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Energy Management of Internet Data Centers in Smart Grid

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Preface

With the proliferation of cloud computing and Internet online services, more and more data and computation are migrated to geographical distributed Internet data centers (IDCs), which can provide reliability, management, and cost benefits. However, IDC operators encounter several major problems in IDC operations, such as huge energy consumption and energy cost, and high carbon emission. To deal with the above problems, IDC operators have to efficiently manage the way of energy consumption and energy supply. Considering the potential of smart grid, we focus on the energy management of IDCs in smart grid from several perspectives, i.e., power outage, carbon emission, heterogeneous service delay guarantees, and operation risk.

With the introduction of smart grid, some cyber-related vulnerabilities may also be created and may ultimately lead to power outages when cyber attacks are launched. When power outages occur in main grids, the energy cost of IDC operators increases. If power outages caused by cyber attacks occur frequently, the increased energy cost of IDC operators become very large. Therefore, it is necessary to consider power outages when running the IDCs in smart grid. In this book, we study the problem of minimizing the long-term energy cost of distributed IDCs in smart grid considering power outages. Moreover, we propose an operation algorithm to achieve the above aim based on Lyapunov optimization technique by jointly considering the use of renewable and backup generators, battery management, and electricity purchasing/selling. Note that the proposed algorithm can operate without requiring any statistical information about system dynamics.

Some socially responsible IDC operators (e.g., Google) expect to reduce energy cost and carbon emission simultaneously. In this book, we consider the problem of minimizing the long-term weighted summation of energy cost and carbon emission with guaranteed quality of service for incoming requests in smart grid by deciding the service request distribution, number of active servers, operations of energy storage, schedule of backup generators, and quantity of power transactions between microgrids and main grids. Moreover, we propose an operation algorithm and analyze the feasibility of the proposed algorithm as well as its performance guarantee.

Providing homogeneous service delay (or average delay) guarantees may lead to violations of service level agreements for delay-tolerant requests. Moreover, IDC operators could reduce energy cost by fully exploiting the temporal diversity of electricity price when heterogeneous service delay guarantees are provided. Thus, it is necessary for IDC operators to provide heterogeneous service delay guarantees for delay-tolerant requests. In this book, we investigate the problem of minimizing the energy cost for an IDC in deregulated electricity markets considering heterogeneous service delay guarantees for delay-tolerant requests. Moreover, energy storage devices are adopted to fully exploit the temporal diversity of electricity price. In addition, we design an operation algorithm to schedule workload and battery jointly.

When IDC operators only procure electricity from spot electricity markets to supply IDCs, the spatial and temporal diversities of prices could be fully utilized to reduce energy cost. Meanwhile, spot price and workload uncertainties will result in the uncertain energy cost in the future, which is a risk for IDC operators as they may experience high probability of having high energy cost. To manage such risk, we study the problem of risk-constrained operation for IDCs in deregulated electricity markets. Moreover, we propose an operation algorithm to achieve the optimal tradeoff between operation risk and expected energy cost according to the risk preferences of IDC operators.

All comments and suggestions for improvements to this book are welcome.

Tao Jiang
Liang Yu
Yang Cao

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Contents

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Chapter 1
Introduction

Abstract This chapter introduces the background knowledge on smart grid and Internet data centers. Specifically, the definitions, characteristics, components of smart grid, and the architecture of Internet data centers are elaborated. Since the operations of Internet data centers lead to large power consumption, high energy cost, and carbon emission, Internet data center operators need to manage the way of consuming and procuring energy efficiently. Then, we discuss the energy management of Internet data centers in smart grid and some challenges in energy management. Next, we review the existing works on energy management of Internet data centers and point out the drawbacks within them. Finally, we give the contents and organizations of this book.

Keywords Smart grid · Internet data centers · Energy management

1.1 Smart Grid

A smart grid, also called smart electrical/power grid, or intelligent grid, is regarded as the next generation power grid. In the traditional power grids, power is generally carried from a few central generators to a large number of users or customers as shown in Fig. 1.1. In contrast, smart grid uses two-way flows of electricity and information to create an automated and distributed advanced energy delivery network that is clean, safe, secure, reliable, resilient, efficient, and sustainable [1].

When mentioning the definition of smart grid, different organizations and researchers have given different answers, for example "The smart grid has come to describe a next-generation electrical power system that is typified by the increased use of communications and information technology in the generation, delivery, and consumption of electrical energy[1]" (from IEEE); "The smart grid will be characterized by a two-way flow of electricity and information and will be capable of monitoring everything from power plants to customer preferences to individual appliances. It incorporates into the grid the benefits of distributed computing and communications to deliver real-time information and enable the near-instantaneous balance of supply

[1] http://smartgrid.ieee.org/ieee-smart-grid, Sept. 2013.

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Fig. 1.1 An example of the traditional power grid

and demand at the device level[2]" (from Department of Energy in USA). Note that the above definitions share the same idea that the smart grid needs to be integrated with information and communication infrastructures in order to be "smart." According to a report from NETL (National Energy Technology Laboratory [2]) in USA, the smart grid has several unique characteristics listed as follows when compared with the traditional grid.

- **It will enable the active demand-side participation**: Specifically, the smart grid can give electricity consumers information, control, and options that allow them to engage in new electricity markets.
- **It will accommodate all generation and storage options**: Specifically, the smart grid can seamlessly integrate all types and sizes of electrical generation and storage systems using simplified interconnection processes and universal interoperability standards to support a "plug-and-play" level of convenience.
- **It will enable new products, services, and markets**: Specifically, the smart grid can support the creation of new electricity markets ranging from the home energy management system at the consumers' premises to the technologies that allow consumers and third parties to bid their energy resources into the electricity market.
- **It will assure optimal power quality for all electricity consumers who require it**: Specifically, the smart grid can monitor, diagnose, and respond to power quality deficiencies, leading to a dramatic reduction in the business losses currently experienced by consumers due to insufficient power quality.
- **It will optimize asset utilization and operate efficiently**: Specifically, the smart grid can improve load factors, lower system losses, and dramatically improve outage management performance.
- **It will anticipate and respond to system disturbances**: Specifically, the smart grid can monitor all critical components of the power system to enable automated maintenance and outage prevention.
- **It will operate resiliently against attack and natural disaster**: Specifically, the smart grid can incorporate a system-wide solution that reduces physical and cyber attacks and enables a rapid recovery from disruptions.

In order to realize the above characteristics, NIST (National Institute of Standards and Technology [3]) proposed a conceptual model of smart grid as in Fig. 1.2 from the

[2] http://energy.gov/oe/downloads/smart-grid-introduction-0, Sept. 2013.

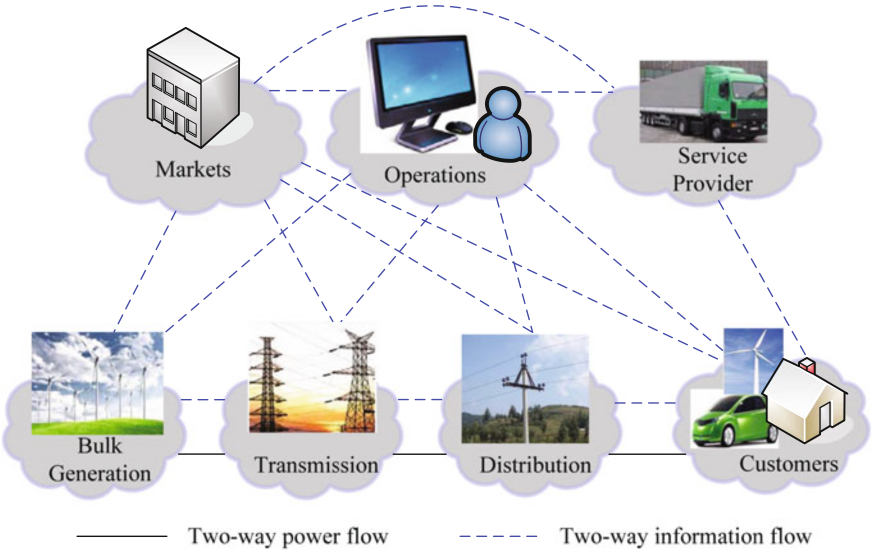

Fig. 1.2 The conceptual model of smart grid

perspective of functionality, which consists of seven domains, i.e., bulk generation, transmission, distribution, customers, service provider, operations, and markets. In the following part, we will describe the function of each domain.

- **Bulk generation**: This domain generates electricity in bulk quantities by using resources like oil, coal, nuclear fission, flowing water, sunlight, wind, and tide. Moreover, it may also store electricity to manage the variability of renewable resources such that the surplus electricity generated at times of resource richness can be stored up for redistribution at times of resource scarcity.
- **Transmission**: This domain transmits electricity to the distribution domain via multiple substations and transmission lines. Moreover, it may also support small-scale energy generation and storage.
- **Distribution**: The distribution domain takes the responsibility of delivering electricity to energy consumers according to the user demands and the energy availability. This domain may also store and generate electricity.
- **Operations**: This domain maintains efficient and optimal operations of the transmission and distribution domains using an energy management system in the transmission domain and a distribution management system in the distribution domain.
- **Markets**: The market domain maintains the balance between the supply and the demand of electricity. Moreover, this domain consists of retailers who supply electricity to end users, suppliers of bulk electricity, traders who buy electricity from suppliers and sell it to retailers, and aggregators who combine smaller distributed generation resources for sale.
- **Customers**: The customer domain consumes, generates, or stores electricity.

- **Service provider**: The service provider domain provides services to electrical customers and utilities, e.g., billing and customer account management for utility companies.

Based on the above descriptions, we know that distributed generation and energy storage widely exist in several domains (e.g., transmission domain, distribution domain, customers domain), which promotes the development of microgrids. Specifically, a microgrid is a localized grouping of electricity generations, energy storages, and loads. In the normal operation, it is connected to a power grid (i.e., macrogrid or main grid). When disturbances and blackouts occur in the macrogrid, the microgrid would operate in the islanding mode. Thus, microgrid can provide highly reliable electricity supply. In addition, microgrid can help to integrate renewable energy sources, improve energy efficiency and power quality, and stabilize price.[3]

1.2 Internet Data Centers

A data center is a facility used to house an enterprise's IT equipment (such as servers, telecommunication, and storage systems) and supporting infrastructures (such as power delivery and cooling systems). Data centers range widely in size, from closet-sized rooms to warehouse-sized custom buildings. An Internet data center (IDC) is a large-scale data center, which consists of thousands of servers. Typical IDC operators are Google, Microsoft, Yahoo, eBay, or Amazon. With the proliferation of cloud computing and Internet online services, more and more data and computation are migrated to or hosted on Internet data centers (IDCs) [4], which can provide several services for enterprises (content service providers, application service providers), such as server hosting/renting, Internet access service and DNS service. IDC offers many benefits including data reliability, ease of management for end users, and low amortized cost of ownership. For example, distributed IDCs use geographical distribution and replication to improve data reliability. Also, IDC operators can use economies of scale and statistical multiplexing to amortize the total cost of ownership over a large number of machines and users.

