A Survey on Green-Energy-Aware Power Management for Datacenters

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Megawatt-scale datacenters have emerged to meet the increasing demand for IT applications and services. The hunger for power brings large electricity bills to datacenter operators and causes significant impacts to the environment. To reduce costs and environmental impacts, modern datacenters, such as those of Google and Apple, are beginning to integrate renewable or green energy sources into their power supply. This article investigates the green-energy-aware power management problem for these datacenters and surveys and classifies works that explicitly consider renewable energy and/or carbon emission. Our aim is to give a full view of this problem. Hence, we first provide some basic knowledge on datacenters (including datacenter components, power infrastructure, power load estimation, and energy sources' operations), the electrical grid (including dynamic pricing, power outages, and emission factor), and the carbon market (including cap-and-trade and carbon tax). Then, we categorize existing research works according to their basic approaches used, including workload scheduling, virtual machine management, and energy capacity planning. Each category's discussion includes the description of the shared core idea, qualitative analysis, and quantitative analysis among works of this category.

Categories and Subject Descriptors: A.1 [**Introduction and Survey**]; C.2.3 [**Network Operations**]: Network management; D.4.1 [**Operating Systems**]: Process Management; C.5.0 [**Computer System Implementation**]: General

General Terms: Design, Management, Algorithms, Performance

Additional Key Words and Phrases: Power management, datacenter, green energy, renewable energy, emission, cost minimization, dynamic pricing

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1. INTRODUCTION

The computing capacity and scale of datacenters are increasing to meet the soaring demand for IT applications and services. Mega datacenter (such as those of Google and Apple) can host thousands of servers and require up to tens of megawatts of electricity. The high power consumption causes two serious consequences. First, generating and delivering this power to datacenters result in large electricity bills. Datacenter operators may face millions of dollars of annual charges from the electrical grid. Second, the enormous energy consumption can lead to negative environmental impacts. Datacenters are still heavily dependent on the brown energy drawn from the current

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electrical grid, which produces much of its power by burning carbon-intensive fossil fuels. Modern datacenters (such as [Google 2013], [Apple 2013] and Microsoft [Miller 2008]) have started taking various initiatives to lower their operating cost as well as reduce their environmental impacts. They are becoming much greener by cutting their carbon emissions and/or by operating with renewable energy.

Earlier research works on power management aim at reducing the power consumption of computing devices within a single datacenter. They propose different hardware and software technologies, including chip multiprocessor [Barroso 2005], dynamic voltage and frequency scaling [Horvath et al. 2007], dynamic power management [Meisner et al. 2009], visualization [Nathuji and Schwan 2007], load balancing [Chen et al. 2008], and the like. There are also some works addressing cooling power reduction [Bash and Forman 2007], cooling–computing power balancing, and energy proportionality [Abbasi et al. 2012; Ganesh et al. 2013]. Recently, many research efforts address green-energy-aware power management for datacenters. Instead of reducing power consumption, they focus on reducing energy cost, cutting emissions, and/or optimizing renewable energy utilization. They take account of several new dimensions including dynamic pricing and time- and space-varying emission factors of grid power, buffering energy using energy storage devices, and deep penetration of renewable energy into the power supply of datacenters.

In this article, we confine ourself to a detailed investigation of green-energy-aware works; that is, those that explicitly consider renewable energy and carbon emission and comprehensively survey and classify these kinds of works until 2013. This focus makes our survey complementary to or differ from other datacenter surveys including those focusing on dataceter networks [Bari et al. 2012; Bianzino et al. 2012; Bilal et al. 2013], studying the energy-efficient design of computing systems [Beloglazov et al. 2011], and mainly addressing cost-aware power management for geographically distributed datacenters [Rahman et al. 2013]. We group these green-energy-aware works into four categories, as follows.

(1) **Green-energy-aware workload scheduling.** The research efforts in this category explore workloads' temporal and spatial flexibility. They schedule and execute workloads when and where the electricity price, emission factor, and/or renewable power generation are favorable.
(2) **Green-energy-aware Virtual Machine (VM) management.** These research efforts consider datacenters in a virtualized environment. They manage VM migration in a temporal and spatial manner similar to those in category (1).
(3) **Green-energy-aware energy capacity planning.** These research efforts focus on the construction or investment phase for datacenters. They design power management plans to match the power supply with the power demand in datacenters.
(4) **Interdisciplinary.** These research efforts address green-energy-aware issues by considering noncomputing aspects such as the manufacture of datacenters and alternative fuel sources.

Works in each category may be further divided into subcategories according to the number of involved datacenters. Table I shows the research works in each category and subcategory. When discussing the research works in each subcategory, we further classify them according to their technical solutions and problem dimensions. Another contribution of this survey is the summarization of the basic idea shared by each category or subcategory. This can provide a quick view on optimization goals and the approaches adopted by a group of research works. Green-energy-aware power management for datacenters is a relatively new research area. Hence, we point out some critical open issues and also propose possible solutions.

Table I. Research Works Belonging to Each Category and Subcategory

Category	Subcategory	Works
Green-energy-aware workload scheduling	Single datacenter	[Liu et al. 2012; Arlitt et al. 2012; Krioukov et al. 2011, 2012; Aksanli et al. 2011; Ghamkhari and Mohsenian Rad 2012a, 2013; Deng et al. 2013; Goiri et al. 2011, 2012; Govindan et al. 2011; Goiri et al. 2013]
	Geo-distributed datacenters	[Stewart and Shen 2009; Le et al. 2009, 2010, 2008; Liu et al. 2011a, 2011b; Zhang et al. 2011; Gao et al. 2012; Doyle et al. 2011; Chen et al. 2012; Chiu et al. 2012; Li et al. 2013; He et al. 2012; Ghamkhari and Mohsenian Rad 2012b]
Green-energy-aware VM management	Single datacenter	[Sharma et al. 2011a; Irwin et al. 2011; Singh et al. 2013; Li et al. 2011, 2012; Deng et al. 2012a]
	Geo-distributed datacenters	[Akoush et al. 2011; Deng et al. 2012b]
Green-energy-aware energy capacity planning		[Gmach et al. 2010b, 2010a; Brown and Renau 2011; Ren et al. 2012]
Interdiscipline		[Hopper and Rice 2008; Kurp 2008; Van Heddeghem et al. 2012; Chang et al. 2012; Seetharam et al. 2010]

The rest of the article is organized as follows. Section 2 provides background for datacenters, the electrical grid, and the carbon market, as well as lists the optimization objectives of research works surveyed. Sections 3–6 investigate research works that belong to each of the four categories. Section 7 discusses several essential open issues for the green-energy-aware power management problem. Section 8 concludes the article.

2. BACKGROUND

In this section, we first give a brief description of the basic components and operations of a green datacenter. Then, we provide background on the power infrastructure and different options for green and brown energy sources. Each option has its advantages and disadvantages in terms of costs, emissions, dispatchability, reliability, and availability. Hence, each one may play a different role in the power infrastructure (e.g., act as a primary or backup power supply). We further point out the right role for each energy source. What follows is the introduction of operations of the electrical grid and policies of the carbon market. Finally, we summarize different optimization objectives of the research efforts surveyed in this article.

2.1. Datacenter Overview

Figure 1 depicts an architectural overview of a green datacenter with different options on green and brown energy sources. IT equipment includes servers for data processing and data storage and networking devices for data communication. It supports applications and services hosted in a datacenter, while cooling devices (called Computer Room Air Conditioning [CRAC] units) extract the heat from IT equipment and control the temperature and humidity in the datacenter. IT and cooling equipment are two major power consumers. The power ratio of the two components is closely related to the Power Usage Effectiveness (PUE), which equals (total datacenter power) / (IT equipment power). Lower PUE means higher power efficiency; that is, a larger portion of power is used for computing devices instead of for supporting facilities. Modern datacenters usually have a PUE of around 1.1–2.

2.1.1. Power Usage. **IT equipment power**. The power usage (p_{IT}) of IT equipment consists of the aggregated power consumed by all servers and by all networking

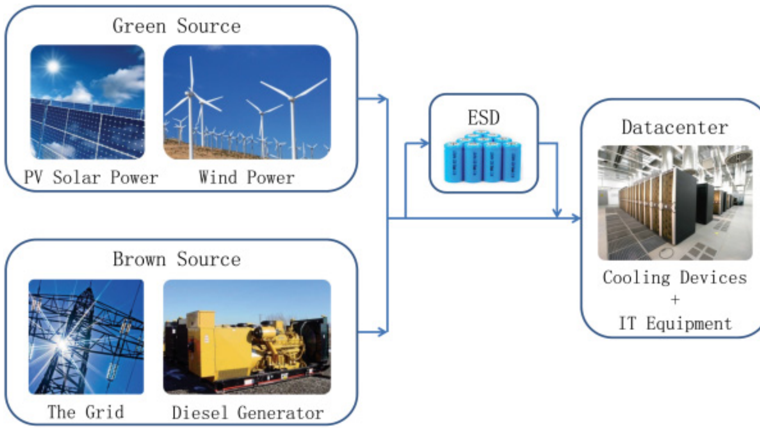


Fig. 1. Green datacenter power infrastructure and different options for green and brown energy sources.

devices:

$$p_{IT}(u) = p_{server}(u) + p_{network}. \tag{1}$$

We can estimate servers' power consumption using a linear power model:

$$p_{server}(u) = \mathcal{P}^{idle} + (\mathcal{P}^{full} - \mathcal{P}^{idle}) * u, \tag{2}$$

where u is the average CPU utilization across all servers, and $\mathcal{P}^{idle}$ and $\mathcal{P}^{full}$ are the power consumption by all servers at idle state and fully utilized state, respectively. This linear power model has been proved very useful and accurate in estimating servers' power consumption [Fan et al. 2007]. Another method to estimate servers' power consumption is based on an assumption of ideal server consolidation or ideal energy-proportionality [Barroso and Holzle 2007]; that is, $u * N$ machines are running at 100% utilization while other machines are turned off with zero power consumption, where N is the number of servers in the datacenter. The power load is calculated by

$$p_{server}(u) = u * \mathcal{P}^{full}. \tag{3}$$

Networking devices' power consumption can be approximated as a constant offset, which is in general less than 10% of the peak power of servers [Hamilton 2010].

Cooling power. A typical cooling process in a datacenter is as follows. Outside air is introduced into the top of a CRAC unit where it is conditioned by passing through some coils containing chilled water. The chilled water is pumped from a chiller that cools down the returned hot water from the CRAC unit using mechanical refrigeration cycles or water-side economizers. The cooled air then enters IT equipment (primarily servers) through a raised floor plenum, and fans pull the cold air into the servers. A number of research works model the cooling power for this process, such as Zhang et al. [2012], Liu et al. [2012], Zhou et al. [2012], and Abbasi et al. [2012]. We provide two widely used cooling power models. One models the cooling power as a function of the inlet (T_{in}) and outlet temperatures (T_{out}) of the CRAC unit [Zhang et al. 2012]:

$$\begin{aligned} p_{cool}(T_{in}, T_{out}) &= \frac{mr * C_p * (T_{in} - T_{out})}{COP(T_{out})}, \\ COP(T_{out}) &= \big(0.0068 * T_{out}^2 + 0.0008 * T_{out} + 0.458\big), \end{aligned} \tag{4}$$

where mr is the mass flow rate; C_p is the specific heat, a constant value; and COP is the coefficient of performance of the CRAC unit. The other models the cooling power

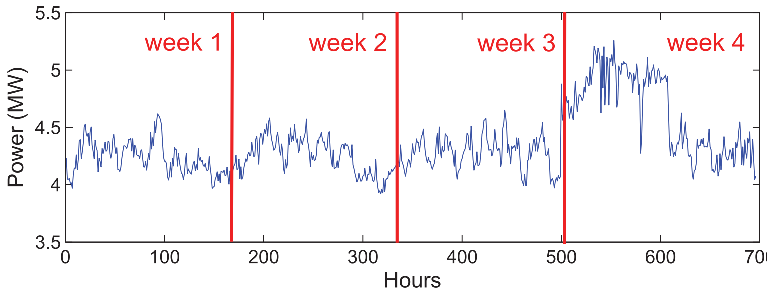


Fig. 2. Hourly power usage of a Google datacenter of 11,000 machines [Google 2013]. Servers are assumed to be homogeneous. Each one has a peak power of 300W and idle power of 150W. Networking devices' power consumption equals 5% of the total peak power of all servers. PUE equals 1.5. These machines are heterogeneous [Reiss et al. 2012], but similar estimation can be made by assigning each type a power consumption value.

(p_{cool}) as a function of IT equipment power [Liu et al. 2012]:

$$p_{cool}(p_{IT}) = \begin{cases} k * p_{IT}^3, & if\ p_{IT} \leq \mathcal{P}_{IT} \\ k * p_{IT}^3 + \gamma * (p_{IT} - \mathcal{P}_{IT}), & otherwise, \end{cases} \tag{5}$$

where $\mathcal{P}_{IT}$ is a threshold that identifies if chilled water cooling is used; parameter k depends on the temperature difference between outside air temperature and the temperature of the (hot) exhausting air from the IT equipment; and γ is a constant depending on the chiller. By this model, outside air is directly used to cool a datacenter at first (when $p_{IT} \leq \mathcal{P}_{IT}$), which is referred to as free cooling; the chiller is then additionally employed if free cooling is insufficient (when $p_{IT} > \mathcal{P}_{IT}$).

