

Minimizing the Effects of Data Centers on Microgrid Stability

Baris Aksanli¹, Alper Sinan Akyurek², Tajana Rosing¹

¹Computer Science and Engineering, ²Electrical and Computer Engineering
University of California, San Diego
{baksanli, aakyurek, tajana}@ucsd.edu

Abstract— With the integration of renewable energy sources and large-scale smart buildings, the electricity grid becomes more prone to instabilities due to unexpected fluctuations in energy consumption. Data centers are a type of smart building because of their innate automation and controllable load. Load controlling in data centers has been studied extensively with scheduling/migration, peak power shaving, load shifting, etc. However, previous studies have not considered how changes in data center power consumption may impact the stability of the electric grid. This paper first shows that well-known power management mechanisms in data centers may lead to voltage instability in the grid. We propose a new method that considers both workload performance constraints and minimizes the instability-causing effects on the grid. Our simulation studies show that our policy can preserve the grid stability 97% of the time and reduces the maximum instability observed by 27%, while effectively managing the workload performance.

I. INTRODUCTION

With the increasing penetration of renewable energy sources and the number of large-scale buildings, it has become more difficult for the electric grid to preserve its internal dynamics. They pose might severe problems especially for smaller circuits, such as microgrids, that might have to keep supply and demand in balance without the help of utilities (e.g. islanding). One such problem is the voltage instability due to large local power consumption. Even though the supply-demand balance is maintained (which maintains frequency stability), high consumption values may still cause local voltage deviations. The grid¹ (microgrid in our case) has to address these voltage deviations, which may harm the grid stability and disrupt normal operation [1]. Large buildings can be very hazardous in this context due to their significant and possibly oscillating power demands. Although they are closely monitored for power prediction and rely on *smarter* power management, they are optimized for building energy savings and not for cooperation with the grid. This makes it increasingly difficult to anticipate the impact of buildings on microgrid stability. As such, it is essential to have a closed loop system where the buildings and the grid have constant communication, with feedback to each other.

Data centers are an important type of large-scale buildings, with their already significant and still increasing power demands, up to 100MW per individual site [2]. Data center energy consumption accounts for 2-3% of overall consumption in the US [3]. Recently, smaller data centers (known as micro data centers) have also become more common as a solution for the scaling problems of big data centers and their enormous

traffic requirements [4]. However, their energy consumption can still be relatively large compared to the other buildings in the same area. To address the energy problem of data centers, researchers have proposed many power management mechanisms, including renewable energy integration [5] [6], peak power shaving [7] [8] [9], energy efficient job scheduling including server consolidation [10] [11], load shifting [12], etc. These mechanisms work well when increasing the energy efficiency of a single or a set of data centers, but they may also increase the unpredictability of the power profile of a data center; hence resulting in unexpected instabilities in the grid. Furthermore, these mechanisms can have a deteriorating impact on the quality of service of the running applications, affecting the service guarantees, such as service level agreements (SLAs) that a data center must fulfill. Although previous studies have well investigated these power mechanisms individually, they do not consider how a data center may affect the grid and its neighbors. In addition to these mechanisms, researchers have also investigated how data centers can help the grid by providing ancillary services, such as regulation [13] [14] [15] and demand response [16] [17] [18]. The ancillary service participation of data centers analyzes how data centers can be helpful by providing flexibility to the grid, but it does not look into how data centers may create instability problems on the grid.

In this paper, we model a realistic microgrid circuit that a smaller data center can reside in. We take this circuit as a subset of one of the openly released EPRI test circuits and use it to model a neighborhood with a small data center. Such data center deployments will be more common with the increasing Internet of Things (IoT) trend. This trend requires distributed infrastructure to handle the computation and communication in a faster way, leading to more local data center deployments closer to the original data sources [19]. Micro data centers can collect the local data (from sensors, smart meters, etc.), store it, apply any preprocessing required and then send it to the cloud.

Although these data centers are small, they can still cause problems to the microgrid. Thus, we first analyze how existing power management mechanisms perform in terms of grid stability, evaluated as a function of voltage deviation. These mechanisms, in addition to their performance overheads, may lead to unacceptable voltage deviation values up to 75% of the time, negatively affecting the other buildings in the circuit, as well as the quality of the whole microgrid. We propose a new method that finds the best mixture among peak power shaving, server consolidation and load shifting. It both minimizes the instability by carefully adjusting the power consumption and

This work is supported in part by Google and Microsoft.

¹ Grid and microgrid are used interchangeably through the rest of the paper.

considers the workload performance constraints by selecting the right mixture of the above mechanisms. To the best of our knowledge, our work is the first analyzing data centers from the grid's point of view and their instability-causing actions. We can preserve grid stability 97% of the time and reduce maximum instability observed by 27%. We meet the workload performance constraints effectively, incurring no more than 10% performance overhead for batch jobs and completing the service jobs within 20% of their target deadlines.

II. RELATED WORK

This section first outlines the data center power management mechanisms and then shows the existing studies on data center participation in ancillary markets.

A. Data Center Power Management Mechanisms

Data center power management mechanisms can be classified as server or data center level. The former includes DVFS-based methods [20] [21], virtual machine migration [22] [23] and consolidation [11] [10]. The latter consists of higher level scheduling solutions such as load shifting [12], renewable energy integration [6] [5] and peak power shaving [9] [8] [24].

DVFS-based power management controls server power by adjusting the CPU voltage/frequency. It is an effective power cap – a last resort to decrease the total consumption. It slows down the CPU, thus often results in serious performance degradation. Also, it is difficult to coordinate this local controller across thousands of servers. Virtual machine (VM) migration is a more high-level solution, where the controller moves a specific VM from its original host to another server. The reasons for this can be collecting VMs in fewer machines and shutting down the rest (server consolidation) or achieving VM heterogeneity across machines to increase resource utilization and energy efficiency [10]. This method also leads to some performance issues due to the delay in moving a VM.

Load shifting is another well-known high-level solution for data center power management. The main idea is to reschedule the starting time of some jobs so that the total power demand matches renewable energy generation [23], cheaper electricity price [25], etc. It is an effective solution only for jobs that are chosen very carefully to avoid performance penalties. While renewable energy combats the increasing negative implications of fossil-based brown energy, much effort is required to navigate their unpredictability and maximize the amount of green energy successfully integrated into the system [6]. Since utility bills are calculated based on the maximum power demand of the data center over a billing period, e.g. a month, peak power shaving can effectively reduce utility charges. Examples include battery-based [9] [8], DVFS-based [7] and VM-migration based solutions. DVFS-based solutions may lead to costly performance overheads, while solutions based on overprovisioned batteries do not interfere with job scheduling decisions. Battery configurations must be carefully designed so that installation and maintenance costs do not neutralize the savings of peak power shaving [8] [9]. These methods increase the power efficiency of data centers but they ignore the effects of data centers on the grid. They can cause unexpected and significant oscillations in the data center demand profile.

