.

4) Varying proportions of delay-tolerant tasks: To illustrate the impact delay-tolerant task proportion has on power fluctuation smoothening, we reduce the proportion to 40% and 20%, and observe how the results differ from the base case with 80% proportion. Detailed parameters of various tasks, including Delay upper limit, CPU utilization, and number proportion, are shown in Table II. The smoothening effects and the probability distribution of data center power curves after optimization are shown in Figures 10(a) and 10(b), respectively. We have noted that the final responses of 40% and 80% are nearly identical, showing that the efficacy of our framework. Furthermore, under the low proportion of 20%, only in the worst period of [881min, 902min] and [960min, 1033min] the standard deviation from the target power reach 84.67kW, in the rest of period our power regulation optimization algorithm still achieves good power fluctuation suppression. The best case is the period of [300min to 360min], in which the standard deviation is only 1.43kW.



(a)Tie-line power with varying proportions of delay-tolerant.



(b) Probability distribution of tie-line power change rates.

Fig. 10. Smoothening effect under different proportions of delay-tolerant tasks.

TABLE.II PARAMETERS OF VARIOUS TASKS

Tasks type		CPU utilization	Delay upper limit	Proportion
40% delay-tolerant tasks case	1	20%	15min	16%
	2	10%	10min	12%
	3	5%	5min	12%
	4	1%	0min	60%
20% delay-tolerant tasks case	1	20%	15min	8%
	2	10%	10min	6%
	3	5%	5min	6%
	4	1%	0min	80%

5) Different Initial Server Cluster Resource Usage Scenarios: To evaluate the algorithm's flexibility in different data center running status, we increase initial server clusters' CPU utilization from $\overline{\gamma}_i$ =[0.3, 0.5] to $\overline{\gamma}_i$ =[0.3, 0.6] and $\overline{\gamma}_i$ =[0.3, 0.7]. The higher $\overline{\gamma}_i$ upper limit means less regulation space leaving for server clusters to smoothen power fluctuation.

From the experiment results shown in Fig. 11, we find our power regulation optimization algorithms also have nice performance under three types of different CPU utilization. The best smoothing effect occurs in the period of [300min to 360min] with $\overline{\gamma}_i$ = [0.3, 0.5], in which the standard deviation is only 1.44kW. The worst case is in the period of [720min to 780min] with the high utilization of $\overline{\gamma}_i$ =[0.3, 0.7] and the

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standard deviation is 50.34kW, shown as the $\Delta P_{TL,i}$ probability distribution in Fig. 12, which is still within acceptable range.

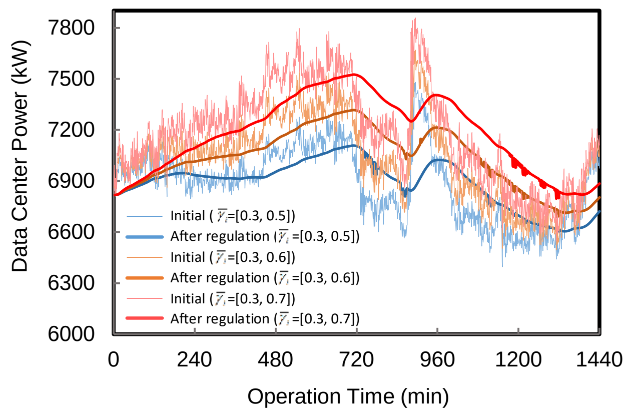

Fig. 11. Data center power fluctuation curves with different initial server clusters' CPU utilization.

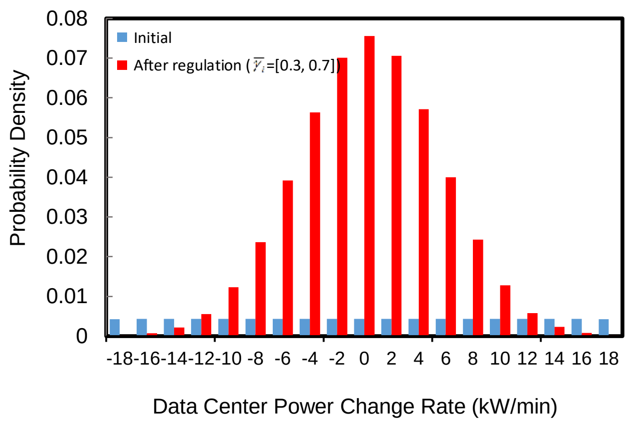

Fig. 12. Probability distribution of tie-line power fluctuation ($\overline{\gamma}_i$ = [0.3, 0.7]).