Datacenter power. The total power load (p_{DC}) of a datacenter approximately equals the sum of IT equipment power and cooling power:

$$p_{DC} = p_{IT} + p_{cool}, \tag{6}$$

Another popular approach to estimate the total power load of a datacenter uses IT equipment's power usage linearly scaled by PUE:

$$p_{DC}(u) = p_{IT}(u) * PUE. \tag{7}$$

These models can be used to track datacenter power load if given the resource or CPU utilization trace. Figure 2 shows an example for which the total power load is estimated using Equations (1), (2), and (7). The estimation is conducted based on a Google trace [Google 2013], which records the utilization data across approximately 11,000 machines over 29 days from 19:00 EDT on May 1, 2011. The power load is highly variable but shows an approximate daily pattern of ups and downs. The first three weeks have a similar power load trace; the last week experiences a load burst. More detailed analysis on the Google trace can be found in [Reiss et al. 2012]. In the absence of such a trace, some machine learning methods, such as autoregression [Liu et al. 2012], can be used to predict the short-term datacenter workload or utilization. Then, the power models just described can be also applied to estimate the corresponding power load.

2.1.2. Power Infrastructure. Different datacenters may have different power infrastructure design. Typically, the power infrastructure generates and/or distributes power for cooling devices and IT equipment through a micro power grid that can integrate on-site power generation, the electrical grid, and Energy Storage Devices (ESDs) or batteries. The micro power grid can be seen as a power hierarchy that has datacenter, Power

Distribution Unit (PDU), rack, and server levels. ESDs can be placed at one or more such levels in a centralized or distributed manner. Different placement strategies come with different reliability and availability depending on the power infrastructure [Govindan et al. 2010; Wang et al. 2012]. Traditionally, ESDs serve as a fail-over mechanism between the electrical grid and backup power sources (such as diesel generators). Upon a grid outage, ESDs keep a datacenter powered up using the energy stored within them until the backup power can either start or ramp up to match the datacenter's power load. Recently, ESDs have been also employed as energy buffer for (i) cost optimization by charging them when electricity price is low and discharging them when the price becomes high [Urgaonkar et al. 2011; Govindan et al. 2011] or (ii) smoothing nondispatchable (wind or solar) power by charging the ESDs when renewable power is abundant and discharging them when the renewable power becomes insufficient to meet the datacenter's power demand [Brown and Renau 2011; Liu et al. 2012, 2011a; Goiri et al. 2013].

There are three important constraints when batteries work as an energy buffer. First, it is critical to guarantee their lifetime. Deep discharges could lower batteries' lifetime. For example, a lead-acid battery with 10% Depth of Discharge (DoD) will last about 13 years, whereas with 20% DoD, it will last about 8 years [Northern Arizona Wind & Sun 2012]. Hence, the DoD should be limited so as to not severely compromise battery lifetime. Second, limiting DoD also aims at satisfying power availability requirements. Batteries will fail at bridging the transition from the electrical grid to backup power sources if they do not work long enough to complete this transition due to little energy stored within them (or too deep discharge). Third, there is a considerable amount of energy loss during battery charging and discharging processes. The energy loss may sometimes out weigh the gain on cost saving or emission reduction by the energy buffering.

2.1.3. Spatial and Temporal Load Balancing. Spatial load balancing, a.k.a, Geographical Load Scheduling (GLB), is defined as spatial workload placement among geographically distributed datacenters. Each datacenter has an architecture as shown in Figure 1 and can draw power from multiple green and brown energy sources. This method explores the spatial flexibilities of workloads and the spatial diversities of parameters. A user request is initially accepted by one front-end server and then routed to one of these geo-distributed datacenters. The selected datacenter processes the request using available resource as required and then returns the result to the user. The routing decision depends on several interrelated parameters including the electricity price, grid emission factor, green power generation, and the like. For example, the energy cost can be reduced by sending requests to datacenters where the electricity price is cheaper. The energy consumption for cooling devices can be lowered by placing workloads on datacenters sited in colder regions. Emission reduction can be achieved by routing requests to datacenters with lower emission factors or with sufficient renewable energy. Other constraints also must be met, including geographical proximity, datacenter/server capacity, service level agreements (SLAs), and the like. For instance, sending requests to datacenters far from clients results in significant access latency. Overloading a datacenter with too many requests may incur serious service delays perceived by clients.

Temporal load balancing is defined as temporal workload scheduling inside a datacenter. This method leverages the temporal flexibilities of workloads and the temporal diversities of parameters. A user request arriving at a datacenter can be delayed for some time for processing. The scheduling decision also depends on those interrelated parameters such as the electricity price, grid emission factor, and the like but in a temporal manner. For example, the energy cost or emission amount can be reduced by

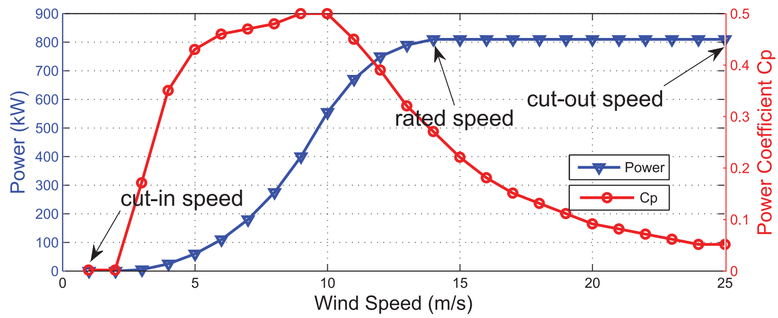


Fig. 3. The output power (the blue curve marked with triangles) and power efficiency (the red curve marked with circles) of ENERCON wind turbine type E48 [ENERCON 2010].

postponing workload execution to the time when the electricity price or emission factor is lower. However, in order to meet SLAs, workloads should be finished before their deadlines.

2.2. Green and Brown Energy Sources

Most brown energy sources (such as fossil fuel power) are dispatchable: they are able to adjust their output power on demand through tuning the power generators, but they come with heavy greenhouse gas emissions. They can behave as either primary or backup power supplies because they will continuously generate electricity as long as a source of fuel is supplied. By contrast, green or renewable energy sources (such as wind and solar power) cause no emissions, but they are intermittent and non-dispatchable. They may not be counted as primary power supplies since they depend heavily on weather conditions for power generation. We describe different characteristics of three popular on-site energy sources available to datacenters.

2.2.1. Wind Power. The amount of usable power converted from a wind resource is closely tied into both the characteristics of the wind resource and the features of wind turbines [Aerostar 2008; Grogg 2005]. The converted power is only a proportion of the total that a wind resource possesses. The proportion (i.e., *power efficiency or coefficient*) varies significantly with wind speed [ENERCON 2010; Wind Power 2013]. The maximum efficiency can reach 50%; the minimum is close to 0% (see the red curve in Figure 3). The power output $p_{wind}(v)$ of a single wind turbine, with respect to wind speed v, can be expressed as a piecewise function:

$$p_{wind}(v) = \begin{cases} 0, & v \leq \mathcal{V}^{in}, \ or \ v \geq \mathcal{V}^{out} \\ g(v), & \mathcal{V}^{in} < v < \mathcal{V}^{rate} \\ \mathcal{P}^{rate}, & v \geq \mathcal{V}^{rate}, \end{cases} \tag{8}$$

where $\mathcal{V}^{in}$ ($\mathcal{V}^{out}$) is the *cut-in speed* (*cut-out speed*), $\mathcal{V}^{rate}$ ($\mathcal{P}^{rate}$) is the *rated speed* (*rated power*), and $g(v)$ is the power curve between the cut-in and rated speed. Specifically, the cut-in speed is the minimum wind speed at which the wind turbine starts to generate usable power. As the wind speed rises higher than the cut-in speed, the power output ($g(v)$) increases rapidly until it reaches the limit that the wind turbine is capable of. The limit is called rated power, and the corresponding wind speed is called rated speed. Then, the power output rises no further; it stays at the rated power level until the wind speed becomes greater than the cut-out speed. At that time, the wind turbine has to cease power generation and shut down to protect itself from damage. As shown in

Figure 3, the cut-in, rated, and cut-out speeds are 2, 14, and 25 meters per second, respectively. The rated power is 800 kW.

2.2.2. PV Solar Power. The amount of usable power converted from a solar resource is closely related to both the characteristics of the solar resource and the features of photovoltaic (PV) solar cells. Unlike wind turbines, the *power efficiency (η_{solar})* of solar cells varies only a little with weather conditions such as the ambient temperature [TheGreenAge 2013]. Solar cells work best at low temperatures, and their efficiency declines as the ambient temperature grows, in general, at a rate of 0.20–0.5% decrease in efficiency for each 1^oC rise. Hence, on a hot day when the temperature reaches 45^oC, solar cells may experience an efficiency reduction of 4–10% compared to when temperatures are 25^oC. Because solar cell manufacturers use a thermally conductive substrate to help vent excess heat from the glass layer of the panels, and installers ensure a free flow of air above and below the solar panels when they are mounted (adding ventilation systems to solar systems if possible), the efficiency variance is much less than 10% throughout almost the whole year. Thus, most research works assume constant efficiency for solar cells. The power output ($p_{solar}(s)$) is determined by the intensity (s in W/m^2) of solar irradiation and the aggregated area (a in m^2) of solar cells installed:

$$p_{solar}(s) = \eta_{solar} * s * a. \tag{9}$$

Although the most efficient PV solar cells publicly announced by the National Center for Photovoltaics (NCPV) have an efficiency of more than 40%, the efficiency of commercially available PV solar cells is usually less than 25% for the sake of cost effectiveness [NREL 2013c].

Models using Equations (8) and (9) can be used to track wind and solar power generation if given meteorological data. We give an example of the estimated wind and solar power capacity factor traces based on the National Solar Radiation Database (NSRDB) [NREL 2013d]. Power capacity factor is defined as the real power output divided by the rated power of a generator. The NSRDB contains multiple meteorological fields including wind speed and solar irradiation from January 1, 1991 to December 31, 2010. The database records hourly meteorological data for more than 1,000 observation sites. Each site is coded with a USAF number (site ID). Figure 4(a) and 4(b) shows wind and solar power capacity factors on April 11 and 24 averaged over the 20 years for two sites. It is more cost effective to install wind power generators at site 726798 because there is a better wind resource (or larger wind power capacity factors), whereas it is better to build solar generators at site 747187 because there is a better solar resource (or larger solar power capacity factors). Figure 4(c) and 4(d) shows the standard deviation for wind and solar power on April 11, from which we can conclude the intermittency and variability of wind and solar power. The solar power exhibits a clear daily pattern, but the wind power does not. Alternatively, some machine learning methods (such as k-nearest neighbor, k-NN) can be used to predict wind and solar power generation [Sharma et al. 2011b; Liu et al. 2012].

Wind and solar power generation have no fuel costs and relatively small Operating and Maintenance (O&M) costs. Their capital costs dominate their lifecycle costs and account for more than 90% of this sum [EIA 2013]. Their capital costs are determined by nameplate capacity; that is, the sum of the rated power of wind turbines or solar cells' area once installed.