B. Data Center – Grid Interactions

Researchers have started to study the relationship between data centers and the electric grid, mainly in the form of ancillary services, and estimated the amount of savings data centers can obtain. These include regulation services [13] [14] [15], demand response [18], voluntary load reduction [17] and spinning and non-spinning reserves [15]. Some studies also consider how buildings should negotiate price with the grid and adjust their operations based on a price-related reward [26].

Out of the ancillary services, participation in regulation markets is most studied due to its higher return. This higher return requires fast responses from the data centers' end, which may be accomplished with server-level DVFS [14]. The data center first chooses which market it participates in, i.e. either hour or day ahead. It then reports the regulation capacity it can provide to the grid. The grid sends requests for either an increase or a decrease in consumption within the previously agreed capacity. The data center then fulfills these requests with DVFS. Aksanli et al. align battery charge/discharge cycles to create the power flexibility to participate in regulation services [13]. Maasoumy et al. use model predictive control for building HVAC systems to create this flexibility [26].

Another well-known service that data centers can provide is demand response (DR). Wang et al. analyze data center participation in DR with clever job scheduling [16]. Another work surveys the recent studies showing how data centers can provide DR, identifying the potential problems [18]. Aikema et al. study different ancillary services and show which one is more profitable given the workload profile [15]. They consider regulation services, spinning and non-spinning reserves, voluntary load reduction and emergency DR. They conclude that the regulation is the most profitable service for data center participation in ancillary services. They use different solutions such as load shifting, DVFS, and job rescheduling to create the necessary changes in data center power demand.

These studies form a good basis for understanding the relationship between data centers and the grid. They show how data centers can make extra profits by participating in grid services. However, they do not model data centers in smaller circuits where they can have higher impacts on the grid stability and they do not analyze how to preserve the stability so that the system is not threatened. In this paper, we first evaluate the grid instability caused by data center actions. Then, we show a new mechanism that addresses the instability problems and minimize their negative effects, while preserving the data center profits without affecting job performance.

III. DATA CENTERS IN THE GRID

This section first shows how we model a data center in a microgrid circuit and then demonstrates that existing power management mechanisms can lead to both significant performance degradations and serious grid instability.

A. Grid Circuit and Simulation

We model both a data center and the microgrid in which it resides. We use a subset of one of the EPRI's openly released test circuits of a small town with 1379 customers [27], which consists of multiple residential and commercial buildings. Our

circuit includes a single substation transformer with 9 local transformers. We modify the circuit by replacing one of the buildings with a data center, scaled to match a power demand typical of micro data centers containing 500 servers. Micro data centers are designed to provide computing capabilities to companies that do not need a large-scale data center [4]. These systems are becoming more common to satisfy the local computation and communication demand required by new IoT applications and expected to have \$4.40 billion market by 2019 [28]. Figure 1 shows the circuit structure we use for our modeling and experiments for the rest of the paper. We also change the location of the data center to analyze the effect of distance to the substation to the voltage deviation. In our experiments, we place the data center to locations H1_1, H5_3 and H9_2. The first one is the physically closest to and the last one is the furthest away from the substation transformer.

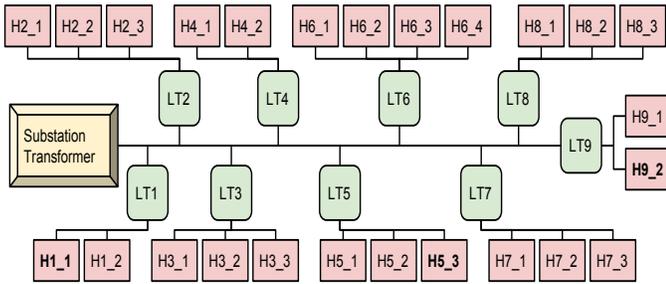


Figure 1. Circuit model based on the EPRI test circuit

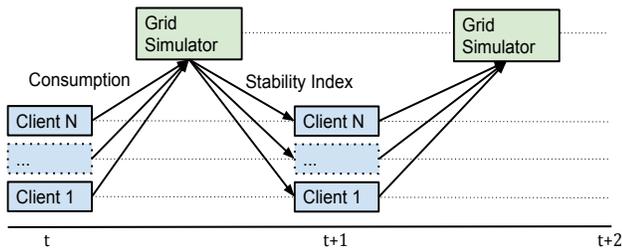


Figure 2. Closed-loop control operation flowchart

We use a grid simulator to study and quantify grid dynamics. It allows connections from external clients as the other buildings in the grid. We handle time synchronization among the clients internally. We expect a power consumption value from each connected client in every interval. Then we use OpenDSS [29], to solve the power flow equations and quantify the grid stability by calculating the voltage deviation

stemming from changes in building power consumption, and compute a stability index. This index is fed back to the client to adjust its consumption accordingly, creating a closed control loop. Figure 2 shows the flowchart outlining the order of these operations. In our study, one of the clients is a data center, where the rest of the clients are other buildings, such as commercial office buildings and/or residential buildings. This closed-loop system, where the buildings and the grid both send feedback to each other, helps the utility preserve grid stability.

B. Workload Performance vs. Grid Instability

For different mechanisms we first show the stability effects of nominal (without any mechanism) consumption, then include the results for the other methods. The metrics we use to quantify the grid stability are: 1) the percentage of the number of intervals where the grid stability is threatened, 2) the maximum voltage deviation caused by the data center. American National Standard for Electric Power Systems and Equipment requires utilities to have operation voltage between 90% and 105% of the nominal value [30]. We use the lower limit, 10% deviation, as the stability threshold.

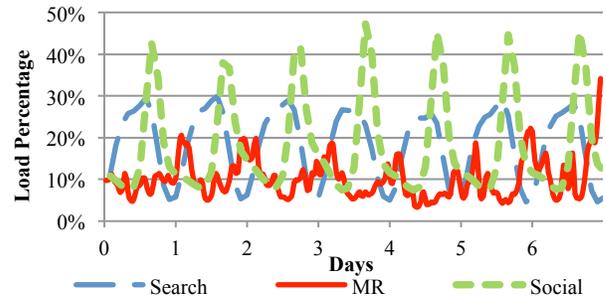


Figure 3. Data center load composition

We obtain the nominal data center power profile based on workloads and traces from real data center applications. We use Google Search, Orkut [31] and Facebook MapReduce traces taken from [32]. We compute the data center power as the aggregated server power values, where power consumption per server is calculated according to utilization [20] [33]. The mixture of time-sensitive service jobs (Search and Orkut) and throughput-oriented batch jobs (MapReduce) form a realistic profile for data center applications [34]. Figure 3 shows load ratio of these three types of workloads in a week. Scheduling based solutions, such as load shifting or VM migration; largely depend on these observable diurnal workload patterns.