A typical architecture of multiple IDCs under smart grid environment is shown in Fig. 1.3, where several components could be identified, i.e., front-end servers and IDCs. The front-end server acts as a load balancer which receives incoming requests from the Internet and dispatches workload to IDCs located in different electric regions for processing according to a designed load balancing rule. The front-end server is also responsible for sending dynamic cluster server configurations and CPU frequency scaling commands to back-end servers in different IDCs to wake up or shut down servers and adjust the servers' current CPU operating frequencies and voltages. To maintain the normal operation, IDCs have to draw enough power

[3] http://www.smartgridnews.com, Sept. 2013.

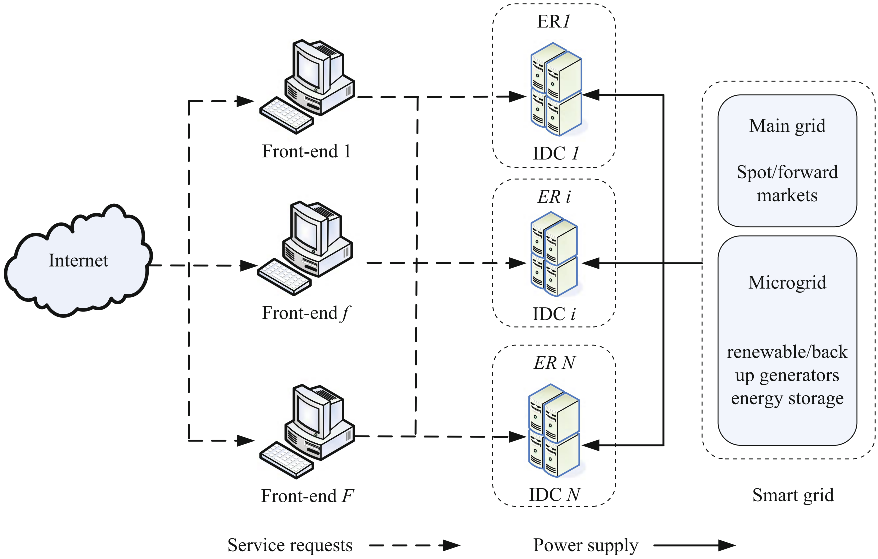

Fig. 1.3 A typical architecture of multiple IDCs

from the smart grid. Specifically, IDC operators can buy electricity in forward/spot markets in main grid and also buy electricity from the microgrids (energy sources could be backup generators/renewable generators, or energy storage). According to a recent study, many IDC operators (e.g., Microsoft and Google) spend more than $30 million on their annual electricity costs, which contribute to a large portion of IDC operational expenditure [5]. Meanwhile, the electricity cost is increasing rapidly [6]. In addition, the environmental impacts of IDCs is severe, for example carbon emission of data centers was 0.6 % of the global carbon emissions in 2008 and the proportion is expected to reach 2.6 % by 2020 [6]. For socially responsible IDC operators, they are expected to mitigate the above problems simultaneously [5]. In order to minimize the energy cost or/and carbon emission of IDCs, lots of optimal load balancing schemes have been designed in existing works, which will be explained later.

1.3 Energy Management of Internet Data Centers in Smart Grid and Challenges

To reduce energy cost/consumption and/or carbon emission, IDC operators should take effective measures to manage the way of consuming energy and procuring energy. Specifically, IDC operators should decide the optimal load balancing scheme, the number of active servers, the quantity of power obtained from the main grid, the quantity of power drawn from distributed generation and distributed energy storage so as to minimize energy consumption/cost or carbon emission while providing the QoS for incoming service requests.

On the other hand, electrical power system is evolving toward smart grid, which has come to describe a next-generation electrical power system that is typified by the increased use of communications and information technology in the generation, delivery, and consumption of electrical energy [7]. Due to its efficiency and potential, lots of works have been done to run distributed IDCs in smart grid environment [8–11], and the benefits are manifold: (1) smart grid technologies (e.g., distributed generation and distributed electricity storage) can provide energy efficiency savings in IDCs [12]; (2) by accessing smart grid's real-time states (e.g., power price, power demand, power availability, carbon emission), the spatial and temporal variations of electricity price and renewable energy could be exploited to reduce energy cost [13]; and (3) IDC can make profits by participating in demand response programs to provide services for smart grid [13].

Considering the advantages of smart grid, this book studies the energy management of IDCs in smart grid. The significance of this study for different entities can be described as follows:

- **IDC Operators**: reducing energy consumption/cost by managing energy efficiently.
- **Smart Grid**: improving the reliability of smart grid when IDCs are involved in demand response.
- **Sociality**: reducing carbon emission. Take USA for example, reducing electricity 1 KWh would lead to the reduction of 0.5 Kg carbon emission. Thus, if all data centers in USA can save 0.1 billion KWh electricity, the emission of 0.5 million tons CO_2 can be avoided, which will contribute to solving environmental problems such as global warming.
- **Nation**: "Green" extent can affect the image of a nation in international society. Thus, reducing carbon emission can help a nation to improve international impression and status, e.g., increasing the possibility of applying for the Olympic Games.

When managing the way of energy consumption and energy procurement, IDC operators have to face several challenges, which can be classified as follows. The first challenge comes from uncertainty. Specifically, the future electricity price, workload, renewable energy output, carbon emission, and power grid state (normal or blackout) are volatile and cannot be accurately predicted. When some long-term performance objectives are considered, IDC operators have to make decisions under uncertainty. The second challenge lies in the conflict of performance objectives, such as energy cost versus carbon emission, energy cost versus operation risk, and energy cost versus bandwidth cost. How to achieve the optimal tradeoff among them according to the preferences of IDC operators remains a open and challenging problem. The third challenge is how to provide QoS guarantees for incoming requests when minimizing energy cost, since degraded QoS may disappoint clients and lead to high churn rate as well as business loss.

1.4 Related Works

In this section, we review the existing works and point out some essential aspects that have not been well investigated yet.

1.4.1 Existing Works

We can divide the existing works into three categories, namely cost-aware energy management, carbon-aware energy management and smart grid impact-aware energy management.

1.4.1.1 Cost-Aware Energy Management

By decreasing power consumption and utilizing the price diversity, IDC operators can reduce energy cost. Specifically, lots of technologies have been proposed to decrease power consumption, such as energy-efficient chips, dynamic speed scaling, dynamic server provisioning, and efficient job scheduling. In deregulated electricity markets, spot prices exhibit both temporal and spatial variations [5], which can be exploited to reduce energy cost for IDCs. In [14], Rao et al. proposed a geographical load balancing scheme to minimize energy cost by utilizing the spatial diversity of electricity price. Shao et al. [15] proposed a geographical load balancing scheme considering transmission delay. Li et al. [16] investigated the problem of minimizing energy cost considering bandwidth cost. In [17], the authors developed an online algorithm to minimize energy cost with batteries, which can utilize the temporal diversity of electricity price. In [18], Yao et al. studied the problem of minimizing energy cost for IDCs considering delay-tolerant workloads. In [19], a scheme was proposed to minimize the energy cost of IDCs considering delay-tolerant and delay-sensitive workloads, which can utilize the spatial and temporal diversities of electricity price. Li et al. [20] proposed an integrated model considering the impacts of electricity prices and power management capability of IDCs. Guo et al. [21] presented a method to minimize the energy cost of sustainable IDCs considering thermal storage and delay-tolerant workloads. In [22], Luo et al. proposed a temporal load balancing scheme to minimize the energy cost of an IDC, which can utilize the temporal diversity of electricity price.

1.4.1.2 Carbon-Aware Energy Management

In addition to energy cost, socially responsible IDC operators also care about the environmental impact of their IDCs [5]. Liu et al. [23] proposed a green geographical load balancing scheme, which considers energy cost and the lost revenue due to the delay violation. Zhang et al. [24] proposed a strategy to maximize the use of renewable energy given the energy cost budget. Gao et al. [6] proposed a request-routing framework that provides a three-way tradeoff between access latency, electricity cost, and carbon footprint. In [25], Gao et al. analyzed the feasibility of achieving "entirely green" cloud-scale services for a distributed IDC system by exploiting multiple uncorrelated wind energy sources. In [26], Ghamkhari et al. studied the problem of minimizing the weighted sum of energy cost and service delay for renewable distributed IDCs. Deng et al. [27] designed a control algorithm to minimize energy cost for an IDC considering some complementary renewable energy sources. Zhou et al. [28] proposed a carbon-aware load balancing scheme to minimize energy cost of IDCs given the carbon budget.

1.4.1.3 Smart Grid Impact-Aware Energy Management

IDCs are large power consumers and their power consumption can be adjusted flexibly, thus, IDCs are very suitable to participate in demand response programs. Compared with the centralized large power consumers, IDC can provide ancillary services to smart grid without sacrificing the user experiences. In [29], Mohsenian-Rad et al. pointed out that IDC can contribute to improve the reliability of smart grid. In [30], Ghamkhari et al. proposed a demand response method for IDCs to make profits. In [31], Chen et al. proposed a demand response method based on virtual machine migration.

1.4.2 Observations

In existing works, some essential aspects have not been well investigated, which are listed below.

1. **Power Outages:** With the introduction of smart grid, some cyber-related vulnerabilities may also be created if no appropriate security control is deployed [32]. Therefore, when cyber attacks are launched, power grid may become unstable due to the cyber-power interdependencies in smart grid [33], which may ultimately lead to power outages. At this time, backup generators would startup. Since the duration caused by power outages is usually several hours and the generation costs of backup generators are far larger than average electricity prices in power grid, higher energy cost would be introduced. When power outages caused by cyber attacks occur frequently, the increased energy cost of IDC operators would be very large. Therefore, it is necessary to consider power outages when running the distributed IDCs in smart grid environment.
2. **Carbon Emission:** Socially responsible IDC operators are expected to reduce energy cost and carbon emission simultaneously. Currently, many IDC operators consider renewable energy sources in IDC operations. However, the output of renewable energy sources is random. In existing works, some schemes have been proposed to maximize the usage of renewable energy. However, when power

supply is larger than power demand, surplus renewable energy is wasted. In fact, the excess energy could be sold back to main grid to save energy cost.