2.2.3. Diesel Power. Diesel Generators (DGs) convert energy stored in fuel into electricity by fuel combustion. The *electrical efficiency (η_{DG})* for a diesel generator is defined as the electricity produced by combustion divided by the calorific value of the fuel. They usually have an electrical efficiency of about 30%. The power output (p_{DG}) is

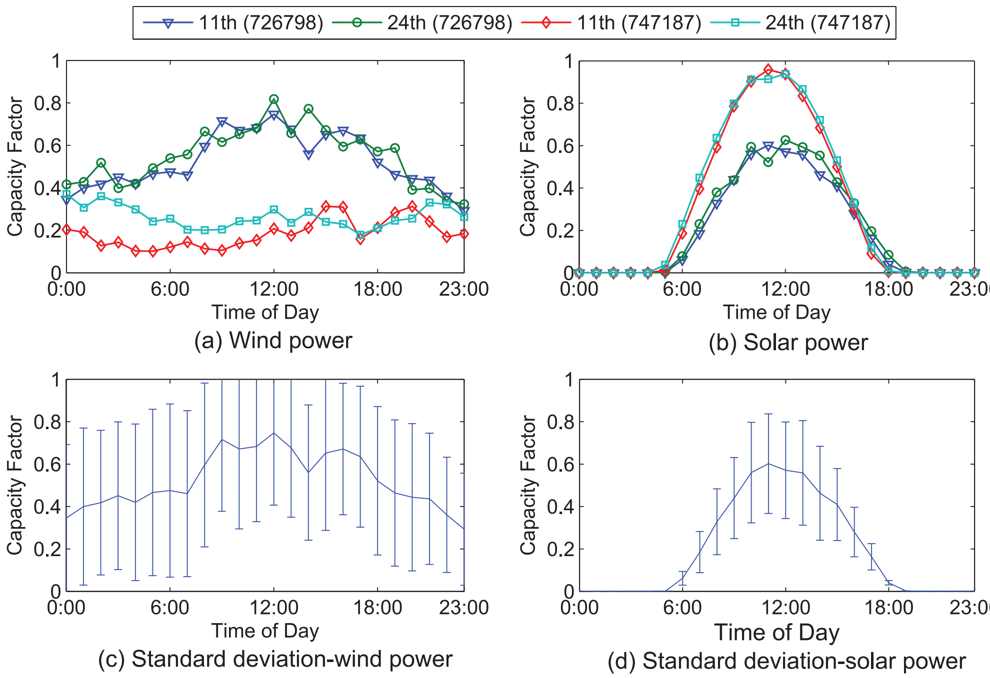


Fig. 4. Wind and solar power capacity factor traces across April 11 and 24 for site 726798 (Livingston Mission Field, MT) and site 747187 (Palm Springs Thermal AP, CA). Site 726798 and 747187 use wind turbine type E101 and E82 (2000kW) [ENERCON 2010], respectively.

determined by the fuel feeding rate (v):

$$p_{DG}(v) = \begin{cases} \eta_{DG} * v, & v < \mathcal{V}^{rate} \\ \mathcal{P}^{rate}, & v \geq \mathcal{V}^{rate}, \end{cases} \tag{10}$$

where $\mathcal{V}^{rate}$ ($\mathcal{P}^{rate}$) is the rated fuel feeding speed (rated power) of a DG. The fuel feeding speed can be measured by watt-hour per time unit, which is converted from gallon per time unit through counting joules stored in 1 gallon of diesel fuel.

DGs have a relatively small capital cost, but they require periodic maintenance. Hence, their O&M and fuel costs dominate, accounting for up to 70% of their lifecycle costs. Moreover, they also come with large emission costs due to heavy emissions from burning diesel.

2.3. The Electrical Grid

Grid power is a mix of brown and renewable energies. It is counted as a kind of brown energy source. The electrical grid has distinct features from on-site brown energy sources, thus we use a separate subsection to discuss its features.

The electrical grid during normal operation is a reliable and flexible power supply from which a datacenter can draw power to fill in any scale of gap between a datacenter's power demand and on-site power generation. This reliability and flexibility allow the integration of nondispatchable energy sources into the power infrastructure and guarantee a smooth and steady power supply for the datacenter. When the electrical grid experiences an outage, ESDs bridge the transition from the grid to an on-site backup power supply. The datacenter must then only rely on its on-site power supply, especially dispatchable energy sources (such as diesel generators). The reason is

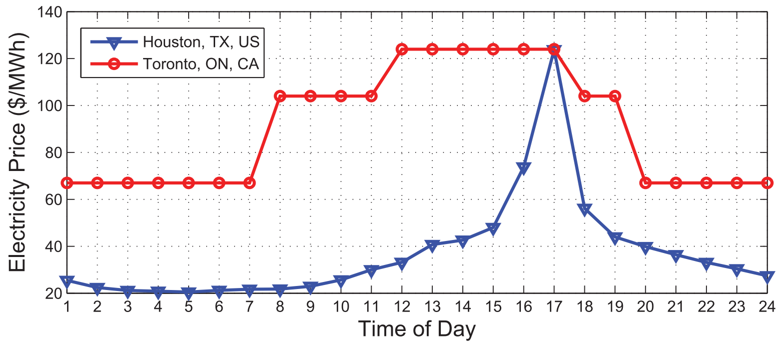


Fig. 5. Hourly electricity price in Houston, TX, US [ERCOT 2013], and on-peak, mid-peak, and off-peak price in Toronto, ON, CAN [Toronto Hydro 2013], across August 9, 2013.

twofold: (i) due to the features of green and brown energy sources discussed in the previous subsection, such as dispatchability and reliability; and (ii) because the occurrence of outages is unpredictable.

2.3.1. Dynamic Pricing. A datacenter's electricity bill as charged by the grid usually consists of two items. One is dependent on how many kWhs the datacenter has consumed, with pricing given in dollars per kWh. Various plans are available, such as *real-time pricing* (e.g., Qureshi et al. [2009], Le et al. [2008], and Rao et al. [2010]) and *time-of-use pricing* (e.g., Brown and Renau [2011] and Goiri et al. [2013, 2012]). The datacenter pays differently for electricity drawn from the grid at different hours of a day or between on-peak, mid-peak and off-peak time periods. Figure 5 shows an example of the two plans. The electricity price is in general more expensive during the daytime than at night. The other item—*peak power charge* or *demand charge*—is determined by how many kWs of spike power the datacenter has used during a period (e.g., a month), with pricing in dollars per kW. The peak power charge can be up to 40% of the overall electricity cost of a datacenter [Govindan et al. 2011]. Utilities monitor the grid power consumption of a datacenter at a sampling rate of every few minutes (e.g., 15 minutes in the US and 30 minutes in the UK). The maximum power consumption in a month is then regarded as the peak power of the month.

In addition, the *long-term electricity market* (e.g., day-ahead or month-ahead market) allows consumers such as datacenter operators to buy electricity beforehand via a forward contract. Suppose that, on July 1, 2013, an operator knows that the datacenter will use 1MWh electricity in 1 month (i.e., by August 1, 2013). The operator can enact a forward contract and agree to buy 1MWh of electricity 1 month forward at a certain price on August 1, 2013. The electricity price in long-term market is usually smaller than the real-time price, and thus the operator may reduce energy cost by such forward contracts. However, the operator risks excess costs if the contracted amount is more than necessary.

2.3.2. Emission Factor. Electrical grid power is counted as a brown energy source because current utilities produce much of their power by burning carbon-intensive fossil fuels, such as coal and natural gas. However, different regions have different emission factors, and there is a significant difference in the fuel mix among different regions [Gao et al. 2012]. For example, Washington state produces greener power than does Texas because Washington employs a much cleaner fuel mix (e.g., hydroelectricity), as shown in Figure 6. The emission factor varies temporally as well. To match electricity demand, the electrical grid turns off some power generators during off-peak times and turns them back on during on-peak times. Figure 7 shows the power production

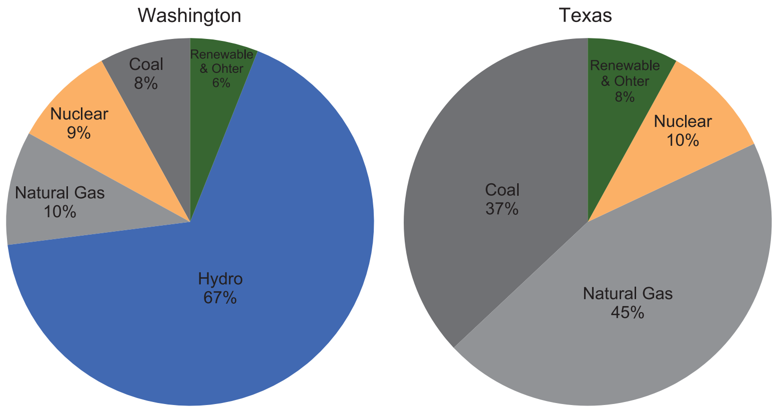


Fig. 6. Renewable and other fuel mixes for Washington and Texas [Edison Electric Institute 2011; Gao et al. 2012].

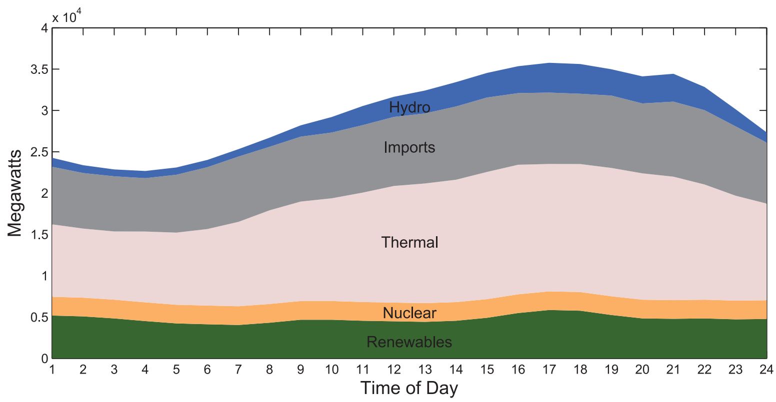


Fig. 7. The production of various generating resources across August 12, 2013, in California [CAISO 2013]. Note that label "Renewables" represents all other renewable sources (e.g., wind and solar power) except those shown in the figure.

of various generating resources across August 12, 2013, in California [CAISO 2013]. Generators turned on and off during a day are usually thermal generators with high emissions due to fossil fuel combustion.

2.4. Carbon Market

Ever since humans realized their negative impact on the environment, many programs have been invent to control carbon emissions. These emission control programs can be approximately categorized into two types: legislation-based ones (e.g., Command and Control (CAC) regulation) and market-based ones. CAC regulations require entities, by legislation, to undertake specific activities to comply with specific emission standards. They were popular when US environmental law was created in the 1970s. However, CAC regulations are criticized for being excessively rigid, and many of them have been reformed [Stuart 2006]. Today, market-based approaches or economic incentives (e.g., *cap-and-trade [EPA 2012]* and *carbon tax [Carbon Tax Center 2013]*), are most widely applied.

2.4.1. Cap-and-Trade. The government sets an overall limit or "cap" on emissions and creates allowances for each compliance period (e.g., 1 year). Although emitters such as datacenters are free to buy or sell allowances, they are required to hold a minimum number of allowances equivalent to their emissions. Emitters that need to continue emitting more than their allowance holdings must purchase allowances to cover the excess. On the other hand, if an emitter is able to cut its emissions, it will have to purchase fewer allowances or even end up with extra allowances. This may turn emission reduction into revenue for the emitter. In addition, since the total number of allowances cannot exceed the level of the cap, net reduction of emissions can be achieved if the government lowers the cap periodically. This also results in the growth in the price of allowances.

2.4.2. Carbon Tax. This program levies a tax on emissions and is different from cap-and-trade in three ways. First, a carbon tax charges emitters after emitting based on the amount emitted, whereas cap-and-trade requires emitters to purchase allowances before emitting, based on an estimation of their future emissions. Second, unlike cap-and-trade, a carbon tax supports no carbon trading between emitters. Third, a carbon tax has no cap or limit on overall emissions and thus cannot guarantee a net reduction of emissions. When a carbon tax is low, emitters may choose to simply pay for their emissions rather than make an effort at cutting emissions. However, this policy imposes an annual increase in the tax. Emitters may have to mitigate their emissions as the tax becomes progressively higher.

2.5. Optimization Objectives

Research works surveyed in this article try to achieve one or more of the following three optimization goals:

(1) **Cost minimization or profit maximization.** Research works with this objective aim at reducing operating cost (e.g., electricity and emission costs for running datacenters), capital cost (e.g., cost for constructing the power infrastructure), and/or revenue loss (e.g., lost revenue due to degraded cloud services).
(2) **Emission minimization.** These research works target efforts to mitigate emissions in the operating phase (e.g., lowering brown energy usage) and/or manufacturing phase (e.g., cutting emissions generated when producing servers).
(3) **Renewable energy utilization maximization.** These research works aim at improving wind and/or solar energy utilization or reducing their waste.

First, these three objectives have some degree of overlap. For example, maximizing renewable utilization may lead to emission decrease and thus emission cost reduction. However, objectives (2) and (3) are not equivalent. As discussed earlier, both the grid emission factor and on-site renewable power generation show significant temporal variabilities, and, most of the time, the two do not align with each other. Hence, the schedule with maximum renewable utilization may be different from the one with minimum emission. Second, the three objectives have some conflicts as well. For instance, to lower electricity cost it is preferable to schedule and execute workloads when or where the price is low. However, this may undesirably cause emissions to increase because the grid's emission factor may be high at that time or in that place. Some research efforts also address efforts to strike a balance among various factors.

2.6. The Ideal Solution

Qualitative features and quantitative results are two important criteria to evaluate a solution. Hence, we provide both qualitative and quantitative analyses about the ideal solution to the green-energy-aware datacenter power management problem.

2.6.1. Qualitative Analysis. The ideal solution should at least possess the following four qualities or features:

Table II. Parameter Setting

c_{grid}	e_{grid}	c_{brown}	e_{brown}	p_{green}	p_{DC}
3	1	2	2	300	500

(1) **Accurate modeling of all dimensions discussed in this section.** All of the dimensions have a great effect on optimization objectives. A lack of or inaccurate modeling of any dimension can make the solution deviate from the optimum or the actual case. For example, to maximize renewable energy utilization, overestimating renewable power generation may cause execution of more workloads and use more power than is actually generated. As a result, more grid power is used to fill the gap, which causes more emission.
(2) **Joint exploration of spatiotemporal diversities and flexibilities.** Spatial diversity means that datacenters in different regions have different parameters, such as different electricity prices, different amounts of renewable energy, and different grid emission factors. Temporal diversity means that these parameters vary over time. Spatial flexibility means that a request can be routed to and processed at different datacenters. Temporal flexibility means that delay-tolerant works' execution can be postponed.
(3) **Computational inexpensiveness** and **easy implementation into existing applications.** These two qualities determine whether the solution can be applied to real applications.