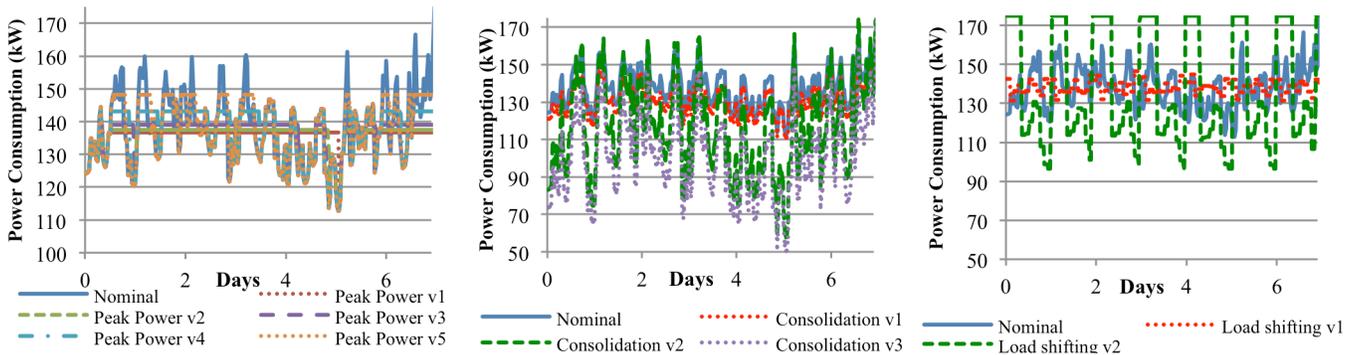


Figure 4. Power profiles for different mechanisms. Peak power shaving (top). VM migration and consolidation (middle). Load shifting (bottom).

TABLE I. PERFORMANCE IMPLICATIONS OF DIFFERENT POWER MANAGEMENT MECHANISMS

Mechanism	Extra Infrastructure (LFP Battery Capacity)	Service Job QoS (avg. – max)	Batch Job Performance Overhead (avg.-max %)	Energy Cost Savings (%)	Peak Power Shaving (%)
<i>Peak power v1</i>	240 kWh	No effect		0	21.9
<i>Peak power v2</i>	192 kWh				21.4
<i>Peak power v3</i>	144 kWh				20.5
<i>Peak power v4</i>	96 kWh				18.2
<i>Peak power v5</i>	48 kWh				15.3
<i>Consolidation v1</i>	n/a	0.047 – 0.047	14.5 – 19	4.7	0
<i>Consolidation v2</i>		0.26 – 0.93	15 – 19	15.9	0
<i>Consolidation v3</i>		0.52 – 0.93	16.7 – 19	26.7	0
<i>Load shifting v1</i>		0.05 – 0.1	7.8 – 17	-0.2	16.2
<i>Load shifting v2</i>		0.09 – 0.93	11.5 – 19	4	0

TABLE II. STABILITY STATISTICS OF DIFFERENT POWER MANAGEMENT MECHANISMS

Mechanism	DC location = H1 1				DC location = H5 3				DC location = H9 2			
	Max Dev.	Avg. Dev.	#Unstable Points	%Unstable Points	Max Dev.	Avg. Dev.	#Unstable Points	%Unstable Points	Max Dev.	Avg. Dev.	#Unstable Points	%Unstable Points
<i>Nominal</i>	15.8	11.1	243	72.3	15.9	11.1	257	76.5	15.8	11.1	248	73.8
<i>Peak power v1</i>	11.1	10.8	319	94.9	11.2	10.9	322	95.8	10.9	10.7	320	95.2
<i>Peak power v2</i>	11.2	10.8	311	92.6	11.4	10.9	317	94.3	11	10.8	312	92.8
<i>Peak power v3</i>	11.3	10.8	290	86.3	11.5	11	298	88.8	11.2	10.8	292	86.9
<i>Peak power v4</i>	11.9	10.9	257	76.5	12	11	269	80.1	11.7	10.9	260	77.4
<i>Peak power v5</i>	12.5	11	245	72.9	12.6	11.1	258	76.8	12.3	10.9	249	74.1
<i>Consolidation v1</i>	15.8	10.2	176	52.4	15.9	10.3	193	57.4	15.8	10.2	181	53.9
<i>Consolidation v2</i>	16.5	8.4	101	30.1	16.7	8.5	111	33	16.5	8.4	104	30.1
<i>Consolidation v3</i>	15.8	6.6	39	11.6	15.9	6.7	40	11.9	15.8	6.6	39	11.6
<i>Load shifting v1</i>	12.2	11	336	100	12.3	11.1	336	100	12.1	11	336	100
<i>Load shifting v2</i>	15.8	11.1	151	44.9	16	11.2	168	50	15.8	11.1	147	43.7

We apply three mechanisms introduced by previous studies to create different power profiles. Load shifting is performed to align consumption with the cheaper electricity price or it shifts workloads to intervals with less demand [12]. With migration and consolidation [10] [35], VMs are put into a subset of all servers and the rest are turned off. Peak power shaving is performed with multiple batteries placed together. Their output is connected to the mains with a grid-tie inverter. We choose lithium iron phosphate (LFP) batteries over lead acid (LA) ones as they are more cost effective and better at peak power shaving [9]. The battery charge/discharge cycles are adjusted to meet a predefined peak threshold.

Figure 4 has three graphs showing the power profile of each controller class. Each graph has the power demand as the y-axis and the time as the x-axis. The leftmost graph compares the nominal power with five different peak shaving methods. Each has a different threshold, and the peak shaving is handled with batteries. The batteries discharge when the nominal power is over the threshold and recharge when it is lower. This explains why the lowest power is also high. The power demand is adjusted around the threshold, achieving an unexpected profile. The middle graph shows three versions of VM consolidation and how they compare to the nominal case. The first one moves batch jobs together and keeps the rest ready for service jobs. The second one combines batch and service jobs separately and puts the rest into sleep. The last one mixes batch and services jobs together. We see that the new power profiles achieve consistently lower values than the nominal case. This is due to the servers shut down. However, this method affects application performance negatively because of resource contention and VM migration overhead, up to 20% overhead to batch jobs and 10x slower response times for service jobs. The last graph shows two load shifting methods compared to the base. The first one shifts the batch workloads to the intervals with fewer active service jobs. The second one moves the batch

workloads to intervals with cheaper electricity price. The second version assumes that the electricity price is based on a time-of-use (TOU) scheme, with the cheapest prices occurring daily between 10PM and 6AM, using SDGE’s TOU pricing numbers [36]. The service jobs are not shifted due to their tight delay requirements. The last graph shows that load shifting can create new peaks that need to be considered by the utilities to avoid any instability events and/or supply/demand mismatches.