3. **Heterogeneous Service Delay Guarantees:** When minimizing energy cost, IDC operators should guarantee service level agreements (SLAs) for all requests since SLA violation would result in the loss of business revenue. The SLA requirements of different requests are different, for example average delay (or 95th percentile delay) is usually adopted as the SLA metric for delay-sensitive requests (e.g., web search requests), while service delay deadline (or completion time) is used as the SLA metric for delay-tolerant requests (e.g., batch jobs). In most existing work on delay-tolerant requests, average delay (or the same worst-case delay, or the same service delay guarantee) is considered in IDC operations, which may lead to SLA violations for delay-tolerant requests. Moreover, IDC operators could reduce energy cost by fully exploiting the temporal diversity of electricity price when heterogeneous service delay guarantees are provided. Thus, it is necessary for IDC operators to provide heterogeneous service delay guarantees for delay-tolerant requests.
4. **Operation Risk:** In smart grid, IDC operators can reduce the energy cost by utilizing the spatial and temporal diversities of spot prices. When IDC operators only buy electricity from spot markets to supply IDCs, the spatial and temporal diversities of prices could be fully utilized to reduce energy cost. Meanwhile, prices in spot markets and workloads are volatile, price and workload forecasting tend to be less accurate with the increase of planning horizon (e.g., from day to month or year). Consequently, the future energy cost of IDCs is uncertain (or random), which is a risk for IDC operators since they may experience high probability of having high energy cost in the future. To manage the risk mentioned above, the risk metric should be proposed. In existing work, the variance is adopted as the operation risk metric. Minimizing the risk metric can help IDC operators to reduce the downside and upside deviations from expected cost. However, downside deviations from expected cost are desirable. Thus, variance is not very suitable for measuring the risk in IDC operations.

The above aspects are related to the opportunities and challenges faced by IDC operators in smart grid. On one hand, IDC operators can reduce energy cost and carbon emission in smart grid. On the other hand, IDC operators have to face the challenges brought by smart grid environment, such as operation risk and power outages.

1.5 Contents and Organizations

Taking the above observations into consideration, we study the energy management of Internet data centers in smart grid from four perspectives. Specifically, we investigate the problem of minimizing energy cost for distributed IDCs in smart grid considering power outages and carbon emission in Chaps. 2 and 3, respectively. In Chap. 4, we investigate the problem of minimizing the long-term energy cost for an

IDC in deregulated electricity markets while providing heterogeneous service delay guarantees for delay-tolerant workloads. In Chap. 5, we study the problem of managing the risk in IDC operations in deregulated electricity markets. Finally, further research directions are discussed in Chap. 6.

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Chapter 2
Energy Cost Minimization for Internet Data Centers Considering Power Outages

Abstract With the adoption of smart grid, some cyber-related vulnerabilities may also be introduced. When cyber attacks are launched, the power grid may become unstable and ultimately power outages may occur. In this situation, backup generators would be scheduled to support the operation of Internet data centers. Since the generation cost of backup generators are far higher than the average price of electricity in main grids, higher energy cost for Internet data center operators would be incurred. When power outages caused by cyber attacks occur frequently, the increased energy cost of Internet data center operators would be very large. Thus, it is necessary to consider the operation of Internet data centers in power outage environment. Since Internet data center operators can reduce energy cost by fully utilizing the spatial and temporal diversities of renewable energy in smart microgrids when there are power outages, we consider a scenario that running Internet data centers in smart microgrids and propose an efficient algorithm to minimize the long-term energy cost.

Keywords Smart microgrid · Internet data centers · Energy cost · Energy storage · Power outages

2.1 Introduction

The past decade has witnessed tremendous growth of online applications and services. Together with the recent trend of cloud computing, massive Internet data centers (IDCs) are deployed for reliability, management, and cost benefits. For IDC operations, a critical issue is the energy consumption. According to a recent study, many IDC operators (e.g., Microsoft and Google) spend more than $30 million on their annual electricity costs, which contribute to a large portion of IDC operational expenditure [1, 2].

On the other hand, electrical power system is evolving toward smart grid, which has come to describe a next-generation electrical power system that is typified by the increased use of communications and information technology in the generation, delivery, and consumption of electrical energy [3]. Due to its efficiency and potential, lots of research has been done to run distributed IDCs in smart grid environment [4–6], and the benefits are manifold: (1) smart grid technologies (e.g., distributed

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generation and distributed electricity storage) can provide energy efficiency savings in IDCs [7]; (2) by accessing smart grid's real-time states (e.g., power price, power demand, power availability), the spatial and temporal variations of electricity price and renewable energy could be exploited to reduce energy cost [8].

With the introduction of smart grid, some cyber-related vulnerabilities may also be created if no appropriate security control is deployed [9]. Therefore, when cyber attacks are launched, power grid may become unstable due to the cyber-power interdependencies in smart grid [10], which may ultimately lead to power outages [11–13]. When power outages occur in main grids to which distributed IDCs are connected, the energy cost of distributed IDCs would increase. The reason is that: (1) fewer spatial and temporal diversities of electricity price could be utilized; (2) backup generators (typically, diesel generators are adopted) in IDCs have to run for a long time (usually several hours [12]) when local renewable energy is in shortage or uninterruptible power system (UPS) capacity is limited. Since the generation cost of backup generators is far higher than the average real-time electricity prices [14–16], higher energy cost would be incurred. When power outages caused by cyber attacks occur frequently, the increased energy cost of IDC operators would be very large. Therefore, it is necessary to consider power outages when running the distributed IDCs in smart grid environment.

To reduce energy cost caused by power outages, it is possible to operate distributed IDCs in smart microgrids (SMGs, which are evolved from microgrids in smart grid environment [17]). The reason is that IDC operators can still exploit the spatial and temporal diversities of renewable energy to reduce energy cost, even if there are power outages in main grids. Specifically, by scheduling workload to the SMGs with abundant renewable energy, the dependence on backup generators in the SMGs with inadequate renewable energy could be reduced, resulting in lower energy cost (i.e., spatial diversity is utilized). On the other hand, energy storage devices can be scheduled to store excess renewable energy and to discharge energy when IDC demands are high, leading to reduced reliance on backup generators and lower energy cost (i.e., temporal diversity is utilized).

As motivated, we study the problem of minimizing the energy cost of distributed IDCs in SMGs considering power outages. Specifically, we consider an IDC operator having some IDCs geographically distributed in several of its own SMGs, which are located in independent electric regions (ERs). Moreover, the IDC operator needs to meet the power demand of IDCs using backup generators, renewable energy sources, and energy storage devices in SMGs and the power purchased from main grids in case of no power outages. The objective of the IDC operator is to minimize the long-term energy cost by deciding the service request distribution, the number of active servers, the operation of energy storage devices, the schedule of backup and renewable generators, as well as the power transactions between SMGs and main grids.

To achieve the above target, the challenge is how to effectively manage the operation of energy storage devices in SMGs [18–20]. Since energy storage devices can bring the time coupling effects to the system, the formulated optimization problem is very difficult to solve. In existing work on data centers [21, 22], several schemes have been developed for exploiting energy storage devices based on Lyapunov optimization technique [23], which can operate without any statistical information about future uncertain parameters. However, the existing works do not consider running IDCs in SMGs and power outage environment. Thus, new design and analysis are required for an operation algorithm.

The main contributions of this chapter are summarized below:

- By taking SMGs and power outage into account, we formulate a stochastic program problem to minimize the long-term energy cost of distributed IDCs, which captures the service request distribution, server provisioning, battery management, generator scheduling, power transactions between SMGs and main grids.
- We design an operation algorithm to solve the problem based on Lyapunov optimization technique by jointly considering the use of renewable and backup generators, battery management, and electricity purchasing/selling. Moreover, the proposed algorithm can operate without requiring any statistical information about system dynamics.
- We provide the performance guarantee of the proposed algorithm when future random parameters are independent and identically distributed (i.i.d.) over slots. Theoretical analysis shows that the proposed algorithm enables an explicit tradeoff between energy cost saving and battery investment cost.
- Extensive evaluations based on real-world data show the effectiveness of the proposed operation algorithm.

The rest of this chapter is organized as follows. Section 2.2 describes the system model. Problem formulation and algorithm design are conducted in Sect. 2.3. Section 2.4 gives the algorithmic performance analysis and simulations. Finally, conclusions are made in Sect. 2.5.

2.2 System Model

We consider an IDC operator with some SMGs located in some independent ERs as shown in Fig. 2.1, where these SMGs are connected to main grids in corresponding ERs. IDCs act as the load in SMGs, while a front-end server acts as a load balancer that receives incoming service requests and dispatches them to IDCs for processing. The architecture of SMG under study is given in Fig. 2.2, where several parts could be highlighted, i.e., generators, loads, storage banks, and energy management system. Generators include backup generators (typically diesel generators) and renewable generators (e.g., solar panels or wind turbines). In this chapter, diesel generators and wind turbines are considered. Diesel generators are fast-responding and dispatchable, and they are typically incorporated in data centers for reliability considerations [2, 24]. By contrast, wind turbines are nondispatchable and their generation outputs depend on weather conditions. Loads in Fig. 2.2 denote IDCs, while storage bank denotes battery. SMGs have two operation modes, i.e., grid-connected and islanded. When there are power outages in main grids, SMGs can isolate themselves from main grids and supply their IDCs using energy storage devices, renewable energy

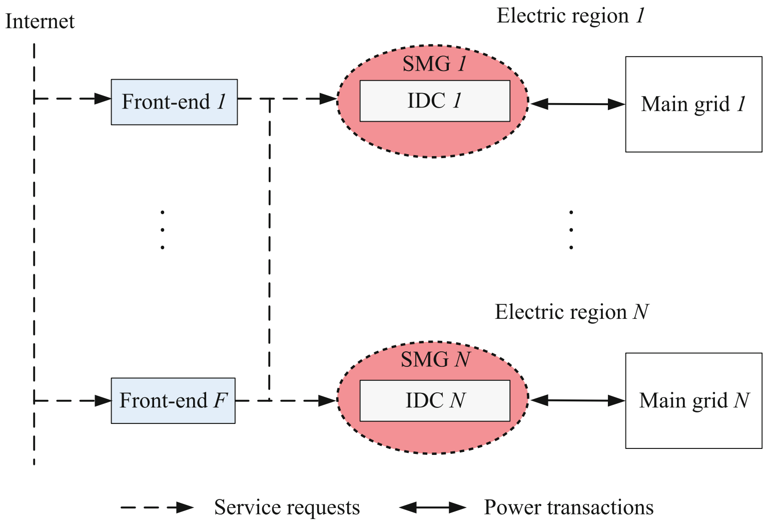

Fig. 2.1 System model

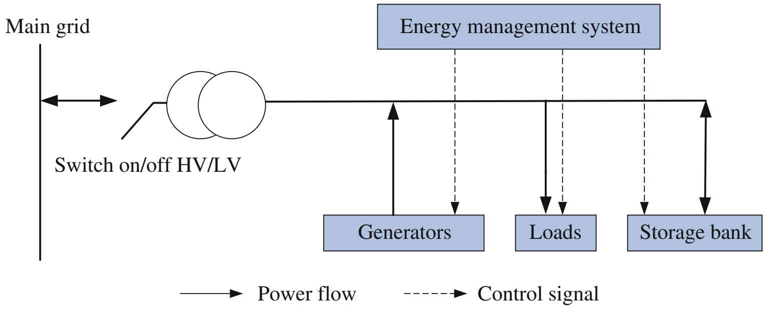

Fig. 2.2 SMG architecture under study

sources as well as backup generators. In the grid-connected mode, power transactions between SMGs and main grids can be conducted.