2.6.2. Quantitative Analysis. The optimality of a solution's quantitative result depends on the objective that the solution aims to optimize. Hence, we define a metric for each of the objectives in Section 2.5. We also provide examples to analyze how good the ideal result should be based on the metrics. Moreover, these examples assume oracular knowledge of parameters including the grid electricity price and emission factor, datacenter workload, and renewable power generation.

(1) **The metric for energy cost.** We consider two main kinds of costs for energy sources: operating cost and capital cost. First, according to the discussion in Section 2.2 and 2.3, the operating cost mainly includes the grid power cost and on-site brown energy fuel cost in a period (T):

$$\begin{aligned} Tot_{op} &= \int_o^T (c_{grid}(t) * p_{grid}(t) + c_{brown}(t) * p_{brown}(t))dt, \\ p_{grid}(t) &= p_{DC}(t) - p_{green}(t) - p_{brown}(t), \end{aligned} \tag{11}$$

where the subscript "brown" includes all on-site brown energy sources; $p_{grid}(t)$, $p_{brown}(t)$, and $p_{green}(t)$ are the grid power, on-site brown, and green power at time t, respectively; and $c_{grid}(t)$ and $c_{brown}(t)$ are the grid power price and on-site brown energy fuel price, respectively. One solution needs to decide how much power is drawn from the grid ($p_{grid}(t)$) and how much power is generated by brown sources ($p_{brown}(t)$). The ideal solution should have the minimum operating cost Tot_{op}. To give a numerical example, the ideal solution assumes knowing the parameters in 1 hour, as shown in Table II. The cost-ideal solution is $Tot_{op} = 400$ and $p_{grid} = 0$, $p_{brown} = 200$ because the grid power price is higher than the on-site brown energy fuel price. Second, both on-site brown and green energy sources contribute to the capital cost:

$$Tot_{cap} = a_{brown} * P_{brown} + a_{green} * P_{green}, \tag{12}$$

where P_{brown} and P_{green} (a_{brown} and a_{green}) are the capacities (unit capital costs) of the on-site brown and green power generator, respectively. The capacities can be seen as the upper bounds of the green (p_{green}) and brown (p_{brown}) power generation and thus have an influence on the operating cost. One ideal solution to minimize both operating cost and capital cost can be found in Kong et al. [2014b], which assumes knowledge of parameters over 20 years.

(2) **The metric for emission.** Emissions come from brown energy sources:

$$Tot_{emis} = \int_0^T (e_{grid}(t) * p_{grid}(t) + e_{brown} * p_{brown}(t))dt, \tag{13}$$

where the subscript "brown" includes all on-site brown energy sources; and e_{grid} and e_{brown} are emission factors from the electrical grid and on-site brown energy sources. The ideal solution in this case should have the minimum emission Tot_{emis}. Using the same example in Table II, the emission-ideal solution is $Tot_{emis} = 200$ and $p_{grid} = 200$, $p_{brown} = 0$ because the emission factor of on-site brown energy sources is larger than the grid emission factor.

(3) **The metric for renewable energy utilization.** This metric is defined as the renewable power used ($\widehat{p}_{green}(t)$) divided by the renewable power generation ($p_{green}(t)$) in a time period:

$$U_{green} = \frac{\int_0^T \widehat{p}_{green}(t)dt}{\int_0^T p_{green}(t)dt}. \tag{14}$$

With the knowledge of future renewable power generation, the ideal solution should have a utilization of 100%. As in the example in Table II, all of the green power, which is 300, is consumed by the ideal solution. However, actual utilization could be much lower than 100% in reality because it is difficult to accurately predict future renewable power generation due to the nature of large variabilities in renewable energy sources (e.g., wind or solar power).

In the following analysis, we describe the gaps between the existing and ideal solutions, such as which dimension is missing or inaccurately modeled, whether the solutions are efficient and applicable, and the like.

3. GREEN-ENERGY-AWARE WORKLOAD SCHEDULING

Datacenters usually support several types of IT requests or workloads ranging from critical interactive jobs such as Internet services, to delay-tolerant batch jobs such as scientific applications. Requests for a service can be routed to any of the datacenters that host the service. This enables geographical load balancing between distributed datacenters. Batch jobs can be scheduled to execute at any time as long as they finish before their deadlines. This enables temporal flexibility of workload management. This section investigates research efforts that adopt job scheduling techniques and exploit temporal or spatial flexibility for power management.

3.1. Single Datacenter Workload Scheduling

3.1.1. Problem Description. Research efforts in this category leverage various job scheduling techniques to optimize costs, emissions, and/or renewable energy utilization for a single datacenter. As discussed in Section 2, the grid electricity price and emission factor vary with time and demand, and renewable energy is variable and intermittent due to its dependence on weather conditions. The major difficulty is how to align datacenter workload with these variabilities. The basic idea here is to schedule workloads in a *temporal* manner; that is, to schedule and execute workloads *when* the electricity price is cheap, *when* the emission factor is low, and/or *when* the renewable power generation is adequate.

3.1.2. Qualitative Analysis. In this section, since all the investigated research efforts consider on-site renewable energy, we use another important characteristic to group their qualitative analysis. The characteristic is cooling; that is, how their scheduling methods deal with a datacenter's cooling power.

Cooling-oblivious workload scheduling. The research efforts in this group neglect cooling power and only take account of IT equipment power to do workload scheduling. Goiri et al. [2011] focus on a datacenter equipped with an on-site PV solar array. They propose GreenSlot, a parallel batch job scheduler for scientific workloads. GreenSlot schedules the workload to maximize the on-site solar energy utilization and/or minimize the brown energy cost while meeting jobs' deadlines. The scheduler integrates solar power generation prediction and least-slack-time-first job ordering. A job's slack time is defined as deadline minus the remaining execution time. Jobs are first queued in a decreasing order of their slack times. Then, the scheduler tries to run as many jobs as possible in the sorted queue according to the amount of renewable energy and/or the electricity price.

Goiri et al. [2012] propose GreenHadoop, a MapReduce framework for a PV solar-powered datacenter. GreenHadoop maintains two job queues: Run and Wait. High-priority jobs are sent straight to a Run queue that behaves like standard a Hadoop; that is, it executes them as soon as possible. Low-priority jobs initially go to the Wait queue. It is worth noting that Goiri et al. [2011] cope with scientific workloads, where the scheduler assumes knowledge of the resource requirements for each job before running the job. By contrast, MapReduce jobs do not specify the number of servers to use, their running time, or their energy needs. Hence, for those low-priority jobs, GreenHadoop first estimates the number of servers to use, running time, energy needs, and data availabilities using historical statistics. These jobs are then scheduled using a similar job scheduling approach as that in Goiri et al. [2011].

Deng et al. [2013] optimize the operating cost of a datacenter and propose an online control algorithm called MultiGreen. Compared with other works, the novelty of this work lies in two aspects. First, MultiGreen considers two time scales of the electricity market: real-time and long-term markets. It decides the amount of energy drawn from each source in the two stages, including the amount of electricity purchased from the electrical grid and the amount of energy charging to or discharging from the energy storage device. In the first stage, MultiGreen decides on the amount of energy to purchase from the electrical grid's long-term market at each coarse-grained timeslot (e.g., 1 day). In the second stage, MultiGreen decides the amount of electricity to buy from the real-time market at each fine-grained timeslot (e.g., 5 minutes).

The second aspect is that the authors analyze the performance bound of the proposed algorithm. MultiGreen applies the Lyapynov optimization technique. Lyapynov optimization is developed to enable constrained optimization of time averages in stochastic systems, especially in networking and queuing systems [Neely 2010]. Instead of directly minimizing an objective function, the technique minimizes the bound of drift-plus-penalty (i.e., Lyapynov drift plus the objective function) to stabilize the network while minimizing the objective. A salient feature of MultiGreen is that, even without any a priori knowledge of the system dynamics, its result can arbitrarily approach the optimal offline cost, which is computed with full knowledge of the system, within a provable $O(1/V)$ gap. The parameter V is a control knob with which MultiGreen can control the tradeoff among cost minimization, the satisfaction of datacenter availability, and the lifetime of energy storage devices.

All of these three works mainly focus on designing workload scheduling algorithms. Similar to them, Krioukov et al. [2011, 2012] present two different workload scheduling methodologies. One is electricity-price driven, which explores the quality slack for interactive workloads to minimize electricity cost. The other is renewable-power driven, which explores the temporal slack for batch workloads to maximize renewable utilization. This is a supply-following method that schedules batch jobs to align with the time-varying renewable energy available to a datacenter. However, what needs to be noted here is that Krioukov et al. [2011, 2012] further devise a prototype of energy-agile clusters that can dynamically adapt their energy consumption. They conduct extensive simulations based on real-world data traces to evaluate the proposed prototype. The data traces used in their simulations are parallel to those discussed in Section 2. They are rather widely used and well recognized, too: The interactive workload trace is from Wikipedia, a multitiered web application, whereas the batch workload trace is a month-long trace from the Franklin cluster at the National Energy Research Scientific Computing Center (NERSC) [NERSC 2013]. The wind speed/power trace is from the National Renewable Energy Laboratory (NREL) Wind Integration Dataset [NREL 2013b].

Compared to Krioukov et al. [2011, 2012], [Goiri et al. 2013] not only give a prototype design of a datacenter, but also go much further by implementing it. The authors, who are from the DARK Lab at Rutgers University, justify their design by building a research micro-datacenter called Parasol. Parasol comprises a small container, a set of solar panels, batteries, and a grid-tie. The container holds two racks of servers and networking devices. Parasol uses free cooling when ambient temperatures are low enough and regular air conditioning otherwise. Similar datacenter implementation concepts are also applied to datacenters descirbed in Sharma et al. [2011a] and Arlitt et al. [2012]. They then extend GreenSlot [Goiri et al. 2011] and GreenHadoop [Goiri et al. 2012] by considering interactive as well as batch jobs, and they propose GreenSwitch, an optimization-based workload scheduling approach with an objective of minimizing grid electricity cost when the grid is on and minimizing performance degradation when the grid is down.

GreenSwitch is fomulated as a Mixed Integer Linear Programming (MILP) problem and solved by Gurobi solver [Gurobi Optimization 2013]. Using datacenter workload and solar power prediction as inputs, GreenSwitch determines the energy sources' schedule, including brown energy from the electrical grid, energy sold back to the grid by net metering, and energy charged to or discharging from batteries. It is worth noting that GreenSwitch captures all constraints about battery operations discussed in Section 2.1.2, and, more importantly, it models the grid outage. Hence, the approach can lose the dependence of Parasol on the electrical grid and can improve datacenter service availability. One common limitation of these three green works (GreenSlot, GreenHadoop and GreenSwitch) is that they do not consider the modeling and management of the cooling power.

Static-cooling workload scheduling. To estimate cooling power, the research efforts in this group treat the cooling efficiency as constant. They assume cooling power is $x\%$ of IT equipment power and thus PUE equals $1 + x\%$. Aksanli et al. [2011] extend the workload scheduling method in Krioukov et al. [2011] by adopting renewable power prediction. They propose a heuristic algorithm that utilizes renewable energy to improve a datacenter's job throughput without sacrificing quality of service. The proposed algorithm can reduce the number of cancelled jobs and thus increase renewable energy utilization. Computing frameworks such as MapReduce and Dryad allow (1) the execution of a subset of the tasks in a job to match renewable power generation and (2) the re-execution of cancelled jobs that have been stopped because of power shortages. With renewable energy prediction, the algorithm can make the workload better align with the availability of renewable power and allow more jobs to continue their execution. This ultimately reduces the waste of renewable energy and improves its utilization.

Different from other works, Ghamkhari and Mohsenian Rad [2012a, 2013] assume multiple SLAs for different Internet service classes such as cloud-based, video streaming, HTML web services, and the like. SLAs are differentiated according to service deadlines, service payments, and service violation penalties. A cloud-based service allows users to offload their computing (hardware/software/data) to the cloud (e.g., Amazon EC2), whereas an HTML web service supports users getting data from the Internet (e.g., webpage browsing). However, the research work provides no example of a real-world datacenter that hosts such multiple services at the same time. They then propose an optimization-based framework to maximize a datacenter's profit (revenue minus cost). The framework employs a mathematical model that captures the tradeoff between minimizing the electricity cost and maximizing the revenue received from providing various services. The framework uses the datacenter power model of Equations (2) and (7). It further assumes that the amount of renewable power generation is already known for profit optimization in each timeslot. This assumption makes the framework less practical. In general, there are two ways to deal with renewable power generation in power management. The first is to employ machine learning methods to predict power generation for the future, such as the autoregressive (AR) model and k-NN algorithm used in Liu et al. [2012]. The second is to perform the current decision making based on the amount of renewable energy stored in batteries so far, instead of using the predicted amount for the future. However, the framework here adopts neither of these ways.