Table I outlines the tradeoff between savings (energy cost savings and peak power reduction) and performance (extra infrastructure and overhead) for each mechanism. We compute savings using SDGE’s TOU pricing and compare the peak power shaving percentage against the absolute peak value. We estimate the effects of consolidation for different types of jobs using the analysis provided in [6], where the authors quantify the quality of service (QoS) degradation for service jobs and performance overhead for batch jobs when multiple VMs are consolidated on a single server. Service job QoS gets better with smaller numbers and is based on 90th percentile response time over their target deadlines and batch job performance is shown as the normalized job throughput rate as in [6]. Table I gives average and maximum performance degradation values.

Battery-based peak power shaving methods do not interfere with job performance, but they require large size battery deployments, whose capacity depends on the peak power shaving goal. The savings can be significant, up to 22%, but the fact that batteries are expensive devices with lifetime constrains makes it necessary to have a careful analysis. Consolidation methods cannot reduce the overall peak power but decrease the energy cost by up to 26% without additional infrastructure. Their effects on job performance can be quite significant, up to 20% performance overhead to batch jobs and more than 10x slower response time for service jobs. Load shifting, in contrast, does not require additional infrastructure

and does not have as high negative impacts on job performance as consolidation methods, while achieving limited benefits.

Since each method has its own pros and cons, we are led to consider a hybrid solution. We now introduce another tradeoff dimension: grid stability. We evaluate the effect of each profile separately using a grid simulator. We place the data center in 3 locations in the circuit, showing the effects of placement on the grid stability. Table II shows the stability statistics with different profiles over a week. The existing solutions do not consider these effects. These statistics include the average and maximum voltage deviation, the number of unstable intervals, i.e. the intervals with deviation higher than the threshold (10%) and the percentage of unstable intervals over the simulation duration. The nominal demand already results in significant grid instability, regardless of the location. The peak shaving methods decrease the gap between average and maximum deviation numbers, but still lead to instability more than 70% of the time. In contrast, some methods, e.g. consolidation v2 and v3, can reduce the number of unstable points with severe performance overhead. Also, as the data center gets further away from the substation and if it shares the local transformer with more buildings, the instability increases. This analysis shows the necessity of a mechanism that considers both performance and grid instability caused by the data center.

IV. STABILITY PRESERVING POWER MANAGEMENT

This section presents our solution to the instability problem. Our framework consists of two different components: 1) the data center, which aims to minimize the performance overhead from various power management mechanisms and the penalty issued by the utility to preserve the grid stability, 2) the utility, whose goal is to encourage its customers by imposing a penalty on their power consumption causing instability.

A. Data Center Point of View: Problem Formulation

We divide the time horizon into equal intervals, t . The data center receives both service (response time critical) and batch job (flexible deadline) requests in the beginning of each time interval (30 min for our experiments). It also communicates with the utility and receives a power threshold. Any violation of that power threshold will incur a price penalty. To achieve this threshold, the data center can use a combination of power management mechanisms, outlined in section III.B.

Because multiple neighbors could be affected by instability, it is difficult to evaluate future intervals even though we can predict the data center power demand. Therefore, we focus on a single time step and formulate a problem to make the best decision to avoid penalties from the utility and performance degradations. In interval t , we represent incoming service job load ratio as s_t and batch job ratio as b_t , with total load ratio:

$$load_t = s_t + b_t + sh_{t-1} \quad (1)$$

where sh_{t-1} is the load ratio shifted from the previous interval (where $s_0 = 0$, i.e. no jobs shifted to the first interval) to the current one. We divide servers into two sets to process service and batch jobs separately, using the results of [6]. The ratios of servers processing service and batch jobs are s_r and b_r , where $s_r + b_r = 1$. The data center chooses the consolidation ratios for service, $conS_t$, and batch jobs, $conB_t$ (between 0 and 1),

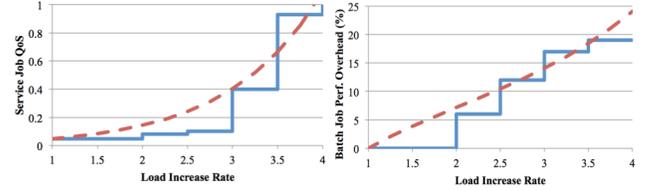


Figure 5. i) Service and ii) batch job overhead due to consolidation

along with the shifted batch job load ratio to the next interval, sh_t . These values show what percentage of the workloads of each type is consolidated. To avoid response time violations, we do not shift service jobs. We impose an upper limit on sh_t to avoid indefinite batch job postponement, $limShiftBatch$. Since batch jobs do not have tight deadlines, in the beginning of an interval, the data center can always start processing the batch jobs from an earlier interval. We assume that the shifted batch workloads have higher priority than the ones newly arriving so that they can be executed first. If the power manager decides to shift batch workloads again, they are selected among the ones newly arriving. Equation 2 shows the limits for these decision variables.

$$\begin{aligned} 0 \leq sh_t \leq \min(limShiftBatch, b_t + sh_{t-1}) \\ 0 \leq conS_t \leq 1 \\ 0 \leq conB_t \leq 1 \end{aligned} \quad (2)$$

We then calculate performance penalties for consolidating service and batch jobs. The service job penalty is computed with QoS ratio and batch job penalty in terms of job throughput rate. We model the penalty based on current load ratios, s_t and b_t with consolidated load ratios, $conS_t$ and $conB_t$:

$$\begin{aligned} penConService_t &= f_s(liS_t) \\ penConBatch_t &= f_b(liB_t) \end{aligned} \quad (3)$$

where f_s and f_b reflect the penalty relation between current and consolidated load ratios. We model the relation based on the work in Aksanli et al. [6] where multiple VMs are co-located on a single machine. The performance of service and batch jobs is measured in terms of QoS ratio (observed response time over the target deadline) and percentage decrease in job throughput rate, respectively. Figure 5 shows how we model these functions for both service (i) and batch jobs (ii). The x-axes represent the load increase rate due to consolidation. Y-axes denote service job QoS in (i) and percentage decrease in job throughput rate in (ii). The solid lines show measurement points and the dashed lines present their exponential and/or logarithmic interpolations. We compute the load increase rate for each type of job, liS_t and liB_t , using consolidation and load ratios, in equations 4 and 5. The consolidated jobs end up in servers with full utilization and the remaining jobs stay in their previous hosts with the original utilization value.