2.2.1 Models Related to Front-End Servers and Internet Data Centers

2.2.1.1 Workload Allocation Model

We consider an IDC operator having N IDCs geographically distributed in N independent ERs, and each IDC acts as the load in an SMG connected to a main grid, i.e., N SMGs and N main grids are considered. For simplicity, we use the common index i for IDCs, SMGs, and main grids, where $1 \le i \le N$. In this chapter, we mainly focus on delay-sensitive workloads (e.g., "request-response" type web services [5]). Suppose IDC i have M_i homogeneous servers and $m_i(t)$ of them are turned on to process service requests at slot t. Define $\mathbf{m}(t) = (m_1(t), \ldots, m_N(t))$ as the active server vector. Moreover, $m_i(t)$ is assumed to be unchanged at slot t due to the reliability considerations [25]. We denote the arrival rate of requests at front-end server f $(1 \le f \le F)$ as $R_f(t)$. Let $\mathbf{R}(t) = (R_1(t), \ldots, R_F(t))$ be the workload arrival vector, where F is the total number of front-end servers. Let $\lambda_{f,i}(t)$ be the workload that is assigned from front-end f to the servers at IDC i at slot t. $\boldsymbol{\lambda}(t) = (\lambda_{f,i}(t),\ \forall f, i)$ is denoted as the service request distribution. In order to assure that all service requests would be handled, we have

$$\sum_{i=1}^{N} \lambda_{f,i}(t) = R_f(t). \tag{2.1}$$

2.2.1.2 Service Delay Model

To satisfy the quality of service requirements, the average response delay for incoming service requests should be limited within a certain range that is specified in *service level agreement* (SLA).[1] Otherwise, penalties would be incurred. In this chapter, the M/M/n queueing model is adopted to process the incoming workload as in the previous work [4]. Note that the queueing model is not necessarily the most accurate for the practical workload, but it will not affect the nature of the energy cost minimization problem and the proposed operation algorithm. Adopting some general queuing models (e.g., G/G/n as in [26]) would be considered in future work. Let $D_i^{\max}$ be the threshold that identifies the revenue/penalty region at IDC i, μ_i be the average service rate of servers in IDC i. To avoid penalty, the average response delay constraints should be satisfied, i.e.,

$$\frac{1}{m_i(t)\mu_i - \sum_{f=1}^{F} \lambda_{f,i}(t)} + \frac{1}{\mu_i} \le D_i^{\max}, \tag{2.2}$$

$$0 \le m_i(t) \le M_i. \tag{2.3}$$

2.2.1.3 Power Consumption Model

The energy efficiency of an IDC is always measured by *power usage effectiveness* (PUE), which is defined as the ratio of the total power consumption at an IDC to the power consumption at IT equipment. Currently, the typical value of PUE is 2 [1]. Let PUE_i be the PUE of IDC i, P_i^{idle} and P_i^{peak} represent the idle power and peak power of a server in IDC i, respectively. Let $U_i(t)$ be the average server utilization at

[1] Here, a simple SLA is adopted as in [26]. Other more complicated SLAs could also be incorporated.

slot t, which is equal to $\lambda_i(t)/(m_i(t)\mu_i)$. Denote the total power consumption of IDC i at slot t as $P_i(t)$ and $\mathbf{P}(t) = (P_1(t), \ldots, P_N(t))$ as the power consumption vector. Following the models in [1], $P_i(t)$ can be estimated by

$$P_i(t) = m_i(t)(\varphi_i U_i(t) + \gamma_i), \tag{2.4}$$

where $\varphi_i \triangleq P_i^{\mathrm{peak}} - P_i^{\mathrm{idle}}$, $\gamma_i \triangleq P_i^{\mathrm{idle}} + (\mathrm{PUE}_i - 1)P_i^{\mathrm{peak}}$. Note that servers in each IDC are assumed to be homogeneous in the above model. For more general situations, the corresponding model can also be incorporated easily.

2.2.2 Models Related to Smart Microgrids

2.2.2.1 Power Supply Model

Suppose that each SMG has a wind farm comprising several identical wind turbines. Then, the total output of the wind farm is the summation of power outputs at different points of the spatial field. Let $G_i^{\mathrm{r}}(t)$ be the available wind energy in SMG i at slot t, which can be approximated by the model in [27]. Let $\mathbf{G}^{\mathrm{r}}(t) = (G_1^{\mathrm{r}}(t), \ldots, G_i^{\mathrm{r}}(t), \ldots, G_N^{\mathrm{r}}(t))$ be the vector of available wind energy at slot t.

As in [28, 29], the piecewise linear production cost model is adopted to model the energy cost of diesel generators in SMGs. Suppose piecewise linear production cost curve has N_B segments, each segment b ($1 \le b \le N_B$) introduces a binary variable $Z_{i,j,b}^{\mathrm{g}}(t)$ and a continuous variable $Q_{i,j,b}(t)$, where $1 \le j \le N_i^{\mathrm{d}}$, N_i^{d} denotes the total number of diesel generators in SMG i. If the energy produced by the diesel generator j in SMG i at slot t falls into the range $[g_{i,j,b}^{\min}, g_{i,j,b}^{\max}]$, $Z_{i,j,b}^{\mathrm{g}}(t) = 1$; Otherwise, $Z_{i,j,b}^{\mathrm{g}}(t) = 0$. $Q_{i,j,b}(t)$ denotes the specific energy quantity when the energy generation of the diesel generator j in SMG i at slot t fall into the range above. Then, we have

$$Z_{i,j,b}^{\mathrm{g}}(t) \in \{0, 1\}, \tag{2.5}$$

$$\sum_{b=1}^{N_B} Z_{i,j,b}^{\mathrm{g}}(t) \le 1, \tag{2.6}$$

$$g_{i,j,b}^{\min} Z_{i,j,b}^{\mathrm{g}}(t) \le Q_{i,j,b}(t) \le g_{i,j,b}^{\max} Z_{i,j,b}^{\mathrm{g}}(t), \tag{2.7}$$

where $g_{i,j,b}^{\min}$ and $g_{i,j,b}^{\max}$ are the lower and upper limit of energy generation of the diesel generator j in SMG i corresponding to the segment b of the piecewise linear production cost model, respectively.

Let $G_i^{\mathrm{a}}(t)$ be the total power produced by diesel generators in SMG i at slot t. Then, $G_i^{\mathrm{a}}(t)$ is given as

$$G_i^{\mathrm{a}}(t) = \sum_{j=1}^{N_i^{\mathrm{d}}} \sum_{b=1}^{N_B} Q_{i,j,b}(t)/\Delta T, \tag{2.8}$$

where ΔT is the duration of a slot. Let $H_{i,j,b}$ and $\alpha_{i,j,b}$ be the slope and Y-intercept of the segment b associated with the diesel generator j in SMG i. Then, the total energy cost of diesel generators in SMG i during time slot t is given by[2]

$$K_i(t) = \sum_{j=1}^{N_i^{\mathrm{d}}} \sum_{b=1}^{N_B} (H_{i,j,b} Q_{i,j,b}(t) + \alpha_{i,j,b} Z_{i,j,b}^{\mathrm{g}}(t)). \tag{2.9}$$

2.2.2.2 Battery Model

$G_i^{\mathrm{g2}}(t)$ and $G_i^{\mathrm{2g}}(t)$ represent the power purchased from and sold back to the main grid i at slot t, respectively. $G_i^{\mathrm{b2}}(t)$ and $G_i^{\mathrm{2b}}(t)$ are the discharging and charging power for the battery in SMG i at slot t. To balance the power supply and demand in SMG i, we have

$$G_i^{\mathrm{a}}(t) + G_i^{\mathrm{r}}(t) + G_i^{\mathrm{g2}}(t) + G_i^{\mathrm{b2}}(t) = P_i(t) + G_i^{\mathrm{2b}}(t) + G_i^{\mathrm{2g}}(t). \tag{2.10}$$

To indicate whether SMG i is buying or selling power or not at slot t, two binary variables are adopted, i.e., $Z_i^{\mathrm{g2}}(t)$ and $Z_i^{\mathrm{2g}}(t)$. Specifically, $Z_i^{\mathrm{g2}}(t) = 1$ if SMG i is purchasing power from main grid i at slot t; Otherwise, $Z_i^{\mathrm{g2}}(t) = 0$. Similarly, $Z_i^{\mathrm{g2}}(t) = 1$ if SMG i is selling power back to main grid i at slot t; Otherwise, $Z_i^{\mathrm{g2}}(t) = 0$. Since it is not reasonable to purchase and sell energy on the market at the same time, we have

$$Z_i^{\mathrm{g2}}(t), Z_i^{\mathrm{2g}}(t) \in \{0, 1\}, \tag{2.11}$$

$$Z_i^{\mathrm{g2}}(t) + Z_i^{\mathrm{2g}}(t) \le 1, \tag{2.12}$$

$$0 \le G_i^{\mathrm{g2}}(t) \le G_i^{\mathrm{bmax}} Z_i^{\mathrm{g2}}(t), \tag{2.13}$$

$$0 \le G_i^{\mathrm{2g}}(t) \le G_i^{\mathrm{smax}} Z_i^{\mathrm{2g}}(t), \tag{2.14}$$

where G_i^{bmax} and G_i^{smax} denote the maximum purchasing power from main grid i and maximum selling power to main grid i, respectively.

Let $E_i(t)$ be the energy level of the battery in SMG i at slot t. Then, $E_i(t)$ is bounded by the following constraints,

$$E_i^{\min} \le E_i(t) \le E_i^{\max}, \tag{2.15}$$

[2] For diesel generators, its minimum on/off periods could be regarded as zero and ramping-up/-down rate could be assumed to be ∞ [30]. Thus, some constraints about minimum on/off periods and ramping-up/-down rate are neglected. In addition, due to the lack of public knowledge about startup cost of diesel generators, we also neglect such cost.

where $E_i^{\max} \geq 0$ is the maximum capacity, and $E_i^{\min} \geq 0$ is the minimum capacity, which may be set by the battery deep discharge protection settings. As in [21], we do not explicitly consider some practical issues, such as energy leakage in the battery or DC/AC conversion loss, which can be readily incorporated. Then, $E_i(t)$ has the following dynamics at SMG i:

$$E_i(t+1) = E_i(t) + \Delta T(G_i^{2b}(t) - G_i^{b2}(t)). \tag{2.16}$$

To indicate whether the battery in SMG i is charging or not at slot t, two binary variables are introduced, i.e., $Z_i^{bc}(t)$ and $Z_i^{bd}(t)$. Specifically, $Z_i^{bc}(t) = 1$ if that battery is charging; Otherwise, $Z_i^{bc}(t) = 0$. Similarly, $Z_i^{bd}(t) = 1$ if that battery is discharging; Otherwise, $Z_i^{bd}(t) = 0$. Without loss of generality, we assume that charging and discharging cannot be done simultaneously [2]. Then, we have

$$Z_i^{bc}(t), Z_i^{bd}(t) \in \{0, 1\}, \tag{2.17}$$

$$Z_i^{bc}(t) + Z_i^{bd}(t) \leq 1, \tag{2.18}$$

$$0 \leq G_i^{2b}(t) \leq G_i^{cm} Z_i^{bc}(t), \tag{2.19}$$

$$0 \leq G_i^{b2}(t) \leq G_i^{dm} Z_i^{bd}(t), \tag{2.20}$$

where G_i^{cm} and G_i^{dm} are the maximum charging and discharging power for the battery in SMG i, respectively.