Dynamic-cooling workload scheduling. The efforts in this group consider dynamic cooling efficiency, which varies as workload/IT equipment power and/or ambient temperature change. Liu et al. [2012] develops a workload scheduling approach for managing both IT equipment and cooling power in a datacenter with the goal of minimizing the electricity cost. The novelty of this work is that the authors consider a "universal" inclusion of dimensions, one incorporating renewable power generation (wind and solar power), energy storage, a cooling micro grid (chiller and outside air cooling), both interactive and batch job scheduling, dynamic electricity pricing, and temperature diversity. A convex function model is assumed for each of the dimensions. For example, they use Equation (2) and Equation (5) to model IT equipment power and cooling power, respectively. The proposed solution splits the time line into discrete timeslots and optimizes the energy cost for each timeslot by the following two steps.

First, at the beginning of each timeslot, it makes a short-term prediction of the workload and solar/wind power generation. The authors adopt several machine learning techniques, such as the AR model and k-NN algorithm, which are widely used in research efforts when doing this kind of prediction. Hence, we present some explanations on how these two algorithms work. The AR model specifies that the output solar/wind power at time t depends linearly on its own previous values at time $\{t-1, t-2, \ldots\}$. The idea of k-NN is to find the most "similar" timeslots in the recent past (such as 1 week) and use the solar/wind power generation during those timeslots to estimate the generation for the target timeslot. The similarity between two timeslots is determined using features such as ambient temperature, humidity, cloud cover, visibility, and the like.

Second, the authors formulate a convex programming problem in which the constraints capture energy buffering behavior, cooling operations, and SLAs. They employ a famous solver called Matlab CVX to solve the convex program. CVX is a Matlab-based modeling system for convex optimization [CVX 2012]. CVX turns Matlab into a modeling language, allowing constraints and objectives to be specified using standard Matlab expression syntax. The following lists several strengths and limitations of the work. One strength of the work is that the "universal" inclusion allows a truly integrated workload management. However, it provides rather rough modeling for energy storage or batteries, and it does not consider important features of a battery, including

Table III. Classification of Objective, Formulation, Solution, and Evaluation Method for Single Datacenter Workload Scheduling in Section 3.1

Research work	Objective	Formulation	Solution	Evaluation
[Liu et al. 2012]	Min cost	Convex programming	Matlab CVX	Trace-based simula-tions & a real testbed
[Arlitt et al. 2012]	Max renewable utilization	—	Prototype design & implementation	A HP production datacenter
[Krioukov et al. 2011, 2012]	Min cost & Max renewable utilization	—	Prototype design	Trace-based simula-tions
[Aksanli et al. 2011]	Max throughput	—	Heuristic	Synthetic setting simulations
[Ghamkhari and Mohsenian Rad 2012a, 2013]	Max profit	Convex programming	Interior point method	Trace-based simulations
[Deng et al. 2013]	Min cost	Online control	Lyapynov optimization	Trace-based simulations
[Goiri et al. 2011]	Max renewable utilization	—	Heuristic	Trace-based simulations
[Goiri et al. 2012]	Max renewable utilization	—	Heuristic	Synthetic setting simulations
[Goiri et al. 2013]	Min cost & Min performance degradation	MILP	Prototype design & Gurobi solver	A real testbed: Parasol

the depth of discharge, charging/discharging loss, and battery lifetime (as discussed in Section 2.1.2). The work also ignores the switching costs associated with cycling servers in and out of power-saving modes. Another strength lies in their evaluation, where they perform both trace-based numerical simulations and real testbed experiments. Their workload management approach is experimentally verified to be a practical and robust solution.

Arlitt et al. [2012] present a detailed description of the design and implementation of the net-zero datacenter prototype in a production HP datacenter. "Net-zero" means that the total energy usage over a fixed period is less than or equal to the local total renewable generation during that period. This concept is also elaborated in Liu et al. [2012]. The difference between these two works is that Liu et al. [2012] focus on the design of workload scheduling algorithm where net-zero is treated as a constraint, while Arlitt et al. [2012] emphasize the prototype design and implementation of net-zero datacenters.

Table III provides a summary of objective, formulation, solution, and evaluation methods for the works discussed in this subsection. Table IV shows a summary of different considered dimensions: electricity price, energy storage, carbon market, renewable integration, and workload types.

3.1.3. Quantitative Analysis. To provide better insight into the single datacenter workload scheduling problem, we describe quantitative comparisons among some of the discussed works in this subsection. We present two comparisons from Liu et al. [2012]: a comparison among different cooling management approaches and a comparison among different workload management approaches. The experimental setting is as follows. The datacenter is equipped with 500 servers (100kW), a 130kW PV solar array, and a cooling system with both outside air cooling and chiller cooling. The interactive workload trace is from an HP datacenter. The total demand ratio between the interactive and batch workload is assumed to be 1:1.5. Half of the batch jobs are submitted at

Table IV. Classification Based on Different Considered Dimensions for Single Datacenter Workload Scheduling in Section 3.1

Research Work	Electricity Price	Energy Storage	Carbon	Renewable	Workload
[Liu et al. 2012]	Real-time	Battery	—	On-site	Interactive & batch
[Arlitt et al. 2012]	—	Battery	—	On-site	Interactive & batch
[Krioukov et al. 2011, 2012]	Real-time	—	—	On-site	Interactive & batch
[Aksanli et al. 2011]	—	—	—	On-site	Batch
[Ghamkhari and Mohsenian Rad 2012a, 2013]	Real-time	—	—	On-site	Differentiated SLAs
[Deng et al. 2013]	Real-time &long-term	Battery	—	On-site	General
[Goiri et al. 2011]	On-/off-peak	—	—	On-site	Batch: scientific
[Goiri et al. 2012]	On-/off-peak & peak charge	—	—	On-site	Batch: Mapreduce
[Goiri et al. 2013]	On-/off-peak & peak charge	Battery & Net metering	—	On-site	Interactive & Batch: Map-reduce

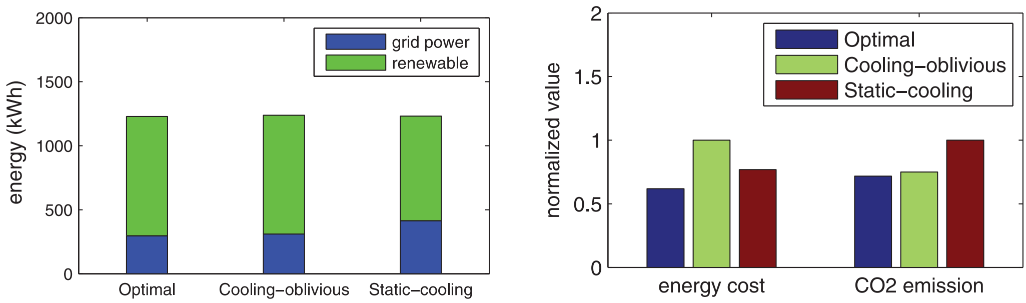
That we treat net metering as a kind of energy storage because energy flowing back can be seen as storing energy in the electrical grid, which is like battery charging. General: not differentiating workload types; On-site: renewable power generators co-located with or close to datacenters; off-site: renewable energy from the electrical grid.

midnight, and the other half are submitted around noon. Real-time electricity price is obtained from FERC [2013]. With on-site renewable energy (the PV solar), the datacenter is assumed to have free renewable power.

Comparison on cooling management. The comparison shows the importance of cooling-aware scheduling. We provide the comparison among the approaches adopted by the three groups discussed in Section 3.1.2: (i) *Optimal or dynamic-cooling*, the algorithm proposed in Liu et al. [2012] and also state-of-the-art, which integrates both renewable energy and cooling information into workload scheduling; (ii) *Cooling-oblivious*, which ignores cooling power and only considers IT equipment power for workload scheduling, such as the algorithms in Goiri et al. [2013]; and (iii) *Static-cooling*, which uses a static cooling efficiency (assuming the cooling power is 30% of IT equipment power) to estimate the cooling power; that is, assumes a constant PUE (of 1.3), as with the algorithm in Aksanli et al. [2011].

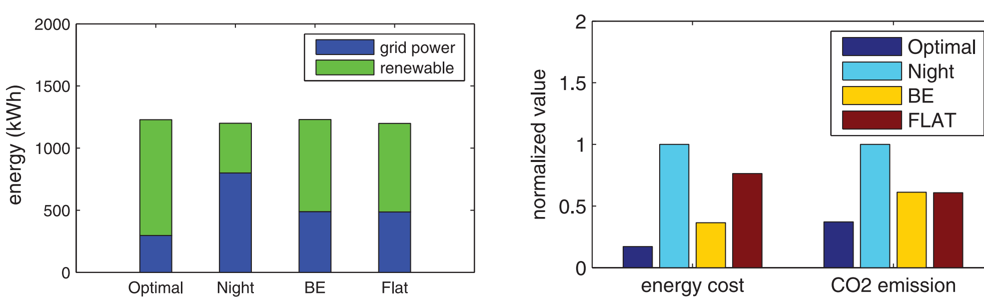
Figure 8(a) shows the comparison on grid energy and renewable energy usage; Figure 8(b) plots the comparison on the energy cost and emission. In Figure 8(a), *Cooling-oblivious* underestimates the power demand, executes more workload than the available on-site renewable power, and thus uses more grid power. *Static-cooling* overestimates the cooling power demand, and less workload is scheduled to run. Thus, it underutilizes the on-site renewable power. By contrast, *Optimal* uses the least grid power and fully utilizes the on-site renewable power because it accurately models cooling power and adapts to time variations in cooling efficiency. As mentioned earlier, the on-site renewable power is charge free, and the electrical grid is responsible for all the cost and emission. Therefore, the algorithm *Optimal* achieves more energy cost saving and more emission reduction than the other two, as shown in Figure 8(b).

Comparison on workload management. The comparison shows the importance of renewable aware scheduling. We provide the comparison among the following four approaches: (i) *Optimal*, which aligns batch jobs' execution with the on-site renewable



(a) Power usage comparisons (b) Energy cost and emission comparisons

Fig. 8. Comparisons on cooling management from Liu et al. [2012]. Note that the energy cost and emission are normalized to the largest value, respectively.



(a) Power usage comparisons (b) Energy cost and emission comparisons

Fig. 9. Comparisons on workload management from Liu et al. [2012]. Note that the energy cost and emission are normalized to the largest value, respectively.

power generation, as in Liu et al. [2012] and Goiri et al. [2013]; (ii) *Night*, a widely used solution in practice, which executes batch jobs at night to avoid interfering with interactive workloads at daytime; (iii) *Best Effort (BE)*, which schedules batch jobs like interactive jobs—it executes batch jobs immediately when they arrive and finishes them as soon as possible; and (iv) *FLAT*, an energy-saving approach that executes batch jobs at a constant speed during their deadline periods.

Figure 9(a) shows the comparison on grid energy usage and on-site renewable energy usage; Figure 9(b) plots the comparison on the energy cost and emission. *Night*, among the four approaches, uses the most grid power (see Figure 9(a)) and has the highest cost (see Figure 9(b)). Executing batch jobs at night significantly decreases the on-site renewable energy utilization and increase grid power use. In fact, only interactive tasks executed at daytime utilize on-site renewable power because there is no solar power at night, and the datacenter draws electricity only from the grid to meet its power demand. Although the electricity is priced cheaper at night, the increase in grid energy usage dominates and thus the cost using *Night* goes up considerably. At the other extreme, the *Optimal* approach reshapes batch jobs to align with on-site renewable energy availability as much as possible, and thus consumes the least grid power and has the lowest cost and emission. In between are the approaches *BE* and *FLAT*. Although they have similar grid energy usage, *FLAT* uses more grid power than does *BE* during the daytime. Since the grid electricity price is higher during the daytime, *FLAT* costs more than *BE*.

3.2. Multi-datacenter Geographical Workload Placement

3.2.1. Problem Description. The research efforts in this category adapt routing policies to optimize the cost, emissions, and/or renewable energy utilization for geographically distributed datacenters. As discussed in Section 2, the grid electricity price and emission factor vary regionally and so does renewable energy availability. The basic idea here is to route requests or schedule workloads in a *spatial* manner; that is, to route and service requests at datacenters *where* the electricity price is cheap, *where* the emission factor is low, and/or *where* the renewable power generation is sufficient for a given time period.

3.2.2. Qualitative Analysis. In this section, we group the research efforts according to whether they assume renewable energy is charge-free to datacenters. This characteristic has significant impact on the decision making of workload placement among multiple datacenters. For example, to minimize cost, if renewable energy is free of charge, more workload should be placed at datacenters with more renewable power; if expensive, less workload should be transferred. We further show the impact through quantitative analysis in Section 3.2.3.