$$liS_t = \frac{conS_t}{s_t} + (1 - conS_t) \quad (4)$$

$$liB_t = \frac{conB_t}{b_t + sh_{t-1} - sh_t} + (1 - conB_t) \quad (5)$$

If the denominator is 0 in equation 5, we set liB_t equal to 1. This way, we make sure that the associated penalty; $f_b(liB_t)$ is 0. We impose limits, $limConService$ and $limConBatch$, on these penalty values to avoid large overheads, which are set manually based on the results of the previous work [6]. This work limits the batch job performance hit to 10% and makes

sure that service jobs complete before their target deadlines. The last power control is the battery-based power management, where the charged/discharged energy is denoted by bat_t :

$$-limDch \leq bat_t \leq limCh \quad (6)$$

where $limDch$ and $limCh$ are maximum allowed battery discharge and charge energy in an interval respectively. If $bat_t > 0$, the battery is charging and it is discharging when $bat_t < 0$. The battery usage is also limited by its state-of-charge (SoC), i.e. we cannot overcharge the battery or drain it further than its capacity. We calculate the SoC in interval t as:

$$SoC_t = SoC_{t-1} + \frac{bat_t}{bat_{eff}bat_{cap}} \quad (7)$$

where bat_{cap} is the battery capacity and bat_{eff} is the battery charging efficiency, which can be specified as:

$$bat_{eff} = \begin{cases} \alpha < 1, & \text{if } bat_t < 0 \\ 1, & \text{if } bat_t > 0 \end{cases} \quad (8)$$

where α is a value between 0 and 1, denoting the discharging efficiency of the battery. Then the battery SoC is limited by:

$$lowSoC \leq SoC_t \leq 1 \quad (9)$$

Equation 9 makes use of a lower bound, between 0 and 1, on battery SoC, $lowSoC$, to better control the battery lifetime. We assume that the batteries are initially fully charged, i.e. $SoC_0 = 1$. We also limit the number of discharging intervals to avoid battery overuse. We count the number of discharging intervals and limit it with average battery usage number, $avgBatUsage$ that is computed as the expected discharging intervals over the battery lifetime:

$$batU_t = \begin{cases} batU_{t-1} + 1, & \text{if } bat_t < 0 \\ batU_{t-1}, & \text{else} \end{cases} \quad (10)$$

$$\frac{batU_t}{t} \leq avgBatUsage$$

We calculate the data center power in interval t , P_t , using active/consolidated load ratios and the battery power. The total consumption has 5 parts: consolidated and unconsolidated server power consumption and the battery component:

$$P_t = Con_{ser} + Con_{batch} + Uncon_{ser} + Uncon_{batch} + Battery \quad (11)$$

We use a linear, utilization based equation to compute the parts of equation 11. We adjust this using load ratios, with and without the consolidated parts, and add the battery component:

$$P_t = N(conS_t s_t)(P_i + P_a) + Ns_r(1 - conS_t)(P_i + P_a s_t / s_r) + N(conB_t(b_t + sh_{t-1} - sh_t))(P_i + P_a) + Nb_r(1 - conB_t)(P_i + P_a(b_t + sh_{t-1} - sh_t)/b_r) + bat_t \quad (12)$$

where N is the number of servers, P_i is the idle server power consumption and P_a is its dynamic power range. Equation 12 assumes that the consolidated jobs end up in servers with full utilization and the remaining jobs stay in their previous hosts with the original utilization value. Finally, we optimize the total consumption, P_t , based on the utility threshold signal:

$$\min Penalty(P_t) = |P_t - P_{th}| \quad (13)$$

The objective function defines the penalty as the deviation of P_t from P_{th} . This way, we 1) consider the cases where the

utility wants the data center to increase its power demand, 2) avoid reducing the consumption further than necessary and 3) provide a motivation for batteries to recharge in some intervals. The optimization problem is summarized by (13) with constraints (1)-(10) and (12). The problem is not necessarily convex as the absolute value does not guarantee it. This means that a unique solution may not exist. The problem is polynomial time as the solution set is limited. It is possible to do a linear search to find the minimizing value(s) if not unique). We solve the problem using MATLAB's constrained nonlinear optimization toolbox [37].

B. Utility Power Threshold Signal

We model the utility as the main entity responsible for maintaining the grid stability. It can access the power demand of all the buildings in the circuit and solves power flow equations by OpenDSS to compute the voltage deviation each building leads to. It then uses our grid simulator to find the feasible power value specifically for the data center. In practice, we can compute this value for each building in the circuit, but in this paper, we are only interested in data centers. Our grid simulator runs multiple iterations to find a feasible value, denoted by P_{th} previously. It represents the power value that the data center should adjust to avoid a potential instability event. This process is similar to the demand response programs utilities have [18]. Different than previous works, we explicitly compute the threshold value considering both the data center and other buildings on the grid. We characterize an instability event as the maximum voltage deviation being over the acceptable threshold. We use the same implementation details for the grid simulator as the authors describe in [1].

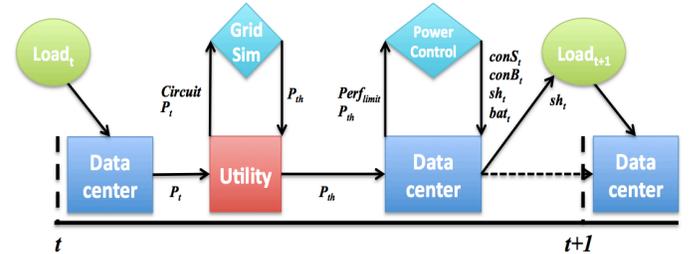


Figure 6. Data center – utility interaction in a time interval

Figure 6 shows the relationship between the utility and the data center in an interval. The data center first computes its expected power demand based on incoming jobs and send this value to the utility. The utility uses this value, with power values from the other buildings as input to the grid simulator. The simulator calculates the power threshold value for the data center and the utility forwards this value to the data center. Then, the data center solves the optimization problem from the previous section with the power threshold and workload performance constraints. Solving the optimization problem determines the power management mechanisms used in the current interval. The same process repeats for the next interval.

Our framework presents an extension to demand response (DR), formalizing the relation between utilities and the consumers (data center in our case). Previous studies almost completely focus on voluntary load reduction, where data centers decrease their consumption to receive a reward. In our system, the utilities explicitly penalize data centers for their

instability causing behavior. On the data center side, we develop a unique power manager: selecting from different mechanisms to find the most effective tradeoff between performance overhead and the penalty imposed by the utility.