2.2.3 *Models Related to Main Grids*

2.2.3.1 Power Outage Model

Power outages could be planned or unplanned. Reasons for unplanned power outages are manifold, for example the faults of transformers and transmission lines caused by environmental or maintenance issues [31], the failures of protective relaying and SCADA caused by cyber attacks [11, 12]. In this chapter, we mainly consider the power outages caused by cyber attacks. Note that the naturally occurring outages could also be incorporated [13]. To analyze the impacts of cyber attacks, RICA approach had been proposed in [12], where power outages caused by cyber attacks are mainly measured by two parameters, i.e., the interval between successful attacks and the time needed to recover from outages, which can be modeled using an exponential-distributed random variable and selected mean time to attack (MTTA) and mean time to recover (MTTR). Let $Z_i^{p}(t)$ be an indicator variable that takes the value one whenever there is no power outage in main grid i at slot t, and takes the value zero otherwise. Let $\mathbf{Z}^{p}(t) = (Z_1^{p}(t), \ldots, Z_N^{p}(t))$ be the power outage vector. Since power transactions between SMG i and main grid i are not allowed when there is power outage, we have

$$0 \leq Z_i^{g2}(t) + Z_i^{2g}(t) \leq Z_i^{p}(t). \tag{2.21}$$

2.2.4 Energy Cost Model

Let $C(t)$ be the total energy cost of IDC operators at slot t. Then, $C(t)$ is composed of several parts, i.e., the energy cost (revenue) associated with buying (selling) electricity, the cost caused by the negative effect of the charging and discharging power [21], and the generation cost of diesel generators in SMGs. That is, $C(t)$ is given by

$$C(t) = \sum_{i=1}^{N} \{G_i^{\mathrm{g2}}(t) S_i(t) - G_i^{\mathrm{2g}}(t) W_i(t)\} \Delta T + \sum_{i=1}^{N} K_i(t) + \sum_{i=1}^{N} (Z_i^{\mathrm{bc}}(t) + Z_i^{\mathrm{bd}}(t)) \rho_i^b, \tag{2.22}$$

where ρ_i^b denotes the cost incurred by battery charging and discharging per time, which are assumed to be the same [2, 21]. $S_i(t)$ and $W_i(t)$ denote the price for purchasing and selling electricity from and to main grid i at slot t, respectively. Let $\mathbf{S}(t) = (S_1(t), \ldots, S_N(t))$ and $\mathbf{W}(t) = (W_1(t), \ldots, W_N(t))$ be the purchasing and selling price vector, respectively. We suppose that $S_i(t) \in [S_i^{\min}, S_i^{\max}]$, $W_i(t) \in [W_i^{\min}, W_i^{\max}]$, which are announced by the utility markets at the beginning of each slot and remains constant in the slot [32].

2.2.5 Some Discussions About Models

Battery Model: G_i^{bmax} and G_i^{smax} are determined by the capacity of transformers and power transmission lines [32]. For simplicity, we assume that the transmission loss is negligible and the capacity of transformers and power transmission lines is large enough [32], i.e., $G_i^{\mathrm{bmax}} \geq \max_t \{P_i(t) + G_i^{\mathrm{2b}}(t)\}$ and $G_i^{\mathrm{smax}} \geq \max_t \{G_i^{\mathrm{a}}(t) + G_i^{\mathrm{r}}(t) + G_i^{\mathrm{b2}}(t)\}$.

Power Outage Model: (1) In RICA approach [12], RICA attack model assumes certain characteristics about the adversary that may not adequately characterize the entire attacker spectrum. For more attacker types, RICA approach needs to be extended [13]; (2) For simplicity, power grid states (i.e., with/without power outages) are assumed to be constant during a slot, but they can change over slots. The assumption is reasonable since the duration of outages caused by cyber attacks is usually several hours [12], which is far larger than ΔT (e.g., 15 min or 1 h).

Energy Cost Model: (1) We ignore all fixed costs associated with wind generation (e.g., capital expenditure and fixed operational and maintenance cost) in the energy cost model since these parts would not affect the optimization results of the formulated problems P2.1–P2.4. Moreover, according to [33], the variable operational and maintenance cost of wind turbines is negligible. Therefore, the generation cost of wind energy can be assumed to be zero; (2) We assume $S_i(t)$ and $W_i(t)$ are independent of the amount of energy to be purchased or sold at slot t. In addition, we suppose $S_i(t) \geq W_i(t)$ for all t [32]. That is, SMG cannot make profit by greedily purchasing energy from the market and then selling it back to the market at a higher price simultaneously.

2.3 Problem Formulation and Algorithm Design

In this chapter, we are interested in minimizing the time-average expected energy cost (i.e., the expected energy cost averaged over the infinite time horizon). Compared with existing works on energy cost reduction for data centers [2, 21], we formulate the minimization problem (i.e., P2.1) by taking SMGs and power outage into account. Specifically, the formulated problem jointly consider the renewable and backup generators, battery management, electricity purchasing and selling, as well as power outage.

$$\text{(P2.1)} \quad \min \quad \limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{C(t)\}, \tag{2.23a}$$

$$\text{s.t. } (2.1)-(2.3),\ (2.5)-(2.7),\ (2.10)-(2.21), \tag{2.23b}$$

where the expectation above is with respect to the stationary distribution of $\{\mathbf{S}(t)$, $\mathbf{W}(t)$, $\mathbf{R}(t)$, $\mathbf{G}^{\mathrm{r}}(t)$, $\mathbf{Z}^{\mathrm{p}}(t)\}$ and possibly random control decisions that are made in reaction to the observed $\{\mathbf{S}(t)$, $\mathbf{W}(t)$, $\mathbf{R}(t)$, $\mathbf{G}^{\mathrm{r}}(t)$, $\mathbf{Z}^{\mathrm{p}}(t)\}$. Specifically, these control decisions are $\mathbf{m}(t)$, $\boldsymbol{\lambda}(t)$, $\mathbf{G}(t)$, $\mathbf{Z}(t)$ and $\mathbf{Q}(t)$. The definitions of $\mathbf{G}(t)$, $\mathbf{Z}(t)$ and $\mathbf{Q}(t)$ are given as follows:

$$\mathbf{G}(t) = \{G_i^{\mathrm{g2}}(t),\, G_i^{\mathrm{2g}}(t),\, G_i^{\mathrm{2b}}(t),\, G_i^{\mathrm{b2}}(t)\}, \tag{2.24}$$

$$\mathbf{Z}(t) = \{Z_i^{\mathrm{bc}}(t),\, Z_i^{\mathrm{bd}}(t),\, Z_{i,j,b}^{\mathrm{g}}(t),\, Z_i^{\mathrm{g2}}(t),\, Z_i^{\mathrm{2g}}(t)\}, \tag{2.25}$$

$$\mathbf{Q}(t) = \{Q_{i,j,b}(t)\}. \tag{2.26}$$

There are two challenges to solve P2.1. First, the future parameters are unknown, including workload, electricity price, renewable generation output, and power outage state. Second, the constraints on the energy level of battery bring the "time coupling" property to P2.1, which means that the current decision can impact the future decision. Previous methods to handle the "time coupling" problem are usually based on dynamic programming, which suffers from the "the curse of dimensionality" problem. In this section, we design an operation algorithm based on Lyapunov optimization technique. Because of the time-coupling constraint (2.16), we first consider a relaxed problem, which fits into the framework of Lyapunov optimization. Then, we design our algorithm base on the insights provided by the relaxed problem.

2.3.1 Relaxed Problem

In this subsection, a relaxed problem of P2.1 is considered. Defining the time-average expectation of charging and discharging power of the battery at IDC i under any feasible control policy of P2.1 as follows,

$$\overline{G_i^{2b}} = \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{G_i^{2b}(t)\}, \tag{2.27}$$

$$\overline{G_i^{b2}} = \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{G_i^{b2}(t)\}. \tag{2.28}$$

Since battery energy levels update according to (2.16), summing over all $t \in \{0, 1, 2, \ldots, T-1\}$, taking expectation of both sides and dividing both sides with T and letting $T \to \infty$, we have $\overline{G_i^{2b}} = \overline{G_i^{b2}}$. Then, a relaxed problem is given as follows, called P2.2.

$$\text{(P2.2)}\ \min\ \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)\}, \tag{2.29a}$$

$$\text{s.t. } (2.1)-(2.3), (2.5)-(2.7), (2.10)-(2.14), (2.17)-(2.21), \tag{2.29b}$$

$$\overline{G_i^{2b}} = \overline{G_i^{b2}}. \tag{2.29c}$$

Let y^* and y^{rel} be the optimal solution of P2.1 and P2.2, respectively. As mentioned before, any feasible solution to P2.1 is also a feasible solution to P2.2. Therefore, we have $y^{\text{rel}} \le y^*$. Obviously, P2.2 is easier to solve than P2.1 due to the removal of "time coupling" property. From the framework of Lyapunov optimization [23], we have the following Theorem for the solution to P2.2:

Theorem 1 *If* $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^r(t), \mathbf{Z}^p(t)\}$ *are i.i.d. over slots, then there exists a stationary and randomized policy that takes control decisions (i.e.,* $\hat{\mathbf{m}}(t)$, $\hat{\boldsymbol{\lambda}}(t)$, $\hat{\mathbf{G}}(t)$, $\hat{\mathbf{Q}}(t)$ *and* $\hat{\mathbf{Z}}(t)$*) every slot* t *as a pure (possibly randomized) function of the observed* $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^r(t), \mathbf{Z}^p(t)\}$ *while satisfying the constraints of P2.2 and providing the following guarantees.*

$$\mathbb{E}\{\hat{G}_i^{2b}(t)\} = \mathbb{E}\{\hat{G}_i^{b2}(t)\}, \tag{2.30}$$

$$\mathbb{E}\{\hat{C}(t)\} = y^{rel}, \tag{2.31}$$

where the expectation operations above are with respect to the stationary distribution of $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^r(t), \mathbf{Z}^p(t)\}$*, and randomized control decisions.* $\hat{C}(t)$ *denotes the value of* (2.22) *under the stationary and randomized policy.*

The proof can be obtained according to *Theorem of Optimality over* ω-only Policies in [23]. Thus, it is omitted for brevity. To obtain such a control policy, we need to know the statistical distributions of all combinations of $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^{\mathrm{r}}(t), \mathbf{Z}^{\mathrm{p}}(t)\}$, which may be unknown and difficult to obtain. Moreover, the control policy may be infeasible for the original problem P2.1 as it could violate the constraint (2.15). However, the existence of such a control policy can help us to derive the performance guarantee of the proposed operation algorithm as shown in the part 3 of the Theorem 2.