Workload placement with free renewable energy. The research efforts in this group assume that datacenters have charge-free renewable energy. Stewart and Shen [2009] give a position paper that outlines several research aspects that need to adapt to the intermittency and variability of renewable energy, including capacity planning, load balancing, job scheduling, and system maintenance. The focus of the work is on geographical load balancing, especially on request routing for renewable energy utilization maximization. The work proposes a request-level power/energy profiling approach (per-request power/energy consumption) and argues that the approach could guide fine-grained request routing across geographically distributed datacenters. However, they give no specific solutions about how to perform the request routing.

By contrast, Liu et al. [2011a] provide a detailed problem formulation for geographical load balancing with the goal of cost minimization. The cost includes the delay cost in capturing lost revenue incurred due to network and queueing delay and the energy cost denoting the bill charged by the electrical grid. They particularly discuss the feasibility of powering an Internet-scale datacenter system entirely using on-site renewable energy sources. They provide numerical analysis on the interplay between the wind power, solar power, and energy storage. One result shows that geographical load balancing can considerably reduce the required capacity of renewable energy if it uses "follow the renewable" routing. A similar method in the temporal dimension, called "demand-follow-supply," is also proposed in Krioukov et al. [2011, 2012]. Another result shows that an optimal mix of renewable energy sources includes significantly more wind than solar power. The reason is that solar power is only available during the daytime, but wind power has no such daily pattern. However, in order to derive more meaningful results, it is better to use real-world wind and solar traces (e.g., as discussed in Section 2.2) instead of a numerical setting.

Other research efforts make various simplifications and/or improvements based on the aforementioned work in this section. Chen et al. [2012] extend the renewable- and cooling-aware workload management problem addressed in Liu et al. [2012] to support geo-distributed datacenters. The work proposes an optimization-based framework to minimize brown energy consumption. The framework prefers to run a computational workload at datacenters with more renewable power generation and cheaper cooling levels. The work, compared to Liu et al. [2012], makes several simplifications in modeling the electricity price, cooling power, battery, and renewable power prediction. He et al. [2012] study how to jointly optimize the electricity cost, performance cost and social cost for multiple datacenters. The performance cost is similar to the delay cost defined in Liu et al. [2011a], and the social cost is the emission cost. They adopt network flow theory and model the problem into a min-cost network flow problem. Ghamkhari and Mohsenian Rad [2012b] extend the energy cost minimization problem in Rao et al. [2010] to support renewable energy. Each datacenter is assumed to have an on-site renewable power generator and pays nothing if the available renewable energy is more than the datacenter power load.

Workload placement without free renewable energy. The research efforts in this group assume that datacenters have to pay for renewable energy usage. Le et al. [2009] introduce an optimization-based request distributing framework that enables geo-distributed datacenters to jointly manage their grid/brown and renewable energy consumption. The work formulates a nonlinear programming problem to minimize energy cost while respecting SLAs. Le et al. [2008, 2010] extend the optimization framework in Le et al. [2009] to support additional aspects including capping brown energy consumption or emissions, different carbon market policies (such as cap-and-trade and carbon tax), multiple types of requests (such as different SLAs), and a brown-green power mix in the electrical grid (or the grid emission factor). This extended framework aims at minimizing both energy and emission costs. It is also worth noting that they provide several detailed solutions to the formulated nonlinear program, including linearization and Simulated Annealing (SA). For linearization, the nonlinear functions are transformed into constant values, and thus the nonlinear problem is then approximated as a linear problem. They then solve the approximation using an LP solver. An SA-based algorithm is then applied to solve the problem. SA is a generic search-based optimization technique. It can give a good approximation of the optimum, but it is computationally intensive. This work is the first one that incorporates emission cost into datacenter power management. It provides a good problem description and formulation.

Gao et al. [2012] first present two novel observations: (1) the grid emission factor shows both spatial and temporal variabilities, and (2) there is no correlation between the fuel mix and the electricity price in a region. The two observations are detailed in Section 2.3. Based on the two observations, the work proposes a request-routing framework, called FORTE. The framework, compared to Le et al. [2008, 2010], additionally considers access latency and aims at balancing the three-way tradeoff among emission, energy cost, and access latency. The framework contains three algorithms. The first algorithm determines the initial data placement according to data flow sizes to datacenters. The second algorithm updates data replication accounting for changes in user request patterns. The third one is a fast algorithm that runs online to determine user-to-datacenter assignment. FORTE can significantly reduce emission without compromising the mean latency or increasing the electricity bill. The framework can be also used to determine datacenter upgrading and expansion plans to meet the continuing growth of Internet services. Interestingly, the work argues that a carbon tax will not affect datacenter operator behavior because emission cost is less than 2% of the electricity cost. This argument is against the one presented in Le et al. [2008, 2010], where emission cost accounts for a considerable portion of the datacenter energy cost. The reason is that the emission price used in Gao et al. [2012] is far lower than that found in the real carbon market.

Zhang et al. [2011] propose GreenWare, an optimization-based framework that maximizes the renewable energy utilization of geo-distributed datacenters. The renewable energy utilization is defined as the renewable energy consumption divided by the total energy usage. It is worth noting that instead of an objective, the work treats energy cost as a constraint by setting an allowed operating cost budget during a time period. Since renewable energy is assumed to be more expensive than brown energy, datacenters can use more renewable energy and cause less emission if they have a large budget rather than for a small one. The framework employs a wind power and solar power model similar to those discussed in Section 2.2. The authors formulate a nonlinear programming problem, which is then transformed into a linear programming problem and solved with the linprog solver in Matlab. The linprog solver uses a simplex method, which has proved to have a low complexity in practice [MathWorks 2014]. The proposed approach here is to balance the energy cost and renewable energy utilization (or emission) between the two extremes: only minimizing cost and only maximizing renewable energy utilization. These argument holds only if brown energy is cheaper than renewable energy. If not, the two goals (energy cost minimization and renewable utilization maximization) can be achieved at the same time.

All of the aforementioned research efforts in this subsection adopt centralized solutions. In contrast to this approach, Liu et al. [2011b] propose two distributed algorithms to minimize the cost of geo-distributed datacenters. Similar to Liu et al. [2011a], the cost here includes the delay cost and energy cost. The first algorithm is based on Gauss-Seidel iteration and the second on gradient projection. Both algorithms decompose the problem and let the datacenter and the client perform optimization separately. Each part's optimization is conducted using intermediate results of the request arrival rate and/or the number of active severs in each datacenter. The intermediate results are communicated between the two parts at the end of each iteration. The provided theoretical proof shows the convergence of the two algorithms. It is worth noting that the authors perform an experiment on social impact or emissions to develop suggestions on grid electricity pricing. In this experiment, they assume off-site renewable energy (i.e., that the renewable energy is also from the electrical grid). The results show that if the grid electricity is dynamically priced in proportion to the instantaneous fraction of renewable energy to the total energy, geographical load balancing could achieve significant reductions in brown energy usage.

For now, most web applications make decisions on client-to-datacenter routing in a centralized manner. One question here is how to apply the proposed distributed algorithms to the implementation framework of existing applications. To involve all of an application's datacenters and clients causes an unacceptable amount of communication overhead between them. One possible solution to reduce the overhead is to employ a proxy to represent a group of clients and run the distributed algorithms between datacenters and proxies.

There are also several works that make various simplifications and/or improvements based on the research efforts discussed so far. Doyle et al. [2011] explore the tradeoff between carbon emission and Quality of Service (QoS). The work formulates a convex optimization problem to minimize the weighted sum of emission and QoS. Chiu et al. [2012] present a position paper that argues that the usage pattern of multiple datacenters could contribute significantly to achieving a balance between energy production and consumption for the electrical grid. Using a scheme of demand response, migrating computational workload across geographical regions to match electricity supply could bring mutual cost benefits for both grid operators and datacenter owners. Along the same line as in Chiu et al. [2012] and Li et al. [2013] further propose an optimization framework to determine a negotiated electricity price that results in minimized cost for both datacenters and utilities.

Table V provides a summary of objective, formulation, solution, and evaluation methods for the works discussed in this subsection. Table VI shows a summary of different considered dimensions: electricity price, energy storage, carbon market, renewable integration, and workload types.

3.2.3. Quantitative Analysis. To provide better insight into the multi-datacenter geographical workload placement problem, we describe quantitative comparisons among

Table V. Classification of Objective, Formulation, Solution, and Evaluation Method for Multi-Datacenter Geographical Workload Placement or Geographical Load Balancing (GLB) in Section 3.2

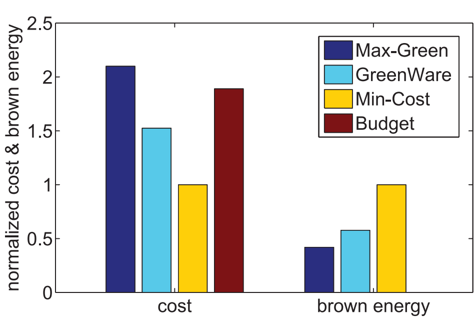
Research work	Objective	Formulation	Solution	Evaluation
[Stewart and Shen 2009]	Max renewable utilization	—	—	Numerical examples
[Le et al. 2009]	Min cost	Non-linear programming	Simulated annealing	Trace-based simulations
[Le et al. 2010, 2008]	Min cost	Non-linear programming	Linearization & Simulated annealing	Trace-based simulations & prototype implementation
[Liu et al. 2011a]	Min cost	Convex programming	—	Numerical simulations
[Liu et al. 2011b]	Min cost	Convex programming	Gauss-Seidel iteration & gradient projection	Trace-based simulations
[Zhang et al. 2011]	Max renewable utilization	Non-linear programming	Linearization & linprog solver	Trace-based simulations
[Gao et al. 2012]	Min cost	Linear programming	Heuristic	Trace-based simulations
[Doyle et al. 2011]	Min weighted sum of QoS and emission	Convex programming	Gradient method	Synthetic setting simulations
[Chen et al. 2012]	Min brown energy usage or emission	—	Heuristic	Trace-based simulations
[Li et al. 2013]	Min cost	Non-linear programming	Cologne solver	Trace-based simulations
[He et al. 2012]	Min cost	Convex programming	Gradient method & heuristic	Synthetic setting simulations
[Ghamkhari and Mohsenian Rad 2012b]	Min self-defined objective	Quadratic programming	—	Trace-based simulations

some of the discussed works in this subsection. We present a comparison among solutions for off-site renewable energy (from Zhang et al. [2011]). In Section 3.1.3, datacenters are assumed to have on-site renewable energy and also assume it to be free. By contrast, this subsection assumes that renewable energy is more expensive than brown energy. We provide the comparison among the following three approaches: (i) *Min-Cost*, which *only* aims at minimizing the energy cost by exploring the varying electricity prices in different locations, as in Rao et al. [2010], Liu et al. [2011b], and Li et al. [2013]; (ii) *GreenWare*, the algorithm proposed in Zhang et al. [2011] and also the state-of-the-art, which balances the energy cost and renewable energy utilization (or emission); and (iii) *Max-Green*, which *only* targets maximizing the renewable energy utilization by distributing more requests to datacenters with more available renewable energy, as in Stewart and Shen [2009], Doyle et al. [2011], and Chen et al. [2012].

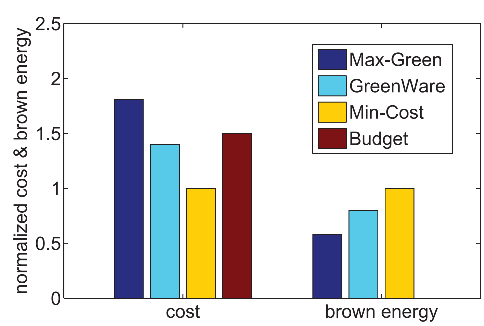
The experimental setting assumes four datacenters located in four different locations. The server configuration in each datacenter is based on the numerical setting from Zhang et al. [2011]: power consumption of 88.88, 34.10, 149.19, and 141.28 Watts, and processing capacity of 500, 300, 725, and 675 requests per second, respectively. The wind electricity price is assumed to be 1.5 cents higher per KWh than brown energy, whereas solar energy is 18.0 cents higher. Brown energy uses the electricity price from NYISO [2013]. The meteorological data in NREL [2013a] are used to emulate the intermittency and variability of renewable energy. Wikipedia trace (November 2007)

Table VI. Classification Based on Different Considered Dimensions for Multi-Datacenter Geographical Workload Placement or Geographical Load Balancing (GLB) in Section 3.2

Research Work	Electricity Price	Energy Storage	Carbon	Renewable	Workload
[Stewart and Shen 2009]	—	—	—	On-site	General
[Le et al. 2009]	Real-time & long-term & constant	—	—	Off-site	General
[Le et al. 2010, 2008]	Real-time & long-term & constant	—	Cap-and-trade & carbon tax	Off-site	General
[Liu et al. 2011a]	Constant	Battery	—	On-site	General
[Liu et al. 2011b]	Real-time	—	—	Off-site	General
[Zhang et al. 2011]	Real-time	—	—	Off-site	General
[Gao et al. 2012]	Constant	—	—	Off-site	General
[Doyle et al. 2011]	—	—	—	Off-site	General
[Chen et al. 2012]	—	—	—	On-site	Batch
[Li et al. 2013]	Constant	—	—	Off-site	General
[He et al. 2012]	Real-time	—	—	On-site	General
[Ghamkhari and Mohsenian Rad 2012b]	Real-time	—	—	On-site	General



(a) Cost and brown energy comparisons with Nov. 2007 Wikipedia trace.