V. EVALUATION

This section first shows the experimental setup and inputs to evaluate our power management solution. We then present the results of our framework. It preserves the grid stability 97% of the time and reduces the maximum voltage deviation by 27%. We achieve the effective tradeoff between performance and grid instability, which is missing in the existing solutions.

A. Methodology

Data Center Workload Mixture: We use the same workload mixture as introduced in section III.B. This mixture includes a year of publicly available traffic data of two Google products Orkut and Search, as reported in Google Transparency Report [31] to represent response time-critical service jobs. We use Facebook MapReduce traces as batch job representatives, produced from the weekly waveforms as reported in [32]. We limit the traces to one week for simplicity. The resulting mixture is shown in Figure 3. This figure shows the diurnal patterns jobs, aligning well with real-world applications. The max load ratio is around 90% while the average is 45%.

TABLE III. EVALUATION PARAMETERS INPUT TO THE OPTIMIZATION

Parameter	Explanation	Value
N	Number of servers	500
P_i	Single server idle power (W)	175
P_a	Single server active power (W)	175
s_r	Ratio of servers allocated to service jobs	0.6
b_r	Ratio of servers allocated to batch jobs	0.4
bat_{cap}	Total battery capacity (kWh)	150
-	Battery type	LFP
$limCh$	Battery charging energy limit (kWh)	15
$limDch$	Battery discharging energy limit (kWh)	15
$avgBatUsage$	Battery discharge intervals ratio	0.5
α	Battery discharging efficiency	0.95
$lowSoC$	Lowest SoC allowed for batteries (1 - depth of discharge limit)	0.4
$limConService$	Service job penalty limit, based on QoS	0.2
$limConBatch$	Batch job penalty limit, based on % throughput decrease	10%
$limShiftBatch$	Max batch load ratio that can be shifted	0.05

Evaluation Parameters: We require several parameters to find the best decision to minimize the grid instability. They are either infrastructure related, such as server and battery properties, or performance related such as service and batch job penalty limits. Table III lists the parameters we use, along with their explanations and values. We model a micro data center with 500 servers to match the data center power demand to a common office building that can reside in the circuit in Figure 1. This size can have multiple containers, where each can take around 200 servers [9]. The server model we use is based on Sun Fire servers, with 175W idle and 350W peak power [8]. We include LFP batteries, as they are more cost efficient with longer lifetime and higher efficiency [9] [8]. We limit their depth of discharge to 60% as in previous studies [9] [8], i.e. setting $lowSoC$ to be 0.4. The total battery capacity is set to 150 kWh, the average capacity of five peak shaving

scenario. We limit the average battery usage to 0.5, i.e. only half of the time batteries can discharge, allowing to recharge in the other half. The maximum allowed QoS ratio for service jobs is 0.2 whereas the maximum throughput decrease of batch jobs is set to 10%. We obtain these values as the lower bounds observed in preliminary results, as reported in Table I.

Grid Simulation and Optimization: We place the data center in 3 different locations on the circuit shown in Figure 1. They range from closest to farthest away from the substation transformer. We use the power demand traces provided by EPRI along with the circuit diagram [27] to account for the other 24 buildings. An example subset of the consumption profiles from 5 buildings for a time of 1 week is shown in Figure 7. We input power demand traces of all 25 buildings to our grid simulator and run a separate simulation for each different data center placement. The data center reports its expected power demand to the grid simulator at the beginning of each interval and then the grid simulator provides the power threshold signal to the data center. Based on this threshold, we solve the optimization problem defined in section IV.A and adjust the data center power demand. The problem is solved using MATLAB's constrained nonlinear optimization toolbox [37]. We find the solution for each time step individually. The process is computationally lightweight. In our experiments, the number of iterations to find the solution ranges between 3 and 28, with the average of 17.

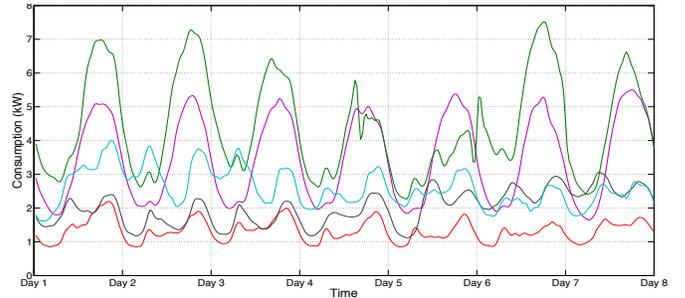


Figure 7. Sample consumption profile for 5 buildings

B. Results

The upper half of Table IV includes performance statistics such as service job QoS and batch job overhead percentage, energy cost savings and peak power shaving percentage. The lower half has stability statistics such as maximum and average voltage deviation, number and percentage of unstable points.

TABLE IV. PERFORMANCE OF OUR MECHANISM

Performance Metrics	H1_1	H5_3	H9_2
Service Job QoS (avg. - max)	0.08 - 0.18	0.08 - 0.2	0.08 - 0.2
Batch Job Performance Overhead (avg. - max %)	2.6 - 10	2.8 - 10	2.7 - 10
Energy Cost Savings (%)	6.2	6.9	6.1
Peak Power Shaving (%)	18.8	18.4	18.5
Max. Deviation	11.6	11.9	11.6
Average Deviation	9.9	9.9	9.9
#Unstable Points	12	16	12
% Unstable Points	3.6	4.8	3.6

Our method significantly reduces the number of instability events caused by the data center. The frequency of these events is as low as 3.6%. The threshold signal shows the maximum

data center power demand to have 10% instability. We track this signal with our framework closely and use most of the allocated power budget. Thus, our average deviation results are close to the limit, 9.9% for all three locations. Our maximum voltage deviation is less than all previous methods, 27% less than the case that does not use any power management solution (nominal). Our method works well in all three locations, i.e. the average deviation stays under 10%. For locations with higher deviation due to either a larger number of neighbors (H5_3) or longer distance to the substation transformer (H9_2), our method increases the workload performance overhead to meet the voltage deviation requirements since the battery capacity is the same. Though, this increase is minimal, around 10% for service jobs and 7% for batch jobs. Here, we show that not only the power mechanism but also data center placement affects grid stability, and by proxy, the performance overhead to meet the voltage deviation requirements.