2.3.2 Proposed Operation Algorithm

The key idea of the proposed operation algorithm is described as follows:

- transforming P2.2 into a queue stability problem according to the framework of Lyapunov optimization technique;
- obtaining the *drift-plus-penalty* term according to the theory of Lyapunov optimization technique;
- minimizing the R.H.S. of the upper bound of the *drift-plus-penalty* term.

Note that the decisions of the proposed operation algorithm do not necessarily satisfy the constraints of P2.1, therefore, we should check the feasibility of the proposed operation algorithm, which would be given in Sect. 2.4.

According to the above key idea, first, we introduce battery virtual queues $X_i(t)$ in order to transform P2.2 into a queue stability problem, where

$$X_i(t) = E_i(t) - E_i^{\min} - V\theta_i^{\max} - \Delta T G_i^{\mathrm{dm}}, \tag{2.32}$$

where $\theta_i^{\max} = \max\{S_i^{\max}, W_i^{\max}, H_i^{\max}\}$, $H_i^{\max} = \max_{j,b}\{H_{i,j,b}\}$. $V \in [0, V^{\max}]$ is a constant for the tradeoff between minimizing expected energy cost and ensuring the stability of virtue queues. The constant $V^{\max}$ is carefully selected to ensure that the evolution of the battery energy levels satisfies the constraints in (2.15). Continually, we have

$$X_i(t+1) = X_i(t) + \Delta T(G_i^{2\mathrm{b}}(t) - G_i^{\mathrm{b}2}(t)). \tag{2.33}$$

Then, according to the framework of Lyapunov optimization in [23], P2.2 can be equivalently transformed to a queue stability problem as follows, named P2.3

$$\text{(P2.3)} \ \min \ \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)\}, \tag{2.34a}$$

$$\text{s.t. } (2.1)-(2.3), (2.5)-(2.7), (2.10)-(2.14), (2.17)-(2.21), \tag{2.34b}$$

$$\text{Queues } X_i(t) \text{ are mean rate stable.} \tag{2.34c}$$

To solve P2.3, we would develop an operation algorithm based on Lyapunov optimization technique. First, we define a Lyapunov function as follows,

$$L(t) \overset{\Delta}{=} \frac{1}{2} \sum_{i=1}^{N} (X_i(t))^2. \tag{2.35}$$

Then, the one-slot conditional Lyapunov drift is given by

$$\Delta(t) = \mathbb{E}\{L(t+1) - L(t)|\mathbf{X}(t)\}, \tag{2.36}$$

where $\mathbf{X}(t) = (X_1(t), \ldots, X_N(t))$, the expectation is taken with respect to the randomness of workload, electricity price, renewable generation output, and power outage rate, as well as the randomness in choosing the control decisions. We define $\chi_i(t) = G_i^{2\mathrm{b}}(t) - G_i^{\mathrm{b}2}(t)$, then

$$L(t+1) - L(t) = \frac{1}{2}\sum_{i=1}^{N}\left[(X_i(t+1))^2 - (X_i(t))^2\right] \leq \sum_{i=1}^{N}\left[\omega_i + X_i(t)\Delta T\chi_i(t)\right], \tag{2.37}$$

where $\omega_i \triangleq \frac{(\Delta T \max\{G_i^{\mathrm{cm}}, G_i^{\mathrm{dm}}\})^2}{2}$. Thus, we have

$$\Delta(t) \leq \sum_{i=1}^{N}\omega_i + \sum_{i=1}^{N}\mathbb{E}\{X_i(t)\Delta T\chi_i(t)|\mathbf{X}(t)\}. \tag{2.38}$$

Continually, following the Lyapunov optimization framework, we add a function of the expected energy cost over one period (i.e., the penalty function) to (2.36) to obtain the *drift-plus-penalty* term as follows,

$$\Delta Y(t) = \Delta(t) + V\mathbb{E}\{C(t)|\mathbf{X}(t)\} \leq \sum_{i=1}^{N}\omega_i + \mathbb{E}\Big\{\sum_{i=1}^{N}X_i(t)\Delta T\chi_i(t) + VC(t)|\mathbf{X}(t)\Big\}. \tag{2.39}$$

Note that the proposed operation algorithm intends to minimize the R.H.S. of the upper bound of the *drift-plus-penalty* term subject to the constraints in P2.3, which is equivalent to minimize P2.4 based on the observed system states at the beginning of slot t. Consequently, the proposed operation algorithm can be described by Algorithm 1.

$$\text{(P2.4)} \;\; \min \;\; \sum_{i=1}^{N}\{X_i(t)\Delta T\chi_i(t)\} + VC(t) \tag{2.40a}$$

$$\text{s.t. } (2.1)-(2.3),\ (2.5)-(2.7),\ (2.10)-(2.14),\ (2.17)-(2.21), \tag{2.40b}$$

Algorithm 1 : Operation Algorithm for IDC Operators

1: **For** each slot t **do**
2: At the beginning of slot t, observe system states: $X_i(t)$, $W_i(t)$, $R_f(t)$, $S_i(t)$, $G_i^{\mathrm{r}}(t)$ and $Z_i^{\mathrm{p}}(t)$;
3: Choose control decisions $\mathbf{m}(t)$, $\boldsymbol{\lambda}(t)$, $\mathbf{G}(t)$, $\mathbf{Q}(t)$, and $\mathbf{Z}(t)$ as the solution to P2.4;
4: Update $X_i(t)$ according to (2.33);
5: **End**

2.3.3 Solution

To solve P2.4, which is a MILP, its certain structure can be exploited, i.e., by fixing the integer variables first, the resulting problem becomes convex for continuous variables. Therefore, Benders' decomposition [34] can be adopted to solve P2.4 in this chapter, which can decompose P2.4 into two problems, i.e., master problem and subproblem. In addition, considering that there are huge number of servers in IDCs and a large fraction of them are active, we can relax the integer constraint on $m_i(t)$ without significant energy cost penalties [4].

Before giving the algorithm to solve P2.4, we define some problems in the following part.

Let $\boldsymbol{x} \triangleq \mathbf{Z}(t)$ and $\boldsymbol{z} \triangleq \{\mathbf{m}(t), \boldsymbol{\lambda}(t), \mathbf{G}(t), \mathbf{Q}(t)\}$. If $\boldsymbol{x}$ is fixed to feasible integer configuration $\overline{\boldsymbol{x}} \triangleq \overline{\mathbf{Z}(t)}$, then, P2.4 can be reduced to P2.5 as follows,

$$
\begin{aligned}
\text{(P2.5)}\ \min_{\boldsymbol{z}} & \sum_i \{X_i(t)\Delta T(G_i^{\mathrm{2b}}(t) - G_i^{\mathrm{b2}}(t))\} \\
& + \sum_i \{V(G_i^{\mathrm{g2}}(t)S_i(t) - G_i^{\mathrm{2g}}(t)W_i(t))\Delta T\} \\
& + \sum_i \sum_j \sum_b VH_{i,j,b}Q_{i,j,b}(t) && \text{(2.41a)} \\
\text{s.t.}\ & \Gamma(\boldsymbol{z}) \leq \mathbf{0}, && \text{(2.41b)}
\end{aligned}
$$

where $\Gamma(\boldsymbol{z})$ is obtained by fixing the discrete parameters in (2.1)–(2.3), (2.7), (2.10), (2.13), (2.14), (2.19), (2.20) with $\overline{\boldsymbol{x}}$.

Let P2.6 be the dual of the P2.5, and the objective function of P2.6 is denoted as $\Upsilon(\overline{\boldsymbol{x}}, \boldsymbol{\phi})$, the constraints of P2.6 are described by $\Lambda(\boldsymbol{\phi}) \leq \mathbf{0}$. Then, P2.6 is given by

$$
\begin{aligned}
\text{(P2.6)}\ \max_{\boldsymbol{\phi}}\ & \Upsilon(\overline{\boldsymbol{x}}, \boldsymbol{\phi}) && \text{(2.42a)} \\
\text{s.t.}\ & \Lambda(\boldsymbol{\phi}) \leq \mathbf{0}. && \text{(2.42b)}
\end{aligned}
$$

Continually, the Benders' subproblem can be defined as follows (P2.7, which is a linear programming problem and can be solved in polynomial time),

$$
\begin{aligned}
\text{(P2.7)}\ \Psi^* = \max_{\boldsymbol{\phi}} & \sum_i V(\overline{Z_i^{\mathrm{bc}}(t)} + \overline{Z_i^{\mathrm{bd}}(t)})\rho_i^b + \Upsilon(\overline{\boldsymbol{x}}, \boldsymbol{\phi}) \\
& + \sum_i \sum_j \sum_b V\alpha_{i,j,b}\overline{Z_{i,j,b}^{\mathrm{g}}(t)} && \text{(2.43a)} \\
\text{s.t.}\ & \Lambda(\boldsymbol{\phi}) \leq \mathbf{0}. && \text{(2.43b)}
\end{aligned}
$$

We define the Benders' master problem below (called P2.8, which is a 0–1 integer programming problem and could be solved by a pseudo-polynomial time algorithm)

$$
\text{(P2.8)}\ \Omega^* = \min_{\boldsymbol{x}} \Omega \qquad \text{(2.44a)}
$$

$$\text{s.t. } \Omega \geq \sum_i V(Z_i^{\mathrm{bc}}(t) + Z_i^{\mathrm{bd}}(t))\rho_i^b + \Upsilon(\boldsymbol{x}, \boldsymbol{\phi}^{k_2})$$

$$+ \sum_i \sum_j \sum_b V\alpha_{i,j,b} Z_{i,j,b}^{\mathrm{g}}(t), \quad 1 \leq k_2 \leq K_2, \tag{2.44b}$$

$$\Upsilon(\boldsymbol{x}, \boldsymbol{\phi}^{k_1}) \leq 0, 1 \leq k_1 \leq K_1, \tag{2.44c}$$

$$(2.5), (2.6), (2.11), (2.12), (2.17), (2.18), (2.21), \tag{2.44d}$$

where the Benders' optimality cut (4b) and the Benders' feasibility cut (4c) are incorporated when the Benders' subproblem P2.7 is bounded and unbounded, respectively. K_1 and K_2 are the number of feasibility cut and optimality cut, respectively. $\boldsymbol{\phi}^{k_1}$ and $\boldsymbol{\phi}^{k_2}$ are the unbounded rays and the extreme points, respectively, where the method to obtain the unbound rays can be found in [35].