(b) Cost and brown energy comparisons with Jun. 1998 World Cup trace.

Fig. 10. Comparisons on off-site renewable energy from Zhang et al. [2011]

[Urdaneta et al. 2009] and 1998 World Cup trace (June 1998) are used as experimental workload traces.

Figure 10(a) shows the cost and brown energy consumption for *Max-Green*, *GreenWare,* and *Min-Cost* with respect to a given monthly budget using the Wikipedia trace in November 2007. The results are normalized against *Min-Cost*. *Min-Cost* has the least cost but the largest brown energy consumption among the three algorithms. The reason is that *Min-Cost* tries to minimize energy cost as much as possible, which eliminates the usage of renewable energy due to the higher price. *Max-Green* comes with the highest cost but the lowest brown energy consumption. The cost is also larger than the budget because, to maximize renewable utilization, *Max-Green* distributes more requests to datacenters with more renewable energy regardless of the higher price. *GreenWare* is a balanced approach that results in less cost than *Max-Green* and less brown energy usage than *Min-Cost*. The approach also respects the budget. Similar results are shown in Figure 10(b), which uses 1998 World Cup trace in June 1998.

Note that for the case of charge-free renewable energy [Liu et al. 2011a; Ghamkhari and Mohsenian Rad 2012b], cost minimization is equivalent to renewable utilization maximization. Hence, in this case, all three approaches yield the same result and also the best result.

4. GREEN-ENERGY-AWARE VM OR SERVER MANAGEMENT

A Virtual Machine (VM) is a software implementation of a machine that executes workloads like a physical machine. A server can run multiple VMs. Each VM may hold multiple applications, and each application can also use multiple VMs. A VM can be migrated among different servers: A VM running in a server is first suspended and then copied and transmitted to another server where the VM resumes execution. Memory, storage, and network connectivity of the VM are transferred from the original server to the destination. Suppose that there are two physical servers, and each has two VMs. If each server has one idle VM or no running workload, the utilized VM in one server can be migrated to the other server. The idle server can be shut down to save energy. VM migration causes significant time, energy, and communication overhead due to memory data copy and transmission between different servers. Hence, we treat VM management as a separate section. Furthermore, we can think of VM management in this section as a kind of coarse-granularity management, whereas Section 3 deals with fine-granularity management.

4.1. Single Datacenter VM or Server Management

4.1.1. Problem Description. Live VMs can be migrated or consolidated onto a fraction of the servers in a datacenter, and the remaining severs can be turned off to save power. The research efforts in this category manage VM consolidation or live migration in a temporal manner to optimize costs, emissions, and/or renewable energy utilization for a single datacenter. The basic idea here is to align VM migration with fluctuations of different parameters, including the grid emission factor and/or available renewable power.

4.1.2. Qualitative Analysis. We group the research efforts in this subsection according to whether they incorporate energy buffering into the designs of their solutions. As discussed in Section 2, buffering energy using batteries plays a key role in utilizing renewable energy. Storing surplus renewable power for future use can further improve its utilization.

VM management with energy buffering. Sharma et al. [2011a] propose a blinking method to adapt servers to an intermittent power supply, such as solar or wind power. The method applies a duty cycle to servers through employing rapid active/inactive state switching via PowerNap [Meisner et al. 2009]. For example, a system blinking every 5 minutes means that the system is ON for 5 minutes and then OFF for 5 minutes, which consumes half of the energy of an always-on system (if ignoring switching overhead). Hence, the key problem of a blinking policy is to determine the time length of the ON and OFF interval for each server. Because there may not always be enough renewable energy to power servers necessary to meet demand, the goal of a blinking method is to minimize performance degradation as renewable power varies. Irwin et al. [2011] apply the blinking policy proposed in Sharma et al. [2011a] to distributed data storage systems in order to optimize I/O throughput, data availability, and energy efficiency.

The blinking policy makes a server switch between ON and OFF states periodically. By contrast, renewable energy is significantly intermittent and variable, which shows no periodic property. Hence, a periodic scheduling policy like the blinking method may be not suitable for improving renewable energy utilization. An adaptive scheduling method that adjusts a server's state according to the availability of renewable energy is preferable to achieve the goal. Along this argument, Singh et al. [2013] propose an adaptive approach, named Yank, that manages VMs according to the level of renewable power generation.

Yank strikes a balance among a datacenter's reliability, energy cost, and carbon emissions. It is worth noting that instead of optimizing the power delivery infrastructure to provide a highly reliable supply of power, Yank focuses on the server side and ensures high availability of software services with relaxation on the requirement for a continuous power source. The authors divide servers into three categories: transient, back-up, and stable. Transient servers are powered by on-site renewable energy, whereas stable servers are connected to the reliable grid energy. During unexpected grid power outages or shortages, transient VMs are backed up and then restored in stable servers. During normal operation, Yank guarantees data consistency by just-in-time synchrony. This method backs up the memory and disk state of transient VMs when the size of dirty memory pages and disk blocks reaches a threshold defined by an advance warning period. The experimental results show that, by using an advance warning time of 10 seconds, a backup server can concurrently support as many as 15 transient VMs with little performance degradation. It is observed that the concept of a transient VM is the key enabler to allow datacenters to shut down servers and make them adaptive to renewable energy.

VM management without energy buffering. Without an energy buffer, a datacenter has to keep tracking renewable power generation and tuning the power load in order to match the two issues. The three operations come with large overhead and cause a significant performance loss to a datacenter. To balance renewable energy utilization and performance loss, Li et al. [2011, 2012] present iSwitch, a lightweight and easy-to-implement renewable energy-driven VM management scheme. iSwitch follows renewable power variation characteristics and applies a supply/load cooperative scheme to mitigate performance loss. The scheme classifies wind power generation into three scenarios: wind power outage period, low wind power generation with frequent fluctuation, and full wind power generation with relatively stable output. For each scenario, the scheme applies different datacenter power management approaches. Hence, the work concludes that this scheme avoids redundant load tuning activities and also minimizes unnecessary power control activities. However, the work does not consider the energy buffering function of batteries in a datacenter, which causes much unnecessary tracking overhead of renewable energy. Using energy buffering would further reduce the load tuning activities and simplify the proposed scheme.

Deng et al. [2012a] discuss one of the fundamental issues about renewable-aware power management: how to account for carbon emissions or how to calculate grid energy usage, which is overlooked by most of the existing works. The work presents a carbon emission accounting mechanism on how to track grid energy usage in grid-tied datacenters. Based on this mechanism, the authors propose a carbon-aware provisioning policy that chooses how many cloud instances (or VMs) to run to maximize the throughput of a cloud application.

Table VII provides a summary of objective, formulation, solution, and evaluation methods for the works discussed in this subsection. Table VIII shows a summary of different considered dimensions: electricity price, energy storage, carbon market, and renewable integration.

4.2. Multi-datacenter Geographical VM Management

4.2.1. Problem Description. The research efforts falling into this category manage VM live migration in a spatial manner; that is, they migrate VMs to datacenters that have preferable parameters such as lower electricity price, smaller emission factors, or more renewable power generation.

Table VII. Classification of Objective, Formulation, Solution, and Evaluation Method for Single Datacenter VM or Server Management in Section 4.1

Research Work	Objective	Formulation	Solution	Evaluation
[Sharma et al. 2011a]	Min performance degradation	—	Prototype design & implementation	Synthetic setting simulations
[Singh et al. 2013]	Balance reliability, cost and emission	—	Prototype design & implementation	A real testbed, benchmark
[Li et al. 2011, 2012]	Balance performance degradation and renewable utilization	—	Heuristic	Trace-based simulations
[Deng et al. 2012a]	Min throughput	Integer programming	Dynamic programming	Trace-based simulations

Table VIII. Classification Based on Different Considered Dimensions for Single Datacenter VM or Server Management in Section 4.1

Research Work	Electricity Price	Energy Storage	Carbon	Renewable
[Sharma et al. 2011a]	—	Battery	—	On-site
[Singh et al. 2013]	—	Battery	—	On-site
[Li et al. 2011, 2012]	—	—	—	On-site
[Deng et al. 2012a]	—	—	—	On-site

Table IX. Classification of Objective, Formulation, Solution, and Evaluation Method for Multi-Datacenter Geographical VM Management in Section 4.2

Research Work	Objective	Formulation	Solution	Evaluation
[Akoush et al. 2011]	—	—	Architectural design	Numerical examples
[Deng et al. 2012b]	Max profit	Integer programming	LP solver	Trace-based simulations

4.2.2. Qualitative Analysis. Only a few existing research efforts address the geographical VM management problem. We discuss two works in this category. One focuses on architecture design [Akoush et al. 2011], and the other deals with algorithm design [Deng et al. 2012b].

Akoush et al. [2011] outline the Free Lunch architecture that enables the exploitation of renewable energy across geo-distributed datacenters. Numerical examples are used to show the effectiveness of the architecture. They also highlight some technical challenges facing the successful deployment of the architecture, including VM migration, storage synchronization, scheduling, and placement of VMs among different datacenters. Deng et al. [2012b] extend the method in Deng et al. [2012a] to deal with geo-distributed datacenters. The work distinguishes cloud service/application managers from datacenter owners. It is worth noting that instead of capping the carbon emissions of datacenters, the work makes the following claims. First, each cloud service/application has an emission cap concerning the environment and throughput constraints representing SLAs. Second, datacenter owners should buy clean energy adaptively in order to maximize their profits. The authors also propose a cloud instances/VMs placement method to determine which datacenters should hold how many instances/VMs of a cloud application/service. There are two limits of this work. First, the profit considered in this work is overcalculated because it overlooks energy cost. Second, the work does not include several important dimensions discussed in Section 2, such as electricity pricing and energy buffering.

Table IX provides a summary of objective, formulation, solution, and evaluation methods for the works discussed in this subsection. Table X shows a summary of

Table X. Classification Based on Different Considered Dimensions for Multi-Datacenter Geographical VM Management in Section 4.2

Research Work	Electricity Price	Energy Storage	Carbon	Renewable
[Akoush et al. 2011]	—	—	—	On-site
[Deng et al. 2012b]	—	—	—	On- & off-site

different considered dimensions: electricity price, energy storage, carbon market, and renewable integration.

5. GREEN-ENERGY-AWARE ENERGY CAPACITY PLANNING

5.1. Problem Description

The research efforts falling into this category design power management plans to match the power supply with datacenter demand. The plan makes a choice among investment for peak grid power consumption and grid energy usage, capacity for different on-site/off-site energy sources and their usage, and/or capacity for energy storage devices and their buffering operations.

5.2. Qualitative Analysis

Gmach et al. [2010b] propose an approach to design energy capacity planning based on the estimation of both renewable power generation and workload demand in a datacenter. The datacenter sources power from the electrical grid, on-site renewable energy sources, and energy storage devices. Gmach et al. [2010a] address how to jointly manage the energy supply and demand side in a datacenter. The authors combine power demand profiling and power supply assessment together. They implement a datacenter simulator that is composed of a workload simulator, a power demand estimator, and a power supply simulator. However, these two works do not include a mechanism to search for optimal capacity planning with minimized energy costs or carbon emissions.

Brown and Renau [2011] propose an extensive but high-level-view simulation framework to evaluate the energy cost of a datacenter that is equipped with on-site renewable energy sources. The framework incorporates different dimensions that affect datacenter operating costs but presents little detail about the optimization approach. In addition, the work does not consider the optimization for carbon emissions from the electrical grid. To cap the datacenter carbon emission, Ren et al. [2012] study energy capacity planning by combining different ways of integrating renewable energy into the datacenter power supply, including self-generation and purchase of renewable power products. However, the work does not provide a method for renewable power estimation. The work considers brown energy sources such as DGs, and the power estimation model in Section 2.2.3 is used here. The work proposes an optimization-based framework to minimize datacenter costs with consideration of renewable power generation, dynamic electricity pricing, and energy storage devices. It shows that, along with reducing carbon footprints, renewable power penetration could also reduce datacenter costs, mainly due to the "peak shaving" effect on grid power resulting from using both renewable energy and energy storage. These research efforts consider either one to a few kinds of costs, or they confine themselves to one to a few types of energy sources and give no detailed analysis of the sources. In the next subsection, we describe a capacity planning framework that "universally" includes all dimensions for a datacenter as discussed in Section 2.