The maximum QoS ratio observed is 0.2 and the largest batch job performance overhead is 10%. Although we hit the performance limits at some intervals, the average performance overheads are considerably less than the maximum values, 0.08 for service job QoS ratio and 2.6% for batch job performance overhead. These average values are significantly smaller than the existing methods (Table I), up to 6.5x better for service jobs and 7x better for batch jobs. This is because we consider different characteristics of service vs. batch jobs during consolidation and aim to minimize the expected performance overhead due to such a process. An interesting observation is that even though we do not consider energy costs in our formulation, our method still achieves 6% energy cost savings. This is because our mechanism obtains a more flat power profile and this can benefit from time-of-use pricing. In contrast, the peak power shaving performance is worse than the original battery-based solutions. We are still within 90% of the peak power shaving solution with similar battery capacities.

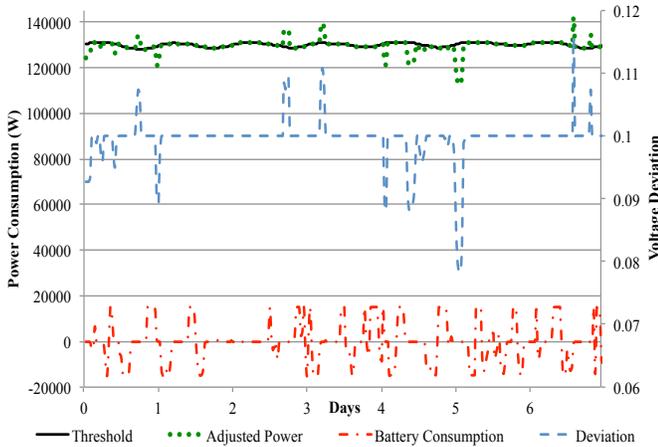


Figure 8. Power consumption vs. deviation for H1_1

Figure 8 shows the data center power profile in location H1_1 with its voltage deviation results. We observe similar patterns for the other two locations and present only H1_1 for the sake of clarity. The first three series are the utility threshold, adjusted data center power demand and the battery power. They use the primary axis. The deviation values use the secondary axis with the long dashed line. We see that the

power demand closely follows the utility threshold. Whenever we cannot guarantee the threshold, the voltage deviation goes above 10%. Although this maximum value is 11.6%, it is still 27% smaller than the maximum deviation with no controller. In the unstable intervals, the battery capacity falls short and cannot discharge further to provide energy. Figure 9 shows workload performance for the same analysis. The upper graph shows service job QoS ratio and the lower one presents batch job performance overhead percentage. Overheads occur when the batteries fall short. To eliminate the few unstable points, the options are: 1) increasing the battery capacity, 2) increasing the battery DoD limit and 3) stretching the performance constraints. The first one increases the capital costs and the second one raises the operational costs due to more frequent battery replacements. The last one depends on the application type and how tight their performance requirements are.

Figure 10 shows a tradeoff between the first and third options listed above. We change the battery capacity and find the new QoS and batch job performance limits to obtain the same instability statistics as the reference case. The reference case has 150 kWh battery capacity, 0.2 QoS limit and 10% batch job performance overhead limit. The primary and secondary axes show the service job QoS and batch job performance overhead percentage. The x-axis denotes the changing battery capacities. We have a 4-tuple for a given capacity value, max and average QoS ratios, max and average batch job performance overhead percentages. As the battery capacity drops, we need to be more flexible with the workload performance. Although the average values obtained do not change significantly, with half the battery size as the reference case, the max QoS ratio can be as worse as 2x and the max batch job performance overhead may increase by 50%.

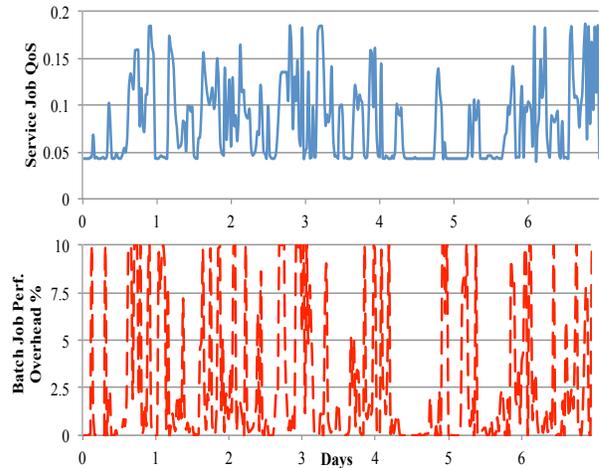


Figure 9. Service job QoS (upper) and batch job performance overhead percentage (lower) for H1_1

We show that using a single power management method may not be the best solution for data centers, especially since the microgrid instability might lead to more challenges in meeting the workload performance constraints. To address this, we present a novel solution with three power control methods to keep the voltage deviation under a specified stability threshold. We prioritize the battery usage since it does not impose any performance overhead, and use the other methods as the backup solutions to maintain the grid stability. The exact

mixture of the power management mechanisms depends on data center design decisions and the workload types. Higher performance overhead can be avoided with larger batteries. Similarly, we can consolidate more of the non-critical jobs to reduce the required battery capacity at a small overhead.

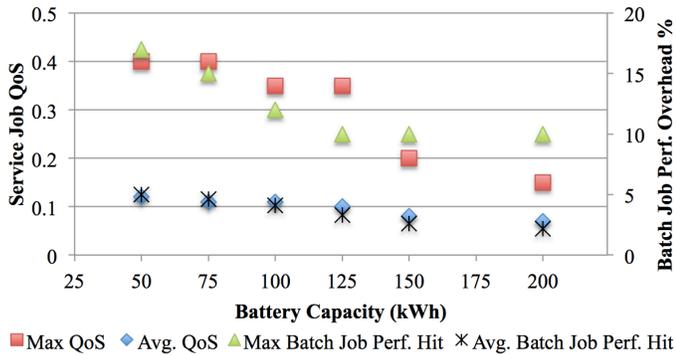


Figure 10. Battery capacity vs. workload performance

VI. CONCLUSION

Alternative energy sources and smart buildings are essential parts of microgrids to ensure its operability. These systems require constant monitoring with sensors and smart meters that need a computational center with communication capabilities. Small, micro data centers can act as the local cloud systems for the microgrids by bringing the computation closer to the data sources. However, the power demand of these small centers can still be high compared to the other buildings in the circuit, which can create high voltage deviations in the electric grid. This paper presents a power management mechanism that minimizes the voltage instability caused by a data center, while considering the workload performance constraints. Our mechanism preserves the grid stability 97% of the time and reduces the maximum voltage deviation by 27%. It uses the allowed performance limits effectively, with no more than 10% performance overhead for batch jobs and completing the service jobs within 20% of their target deadlines.