Based on above optimization problems, an iterative algorithm based on Benders' decomposition to solve P2.4 is proposed in Algorithm 1. Since K_1 and K_2 are finite, the iterative algorithm is expected to converge to the optimal solution within a finite number of iterations.

Algorithm 2 : Procedures of solving P2.4

Input: An initial feasible solution $\boldsymbol{x}^1$
  and a convergence tolerant parameter $\varepsilon > 0$
Output: An optimal solution $\boldsymbol{x}^*$ and $\boldsymbol{z}^*$
{Initialization}
Given initial feasible integer solution $\boldsymbol{x}^1$
$\mathrm{LB}^1 := -\infty$
$\mathrm{UB}^1 := \infty$
$q=1$, $K_1=0$, $K_2=0$;
for iteration q **do**
  {solve subproblem P2.7}
  if unbounded **then**
    Get unbounded ray $\boldsymbol{\phi}^{K_1+1}$, $K_1=K_1+1$
    Add feasibility cut $\Upsilon(\boldsymbol{x}, \boldsymbol{\phi}^{K_1}) \leq 0$ to P2.8
  else
    Get extreme point $\boldsymbol{\phi}^{K_2+1}$, $K_2=K_2+1$
    Add optimality cut $\Omega \geq \sum_i V(Z_i^{\mathrm{bc}}(t) + Z_i^{\mathrm{bd}}(t))\rho_i^b + \sum_i \sum_j \sum_b V\alpha_{i,j,b} Z_{i,j,b}^{\mathrm{g}}(t) + \Upsilon(\boldsymbol{x}, \boldsymbol{\phi}^{K_2})$ to P2.8
    $\mathrm{UB}^q := \min\{\mathrm{UB}^{q-1}, \Psi^*\}$
  end
  {solve master problem P2.8}
  $\mathrm{LB}^q := \Omega^*$
  if $\mathrm{LB}^q + \varepsilon > \mathrm{UB}^q$ **then**
    Obtain the optimal $\boldsymbol{x}^*$
    Solve P2.4 to recover solution by fixing $\overline{\boldsymbol{x}}$ with $\boldsymbol{x}^*$
    return optimal solution $\boldsymbol{x}^*$ and $\boldsymbol{z}^*$
  else
    $q = q + 1$
  end
end

2.4 Analysis and Simulations

As explained in Sect. 2.3.2, we need to check the feasibility of the proposed operation algorithm. In this section, we present a lemma about the operation of battery. Then, based on the lemma, we give a theorem about the feasibility of the proposed algorithm, i.e., the proposed algorithm can operate without requiring any statistical knowledge. Moreover, we provide the performance guarantee of the proposed algorithm when $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^{\mathrm{r}}(t), \mathbf{Z}^{\mathrm{p}}(t)\}$ are i.i.d. over slots. Note that algorithms developed based on Lyapunov optimization technique are also robust to non-i.i.d. and non-ergodic behaviors of the stochastic processes (e.g., [23]). Therefore, performance evaluations in next section are conducted based on practical data without any specific distribution assumption, which shows the robustness of the proposed operation algorithm.

2.4.1 Analysis

First, we present a Lemma that is useful for the analysis of algorithmic performance.

Lemma 1 *Let* $\theta_i^{\min} = \min\{S_i^{\min}, W_i^{\min}, H_i^{\min}\}$, $H_i^{\min} = \min_{j,b}\{H_{i,j,b}\}$, *The optimal solution to P2.4 has the following properties:*

1. *If* $X_i(t) < -V\theta_i^{\max}$, *the optimal solution always choose* $G_i^{b2}(t) = 0$,
2. *If* $X_i(t) > -V\theta_i^{\min}$, *the optimal solution always choose* $G_i^{2b}(t) = 0$.

Proof

1. For each SMG i, suppose that $X_i(t) < -V\theta_i^{\max}$ and $G_i^{\mathrm{b2}}(t) > 0$, then, we have $G_i^{\mathrm{2b}}(t) = 0$. Let $\Gamma_1(t)$ denote the optimal value of the objective in P2.4, which is the summation of $\Gamma_{1,i}(t)$ at all IDCs. To prove that the above decision is not optimal, we choose $\tilde{G}_i^{\mathrm{b2}}(t) = 0$, and $\tilde{G}_i^{\mathrm{2b}}(t) = 0$. Let $\Gamma_2(t)$ denote the value of the objective in P2.4, which is the summation of $\Gamma_{2,i}(t)$ at all IDCs. Given the power demand $P_i(t)$, the decisions about power supply for IDCs can be divided into the following cases:
   Case 1: If $G_i^{\mathrm{g2}}(t) = G_i^{\mathrm{2g}}(t) = 0$, we set $\tilde{G}_i^{\mathrm{g2}}(t) = G_i^{\mathrm{g2}}(t)$, $\tilde{G}_i^{\mathrm{2g}}(t) = G_i^{\mathrm{2g}}(t)$, then, $G_i^{\mathrm{a}}(t) + G_i^{\mathrm{b2}}(t) = \tilde{G}_i^{\mathrm{a}}(t)$. Continually, we have

$$\Gamma_{1,i}(t) - \Gamma_{2,i}(t) \geq -(X_i(t) + VH_i^{\max})\Delta T G_i^{\mathrm{b2}}(t) + V\rho_i^b > 0. \quad (2.45)$$

   Case 2: If $G_i^{\mathrm{g2}}(t) > 0$, $G_i^{\mathrm{2g}}(t) = 0$, we set $\tilde{G}_i^{\mathrm{2g}}(t) = G_i^{\mathrm{2g}}(t)$, $\tilde{G}_i^{\mathrm{a}}(t) = G_i^{\mathrm{a}}(t)$. Then, $G_i^{\mathrm{g2}}(t) + G_i^{\mathrm{b2}}(t) = \tilde{G}_i^{\mathrm{g2}}(t)$. Continually, we have

$$\Gamma_{1,i}(t) - \Gamma_{2,i}(t) \geq -(X_i(t) + VS_i^{\max})\Delta T G_i^{\mathrm{b2}}(t) + V\rho_i^b > 0. \quad (2.46)$$

Case 3: If $G_i^{\text{g2}}(t) = 0$, $G_i^{\text{2g}}(t) > 0$, we set $\tilde{G}_i^{\text{g2}}(t) = G_i^{\text{g2}}(t)$, $\tilde{G}_i^{\text{a}}(t) = G_i^{\text{a}}(t)$. Then, $G_i^{\text{2g}}(t) - G_i^{\text{b2}}(t) = \tilde{G}_i^{\text{2g}}(t)$. Continually, we have

$$\Gamma_{1,i}(t) - \Gamma_{2,i}(t) \geq -(X_i(t) + VW_i^{\max})\Delta T G_i^{\text{b2}}(t) + V\rho_i^b > 0. \quad (2.47)$$

Taking three cases into consideration, we know that when $X_i(t) < -V\theta_i^{\max}$, the optimal decision always choose $G_i^{\text{b2}}(t) = 0$.

2. Similar to the part 1 of Lemma 1, part 2 can be proved. Thus, the proof of this part is omitted for brevity.

Then, we analyze the feasibility and performance guarantee of the proposed operation algorithm in the following Theorem.

Theorem 2 *Suppose the initial battery energy level $E_i(0) \in [E_i^{\min},\ E_i^{\max}]$. Implementing the proposed operation algorithm with any fixed parameter $V \in (0, V^{\max}]$, we have the following properties:*

1. *The battery energy level $E_i(t)$ is always in the range $[E_i^{\min},\ E_i^{\max}]$ for all slots. Moreover, queues $X_i(t)$ are mean rate stable.*
2. *The decisions of the proposed operation algorithm are feasible to P2.1, i.e., the proposed operation algorithm can operate without requiring any statistical knowledge about system dynamics.*
3. *If $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^r(t), \mathbf{Z}^p(t)\}$ are i.i.d. over slots and $\omega = \sum_i \omega_i$, then the time-average expected energy cost under the proposed operation algorithm is within bound ω/V of the optimal value: $\limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{C(t)\} \leq y^* + \frac{\omega}{V}$.*

Proof

1. To show $E_i(t) \in [E_i^{\min},\ E_i^{\max}]$, according to the definition of $X_i(t)$, it is equivalent to show that for each IDC i,

$$X_i(t) \geq -V\theta_i^{\max} - \Delta T G_i^{\text{dm}}, \quad (2.48)$$

and

$$X_i(t) \leq E_i^{\max} - E_i^{\min} - V\theta_i^{\max} - \Delta T G_i^{\text{dm}}. \quad (2.49)$$

As $E_i^{\min} \leq E_i(0) \leq E_i^{\max}$, the above inequalities hold for $t = 0$. We prove that the constraints are satisfied for all periods by induction. Suppose the above inequalities hold for slot t, we need to prove that they also hold for slot $t+1$.

- If $-V\theta_i^{\max} - \Delta T G_i^{\text{dm}} \leq X_i(t) < -V\theta_i^{\max}$, then, according to Lemma 1, the optimal decision would choose $G_i^{\text{b2}}(t) = 0$. Thus, $X_i(t+1) \geq X_i(t) \geq -V\theta_i^{\max} - \Delta T G_i^{\text{dm}}$. If $-V\theta_i^{\max} \leq X_i(t) < E_i^{\max} - E_i^{\min} - V\theta_i^{\max} - \Delta T G_i^{\text{dm}}$, then, according to the dynamics of $X_i(t)$, $X_i(t+1) \geq -V\theta_i^{\max} - \Delta T G_i^{\text{b2}}(t) > -V\theta_i^{\max} - \Delta T G_i^{\text{dm}}$.

- If $-V\theta_i^{\min} < X_i(t) \leq E_i^{\max} - E_i^{\min} - V\theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$, then, According to Lemma 1, the optimal decision would choose $G_i^{2\mathrm{b}}(t) = 0$. Thus, $X_i(t+1) \leq X_i(t) \leq E_i^{\max} - E_i^{\min} - V\theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$. If $-V\theta_i^{\max} - \Delta TG_i^{\mathrm{dm}} \leq X_i(t) \leq -V\theta_i^{\min}$, then, $X_i(t+1) \leq -V\theta_i^{\min} + \Delta TG_i^{\mathrm{cm}} \leq E_i^{\max} - E_i^{\min} - V\theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$, where we have used the following condition,

$$V \leq \frac{E_i^{\max} - E_i^{\min} - \Delta T(G_i^{\mathrm{cm}} + G_i^{\mathrm{dm}})}{\theta_i^{\max} - \theta_i^{\min}}. \tag{2.50}$$

Continually, the upper bound of parameter V is given by

$$V^{\max} = \min_i \frac{E_i^{\max} - E_i^{\min} - \Delta T(G_i^{\mathrm{cm}} + G_i^{\mathrm{dm}})}{\theta_i^{\max} - \theta_i^{\min}}, \tag{2.51}$$

where $\theta_i^{\min} = \min\{W_i^{\min}, S_i^{\min}, H_i^{\min}\}, H_i^{\min} = \min_{j,b}\{H_{i,j,b}\}$. Since $\limsup_{T\to\infty} \frac{1}{T}\mathbb{E}\{|X_i(T)|\}= 0$, we can know that queues $X_i(t)$ are mean rate stable.