Table XI provides a summary of objective, formulation, solution, and evaluation methods for the works discussed in this subsection. Table XII shows a summary of different considered dimensions: electricity price, energy storage, carbon market, renewable integration, and workload types.

Table XI. Classification of Objective, Formulation, Solution, and Evaluation Method for Capacity Planning in Section 5

Research Work	Objective	Formulation	Solution	Evaluation
[Gmach et al. 2010b]	Match supply and demand	—	Analytical method	Trace-based simulations
[Gmach et al. 2010a]	Match supply and demand	—	Analytical method	Trace-based simulations
[Brown and Renau 2011]	Min Cost	—	Genetic algorithm	Trace-based simulations
[Ren et al. 2012]	Min Cost	Linear programming	—	Trace-based simulations

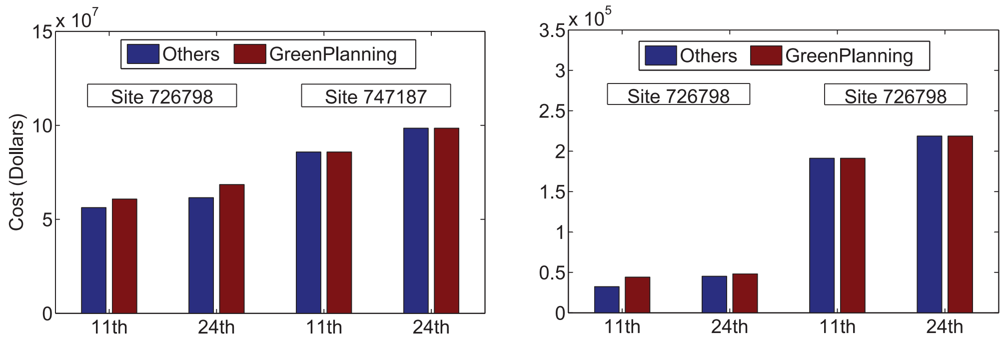
Table XII. Classification Based on Different Considered Dimensions for Capacity Planning in Section 5

Research Work	Electricity Price	Energy Storage	Carbon	Renewable	Workload
[Gmach et al. 2010b]	—	Battery	—	On-site	Interactive
[Gmach et al. 2010a]	—	Battery	—	On-site	General
[Brown and Renau 2011]	On-/off-peak & peak charge	Battery & net metering	—	On-site	Interactive
[Ren et al. 2012]	Real-time & peak charge	Battery & net metering	—	On- & off-site	General

5.3. Quantitative Analysis

To provide better insight into energy capacity planning, we provide quantitative comparisons between our solution proposed in Kong et al. [2014b] and the discussed works in this subsection. We briefly describe our solution (called *GreenPlanning*) as follows. In addition to all energy sources discussed Section 2, *GreenPlanning* also includes energy sources newly available to datacenters, such as fuel cells. The solution considers all kinds of costs of energy sources, including capital cost, O&M & cost, fuel cost, and emission cost. *GreenPlanning* focuses on the whole lifetime of a datacenter and thus includes annual price growth. Furthermore, it captures all datacenter design requirements and operations for the electrical grid during either normal operation or outages, such as limiting battery DoD to meet the datacenter availability requirement. Many dimensions (discussed in Section 2) affect capacity planning, and thus there are many kinds of comparisons for these different dimensions. In the following discussion, we use datacenter availability as an example dimension to conduct cost and emission comparisons. We provide the comparison between two kinds of approaches: (i) approaches considering datacenter availability in problem formulation, such as *GreenPlanning* in Kong et al. [2014b]; and (ii) approaches not considering datacenter availability, such as solutions discussed in this subsection. The experimental setting uses the example traces in Figures 2 and 4. The cost data for different energy sources are from publicly available reports [Wiser and Bolinger 2012; EPRI 2010]. We adopt on-/off-peak electricity pricing with an on-peak time of 9am–9pm and an off-peak time of 9pm–9am; price data are from Goiri et al. [2013] and Ren et al. [2012].

Figure 11 shows the lifetime total cost and emission comparison for *GreenPlanning* (with a 100% guarantee of datacenter availability) and *Others* (with no guarantee of datacenter availability). A 100% guarantee of datacenter availability means that when outages happen to the electrical grid, the power infrastructure guarantees that all services hosted in the datacenter experience no disruption. *GreenPlanning* has a higher lifetime total cost and emission than *Others* (e.g., site 726798) because to achieve higher datacenter availability levels, more reliable energy sources are needed, and these are



(a) Lifetime total cost.

(b) Lifetime total emission.

Fig. 11. Comparisons on lifetime total cost and emission.

less cost effective and emit more than renewable energy. However, this argument does not hold for site 747187; there, both cost and emission remain unchanged because the resulting capacity plan includes no renewable energy. Renewable energy at site 747187 is not sufficient, and thus the gain in operation cost by incorporating renewable energy is not enough to offset its capital cost. Hence, datacenter availability only affects the lifetime cost and emission of those datacenters that incorporate renewable energy. Although *Others* shows capacity plans with less cost and lower emissions, it cannot guarantee datacenter availability. Any service interruption would cause huge economic loss, such as the recent Amazon service shutdown [Tweney 2013].

6. INTERDISCIPLINE

Unlike the previous three sections, this section focuses on efforts that address non-computing aspects of greening datacenters. The focus particularly includes the manufacture and disposal of datacenters, the mobility of datacenters, and alternative fuel sources for datacenters.

6.1. Manufacture and Disposal of Datacenters

Hopper and Rice [2008] provide some challenges and visions on how to reduce carbon emissions during the entire lifecycle of datacenters. The datacenter lifecycle consists of three phases: manufacture, operation, and disposal. The authors also argue that datacenters should be located near renewable energy sources since it is cheaper to transmit data over large distances than to transmit power. Kurp [2008] gives some comments on the perspectives given in Hopper and Rice [2008]. Van Heddeghem et al. [2012] present a theoretical model for geo-distributed datacenters to calculate carbon emissions from the manufacturing phase, as well as to estimate renewable and brown energy consumption in the operation phase. The model is based on some simplified assumptions including uniform-sized datacenters, instant job/data migration, no energy storage for a surplus of renewable energy, and a 0-1 datacenter operation mode (if a datacenter is non-active, all servers are shut down; if active, all severs are turned on). Then, they provide two case studies based on the proposed model. Results show that carbon emissions are highly dependent on the manufacturing phase, geographical diversity, and the scale of datacenters. Chang et al. [2012] first present a new methodology to quantify the environmental impact of server production. The authors employ the thermodynamic metric of energy consumption to measure the impact of server components such as processors, memory, disks, and chassis. They then use this methodology to evaluate the total lifecycle impact of environment-friendly optimized system designs.

6.2. Containerized Datacenters

A containerized datacenter is a portable modular datacenter usually built into a standard shipping container that is then transported to a desired location [Pitchaikani 2011]. Such a datacenter contains tens to hundreds of servers and has a peak power of tens of thousands watts. Containerized datacenters were originally designed for the rapid deployment of high-computing datacenters at a lower cost than that of traditional construction methods. Their mobility may also be leveraged to better utilize renewable energy—a containerized datacenter can be moved anywhere the weather is sunny or windy. The key problem here is how to convert these renewable resources to usable power to supply a containerized datacenter. We provide two possible solutions. The first is to power such a datacenter using utilities like the renewable charging stations used for electric vehicles. A charging point can support up to tens of kilowatts, which can match the power demand of a containerized datacenter. A containerized datacenter can be moved among different stations according to their amounts of renewable power generation. The second solution is to equip containerized datacenters with renewable power generators, such as PV solar panels, to self-generate power. Such datacenters then can chase the sun or avoid cloud cover to get more power generation. In this case, these datacenters move frequently and may have to lease wireless networks for data communication. Another problem that emerges when exploring the mobility of a containerized datacenter is how to achieve a net gain between transportation and renewable utilization. Transportation among different locations also consumes energy and causes emission. Hence, to obtain a net gain, the renewable utilization increase should offset the energy use and emission of transportation.

6.3. Alternative Fuel Sources

In addition to wind and solar power, datacenter operators such as Google and Apple have been exploring other renewable energy sources such as fuel cells, wave power, tidal power, and geothermal power. Apple has built an on-site 10MW fuel cell for its datacenter in Maiden, North Carolina, which is the largest nonutility fuel cell installation operating in the United States [Apple 2014]. A fuel cell is a device that directly converts the chemical energy stored in fuel (hydrogen, typically derived from biogas or natural gas) and an oxidant (air or oxygen) into electricity. A fuel cell operates like a battery, but it does not run down or need recharging. It will continuously generate electricity as long as a source of fuel and an oxidant are supplied. Because the fuel is not combusted, but instead reacts electrochemically, a virtual reduction of carbon emissions is associated with the use of fuel cells. A fuel cell is especially free of emissions when it uses biogas as fuel. Biogas is renewable: It is the product of the natural biological breakdown of crop and animal waste with little oxygen supply, or it is derived from sewage plants and landfills under controlled conditions. In addition, Google has proposed a system of wave-powered floating datacenters, an idea that was granted a patent in 2009 [Johnston 2013]. The system consists of a floating datacenter, a wave-based power generator, and a seawater cooling unit. Wave power is the conversion of the energy created by ocean surface waves into electricity. Wave power is renewable because waves are generated by wind passing over the sea surface. Moreover, Scotland has announced a tidal power project for datacenters on the northwest coast [Miller 2009]. Tidal power is the conversion of the energy of tides into electricity. Tidal power is more predictable than wind and solar power because tides exhibit periodic variations. Furthermore, geothermal power is becoming another power source for datacenters [Mygreenhosting 2011]. Geothermal power is the conversion of thermal energy stored in the Earth into electricity.

7. ESSENTIAL OPEN ISSUES

In this section, we provide two essential open issues shared by the entire green-energy-aware power management problem.

7.1. On-site vs. Off-site

As discussed earlier, there are usually two ways to deliver renewable energy to datacenters: on-site and off-site. On-site means that renewable power generators are constructed locally, and the power is delivered to datacenters directly. Off-site means that the renewable power is part of the mix delivered by grid power, and it is delivered to datacenters by the electrical grid. The essential question here is to determine which one is better in making datacenters green, and the question concerns all datacenter operators. The works discussed so far provide different power management methods for each of the two scenarios, but they give no analysis. Several factors impact decision making. First, one vision of the smart grid is deep renewable energy penetration into the electrical grid, and there are a number of ongoing efforts toward realizing this vision [Bitar et al. 2011; Kong et al. 2014a]. However, this is a long way to go, and for now, most grid power still comes from carbon-intensive fuel sources, such as natural gas and coal. Hence, on-site renewable energy can be seen as a shortcut to green datacenters. Second, a key factor is whether renewable resources in a region are abundant or not [Ren et al. 2012; Kong et al. 2014b]. For regions with plentiful resources, such as where the wind or sun is consistently strong, the levelized energy cost of on-site renewable is lower than the off-site renewable price. Levelized energy cost is an economic assessment of the cost of a power plant, which includes all the costs over its lifetime: capital cost, O&M, and fuel cost. By contrast, for a site with insufficient renewable resources, off-site renewable energy would be a better choice because renewable power could be transmitted from sufficient regions to insufficient regions by the electrical grid. Third, the "smart grid" is expected to allow for many distributed feed-in points and to support bidirectional power flows. With on-site renewable energy, datacenter operators can then behave as power suppliers and supply surplus generated power to other consumers. This action may bring considerable revenue to them through a net metering policy. Therefore, we should take all these factors into consideration to determine whether on-site or off-site is suitable for a specific datacenter.

7.2. Temporality. vs Spatiality

As discussed in Section 2, datacenter workloads show both temporal and spatial flexibilities, and parameters exhibit both temporal and spatial diversities. The ideal solution should jointly explore these spatiotemporal flexibilities and diversities. However, the discussed works in Section 3 and 5 explore them separately. For example, works in Section 3.1 schedule workload to the most favorable time, and the degree of slack time for workloads largely decides the results; by contrast, works in Section 3.2 route requests to the most favorable locations, and the degree of access latency for routing has a large effect on the results. The two flexibilities can compensate each other to some extent. If routing a job to a distant datacenter causes a great increase on the access latency, it may be better to service the job at a local datacenter where the job can be delayed for some time, and vice versa. Moreover, the two diversities expand the optimization space. For example, a solution needs to choose whether to discharge the local batteries to process workloads or to route workloads to other datacenters. Therefore, combining the two flexibilities/diversities must yield much more preferable results such as lower costs, reduced emissions, and/or higher renewable energy utilization.

8. CONCLUSION

This article investigates research works that address green-energy-aware power management for datacenters, and those works explicitly consider renewable energy and/or carbon emissions. To present a full view of the problem, we first introduce some basic knowledge about datacenter components, power infrastructure, energy sources, the electrical grid, and the carbon market. We then discuss the research works and point out several key open issues. Research on datacenter power management is still in its infancy. We hope that this survey will help researchers and engineers from both academia and industry to better understand the state of the art and contribute more to this area.

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