REFERENCES

- [1] B. Aksanli, A. S. Akyurek, M. Behl, M. Clark, A. Donz , P. Dutta, P. Lazik, M. Maasoumy, R. Mangharam, T. X. Nghiem, V. Raman, A. Rowe, A. Sangiovanni-Vincentelli, S. Seshia, T. Rosing, and J. Venkatesh, "Distributed control of a swarm of buildings connected to a smart grid: demo abstract," in *Buildsys*, 2014.
- [2] G. Cook and J. Horn, "How Dirty Is Your Data? A Look at the Energy Choices that Power Cloud Computing," 2011.
- [3] Jonathan G. Koomey, "Growth in data center electricity use 2005 to 2010," 2011.
- [4] Micro-datacentre: What IT problems it solves and what workload systems suit it. <http://www.computerweekly.com/feature/Micro-datacentre-What-IT-problems-it-solves-and-what-workload-systems-is-it-best-suited-for>
- [5] D. Gmach, J. Rolia, and C. Bash, "Capacity Planning and Power Management to Exploit Sustainable Energy," in *CNSM*, 2010.
- [6] B. Aksanli, J. Venkatesh, L. Zhang, and T. Rosing, "Utilizing green energy prediction to schedule mixed batch and service jobs in data centers," in *Workshop on Power-Aware Computing and Systems*, 2011.
- [7] S. Govindan, A. Sivasubramaniam, and B. Urgaonkar, "Benefits and Limitations of Tapping into Stored Energy For Datacenters," in *ISCA*, 2011.
- [8] V. Kontorinis, L. Zhang, B. Aksanli, J. Sampson, H. Houman, E. Pettis, D. Tullsen, and T. Rosing, "Managing Distributed UPS Energy for

- Effective Power Capping in Data Centers," in *ISCA*, 2012.
- [9] B. Aksanli, E. Pettis, and T. Rosing, "Architecting Efficient Peak Power Shaving Using Batteries in Data Centers," in *MASCOTS*, 2013.
- [10] G. Dhiman, G. Marchetti, and T. Rosing, "vGreen: A System for Energy-Efficient Management of Virtual Machines," *ACM Transactions on Design Automation in Electronic Systems*, vol.16, 2010.
- [11] R. Nathuji and K. Schwan, "Vpm tokens: virtual machine-aware power budgeting in datacenters," in *HPDC*, 2008.
- [12] M. Abdullah Adnan, R. Sugihara, and R. K. Gupta, "Energy Efficient Geographical Load Balancing via Dynamic Deferral of Workload," in *IEEE CLOUD*, 2012.
- [13] B. Aksanli and T. Rosing, "Providing Regulation Services and Managing Data Center Peak Power Budgets," in *DATE*, 2014.
- [14] H. Chen, C. Hankendi, M. C. Caramanis, and A. K. Coskun, "Dynamic Server Power Capping for Enabling Data Center Participation in Power Markets," in *JCCAD*, 2013.
- [15] D. Aikema, R. Simmonds, and H. Zareipour, "Data Centres in the Ancillary Services Market," in *IGCC*, 2012.
- [16] R. Wang, N. Kandasamy, C. Nwankpa, and D. R. Kaeli, "Datacenters as Controllable Load Resources in the Electricity Market," in *International Conference on Distributed Computing Systems*, 2013.
- [17] M. Ghamkhar and H. Mohsenian-Rad, "Data Centers to Offer Ancillary Services," in *SmartGridComm*, 2012.
- [18] Z. Liu, I. Liu, S. Low, and A. Wierman, "Pricing Data Center Demand Response," in *In Proceedings of ACM Sigmetrics*, 2014.
- [19] Dell. Internet of Things will require data centers of all sizes. <https://powermore.dell.com/technology/internet-of-things-will-require-data-centers-of-all-sizes/>
- [20] X. Fan, W. Weber, and L.A. Barroso, "Power provisioning for a warehouse-sized computer," in *ISCA*, 2007.
- [21] D. Meisner, B.T. Gold, and T.F. Wenisch, "PowerNap: Eliminating Server Idle Power," in *ASPLOS*, 2009.
- [22] N. Buchbinder, N. Jain, and I. Menache, "Online Job-Migration for Reducing the Electricity Bill in the Cloud," *Networking*, 2011.
- [23] Z. Liu, M. Lin, A. Wierman, S.H. Low, and L.L. Andrew, "Greening geographical load balancing," in *Sigmetrics*, 2011.
- [24] D. Palasamudram, R. Sitaraman, B. Urgaonkar, and R. Urgaonkar, "Using Batteries to Reduce the Power Costs of Internet-scale Distributed Networks," in *ACM SoCC*, 2012.
- [25] L. Rao, X. Liu, M. Ilic, and J. Liu, "Minimizing Electricity Cost: Optimization of Distributed Internet Data Centers in a Multi-Electricity-Market Environment," in *Infocom*, 2010.
- [26] M. Maasoumy, C. Rosenberg, A. Sangiovanni-Vincentelli, and D. Callaway, "Model Predictive Control Approach to Online Computation of Demand-Side Flexibility of Commercial Buildings HVAC Systems for Supply Following," in *ACC*, 2014.
- [27] EPRI Test Circuits. <http://svn.code.sf.net/p/electricdss/code/trunk/Distrib/EPRI/TestCircuits/Readme.pdf>
- [28] Micro Data Center Market Worth. <http://www.marketsandmarkets.com/PressReleases/micro-datacenters.asp>
- [29] OpenDSS. <http://sourceforge.net/projects/electricdss/>
- [30] American National Standard for Electric Power Systems and Equipment - Voltage Ratings (60 Hertz). http://www.pge.com/includes/docs/pdfs/mybusiness/customerservice/energystatus/powerquality/voltage_tolerance.pdf
- [31] Google Transparency Report. <http://www.google.com/transparencyreport/traffic>
- [32] Y. Chen, A. Ganapathi, R. Griffith, and R. Katz, "The case for evaluating MapReduce performance using workload suites," in *MASCOTS*, 2011.
- [33] D. Meisner, C.M. Sadler, L.A. Barroso, W.D. Weber, and T.F. Wenisch, "Power management of online data-intensive services," in *ISCA*, 2011.
- [34] Urs Hoelzle and Luiz Andre Barroso, *The Datacenter as a Computer: An Introduction to the Design of Warehouse-Scale Machines.*: Morgan and Claypool Publishers, 2009.
- [35] G. Dhiman, V. Kontorinis, R. Ayoub, L. Zhang, C. Sadler, D. Tullsen, and T. Rosing, "Themis: energy efficient management of workloads in virtualized data centers," in *Euro-Par 2012*:
- [36] SDGE. Whenergy for businesses. <http://www.sdge.com/whenergy/>
- [37] MATLAB Constrained nonlinear optimization. <http://www.mathworks.com/help/optim/ug/fmincon.html>