6) Data Center OPEX: The main cost of a data center includes CAPEX (Capital Expense) and OPEX (Operating Expense). Once the data center is put into operation, the main OPEX (Operating Expense) is electricity expenses and regular maintenance and replacement of equipment, such as UPS batteries.

Firstly, we calculated the total electrical power consumption of data center and amazing found our proposed data center power control framework not only improve the power supply quality, but also can reduce electrical consumption from the utility power grid and save electricity cost. The 24 hours electrical consumption from 3964.56MW·h reduced to 3960.48MW·h.

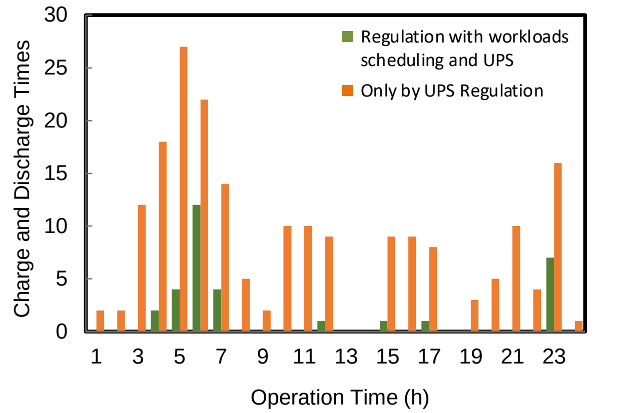

Fig. 13. UPS battery group charging and discharging statistics.

Moreover, we counted the data center UPS charging and discharging time with our proposed power regulation optimization algorithms, as shown green bars in Fig. 13. Because we employed server workloads scheduling algorithm to smoothen the high-frequency power fluctuations, the UPS battery groups only focus on low-frequency fluctuations, with which the charging and discharging frequency is substantially reduced, especially in [0min, 180min], [420min, 660min] and [1080min, 1320min], the frequency of charging and discharging is reduced to zero. Compared to the situation without cluster server's response (UPS only, such as RE-UPS [18]), as shown in orange bars in Fig. 13, Lower frequency of (dis)charging means significant extension of batteries' lives and skyrocketed operating expenses reduction.

VII. Conclusion

In this paper, we have studied smoothening the power fluctuations and ensuring high quality and high reliability of the power supply to data centers. This work is different from the existing energy-efficient data centers studies which focus on how to maximize the use of renewable energy or to minimize the cost of electricity. Collaborating server clusters workload and the UPS in data center as controllable power regulation resource, a novel power regulation framework is proposed to smoothen data center power fluctuations. In the framework, a novel server cluster controllable workload model and scheduling algorithm based on task time migration mechanism is proposed, totally different from previous work to regard IT equipment as uncontrollable power load. The part of low frequency and large-scale power fluctuation is smoothened by UPS battery groups. Table III lists the strengths and possible weaknesses of the proposed power regulation optimization algorithm. The experiments conducted based on real system parameters have extensively evaluated the efficacy of our power control framework. Results proved our claims of smoothening capability of our framework.

TABLE. III STRENGTHS AND POSSIBLE WEAKNESS OF THE POWER REGULATION OPTIMIZAITON ALGORITHM

Strengths	Proposed algorithm	Previous Works
Control strategy	Combine server workload and UPS	Only UPS [17][34][35] Only server workload[19][36]
Time granularity and real-time	1 min	1 hour[37]
Satisfying SLA	Yes	Not consideration[18][25]
MAE	0.0179%	2.71%[33]
Weaknesses	Not considering multiple data centers collaboration	

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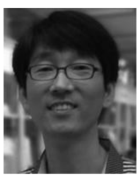

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