2. The proposed operation algorithm can make decisions to satisfy all constraints in P2.4 and update $X_i(t)$ normally (i.e., update $E_i(t)$). Meanwhile, taking the part 1 of Theorem 2 into consideration, we know that all constraints in P2.1 can be satisfied by the decisions of the proposed algorithm. That is, the proposed algorithm can operate without requiring any statistical knowledge.
3. By plugging the policy mentioned in Theorem 1 into the R.H.S. of *drift-plus-penalty* term, then, we have

$$\Delta Y(t) \leq \omega + V\mathbb{E}\{\hat{C}(t)\} \leq \omega + Vy^*. \tag{2.52}$$

Taking the expectation of both sides, using the law of iterative expectation, we have

$$\mathbb{E}[\Delta Y(t)] = \mathbb{E}[\Delta(t)] + V\mathbb{E}[C(t)] \leq \omega + Vy^*. \tag{2.53}$$

Then, summing the above equations over $t \in \{0, 1, 2, \ldots, T-1\}$, we have

$$V\sum_{t=0}^{T-1} \mathbb{E}\{C(t)\} \leq \omega T + VTy^* - \mathbb{E}\{L(T)\} + \mathbb{E}\{L(0)\}. \tag{2.54}$$

Dividing both side by VT, and taking a lim sup of both sides. Let $T \to \infty$, and using the facts that $E\{L(0)\}$ is finite and $E\{L(T)\}$ is nonnegative, we arrive at the following performance guarantee,

$$\limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{C(t)\} \leq y^* + \frac{\omega}{V}. \tag{2.55}$$

It is worth noting that the choice of V controls the optimality of the proposed operation algorithm. Specifically, a larger V leads to a tighter optimality gap. However, according to the definition of $V^{\max}$, we know that larger V requires larger investment on battery capacity, which would result in larger investment cost since batteries are very expensive currently. Therefore, there is a tradeoff between energy cost saving and battery investment cost.

2.4.2 Simulations

In this section, we evaluate the performance of the proposed operation algorithm based on real-world traces. Our purpose is twofold: (1) to show the effectiveness of our proposed operation algorithm under power outage environment; (2) to show the tradeoff between energy cost saving and battery investment cost.

2.4.2.1 Real-World Traces and Experimental Setup

System Parameters. We consider a scenario that the total workload from one front-end web portal server is forwarded to two back-end IDCs located in two independent ERs, i.e., $F = 1, N = 2$. Some parameters about servers in IDCs are set as follows: $P_1^{\text{peak}} = 250\,\text{W}$, $P_2^{\text{peak}} = 240\,\text{W}$, $P_1^{\text{idle}} = 175\,\text{W}$, $P_2^{\text{idle}} = 168\,\text{W}$, $\text{PUE}_1 = 2.5$, $\text{PUE}_2 = 2.4$ [1], $M_1 = 22,000$, $M_2 = 35,000$, $\mu_1 = 2$ requests/s, $\mu_2 = 1.75$ requests/s, $D_i^{\max} = 0.7\,\text{s}$, $\Delta T = 1\,\text{h}$ [2]. In this chapter, we assume that generators in each IDC have the capacity to power the whole IDC, which is quite common in industry. Specifically, each IDC has 10 diesel generators with model TP-C2000-T2-60 (2 MW) and 5 diesel generators with model TP-C100-T1-60 (100 kW) [14], where the parameters $H_{i,j,b}$ and $\alpha_{i,j,b}$ can be estimated as in [29, 36]. According to the recent empirical experiments, we assume that the limits of battery charging/discharging rates are $P^{\text{cm}} = P^{\text{dm}} = 0.5\,\text{MW}$, and charging/discharging cost is $\rho_i^b = 0.1$ dollars [21]. In addition, we set $V = V^{\max}$.
Wind Energy Data. The wind speed information is obtained from the dataset published by the National Renewable Energy Laboratory.[3] Based on the 1 min raw data, we calculate the average wind speed during the disjoint hour. We adopt the V90 wind turbine model in this chapter.[4]
Electricity Price Data. The real-time electricity price traces of the U.S. NYISO and ERCOT markets in 2012 are used. Based on the traces, we calculate the average electricity price during the disjoint hour. Moreover, we set $W_i(t) = 0.9S_i(t)$ [37].
Workload Data. The real-world workload data is taken from FIFA's 1998 World Cup web traces between June 10 and June 30, 1998.[5] Considering the increase of

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[3] http://www.nrel.gov/midc, Sept. 2013.

[4] http://www.vestas.com/en/wind-power-plants/, Sept. 2013.

[5] http://ita.ee.lbl.gov/html/traces.html, Sept. 2013.

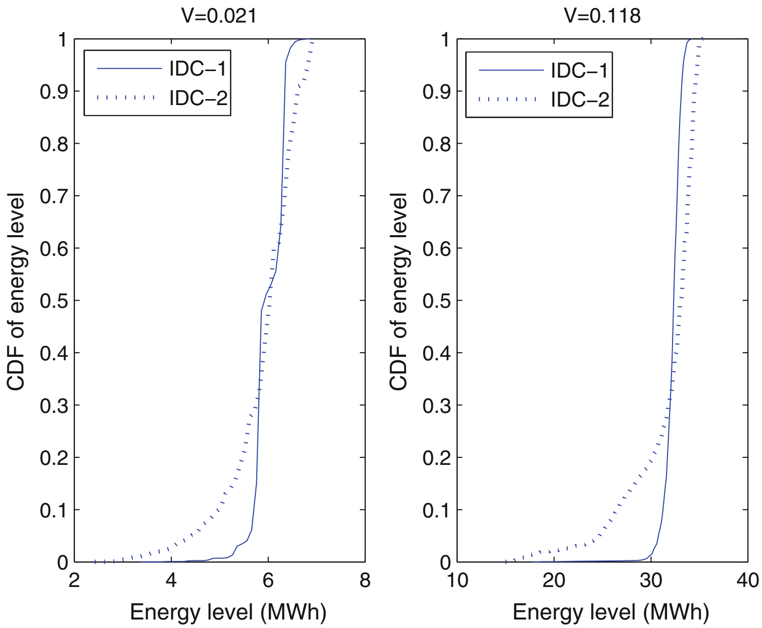

Fig. 2.3 CDF of energy levels with varying V

Internet traffic in the past decade, we modify the original workload by enlarging 60 times[6] and repeat it to get a 365-day workload trace.

Power Outage Data. Power outage process in each ER is modeled using an exponential-distributed random variable and some selected MTTA and MTTR [12]. We set $\text{MTTA}_1 = \text{MTTA}_2 = 876\,\text{h}$, $\text{MTTR}_1 = \text{MTTR}_2 = 8\,\text{h}$, where MTTA-$i$ and MTTR-i are the parameters associated with the main grid i. The method of generating the power outage process can be found in [13].

Benchmark. To show the effectiveness of the proposed algorithm, we adopt a benchmark called cost-aware dynamic provisioning (CDP) based on the scheme proposed by Rao et al. [5]. Note that CDP can exploit the spatial diversity of electricity price by traffic routing. However, renewable energy and battery are not considered in [5]. For more fair comparison, renewable energy is adopted in CDP, which intends to minimize the total energy cost in each slot based on the observed system states.

2.4.2.2 Experimental Results

Figure 2.3 illustrates the cumulative distribution function (CDF) of energy levels under the proposed algorithm and varying control parameter V. It can be observed

[6] E.g., the average workload is smaller than 2 million requests/h, while the average workload of Google search is 121 million requests/h.

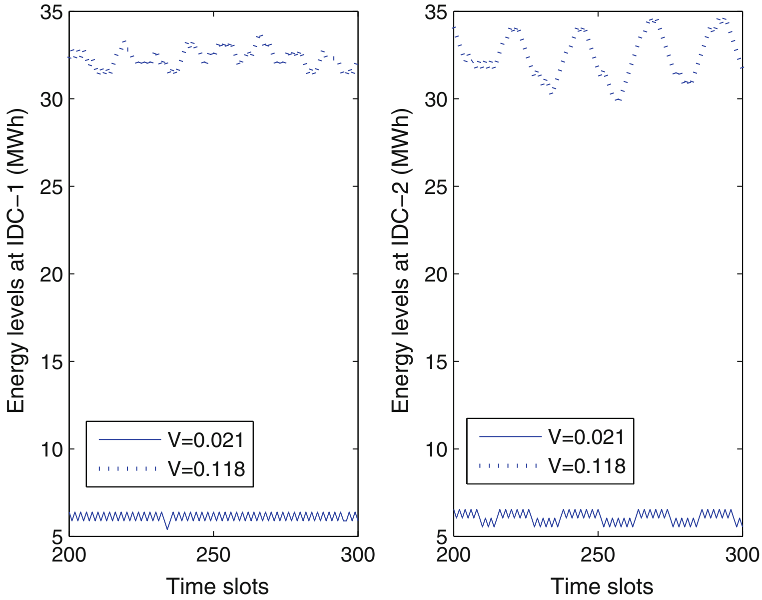

Fig. 2.4 Energy levels at different IDCs

that the proposed algorithm is feasible since the energy levels are fluctuating in their normal ranges. As shown by Fig. 2.4, smaller V would lead to more frequent discharging or charging process since the proposed algorithm at this time put more weight on maintaining the energy queue stability rather than energy cost minimization.

As depicted in Fig. 2.5, larger V would lead to lower energy cost under the proposed algorithm, which validates the algorithmic performance in the part 3 of Theorem 2. Though the part 3 of Theorem 2 holds when $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^{\mathrm{r}}(t), \mathbf{Z}^{\mathrm{p}}(t)\}$ are i.i.d. over slots, the simulation results based on real-world traces (without any specific distribution assumption) show that the proposed algorithm is robust to non-i.i.d. and non-ergodic cases (note that the theoretical basis for such robustness can be found in [23]).

In addition, it can be seen that power outages would lead to the increase of total energy cost under two schemes. Specifically, the increased energy cost is 59,097 dollars and 55,067 dollars under the CDP and the proposed algorithm, respectively. It is expected that the increased energy cost would become larger as MTTA decreases and MTTR increases. Compared with the CDP, the proposed algorithm achieves the better performance and the performance gap between the proposed algorithm and the CDP is larger as V increases. The reason is given as follows: larger V means larger battery capacity, which can better utilize the spatial and temporal diversities of electricity price and wind energy. In contrast, CDP can merely exploit the spatial diversities of electricity price and wind energy. The same reason can be used to explain the phenomenon in Fig. 2.6, i.e., the profit under the proposed algorithm is

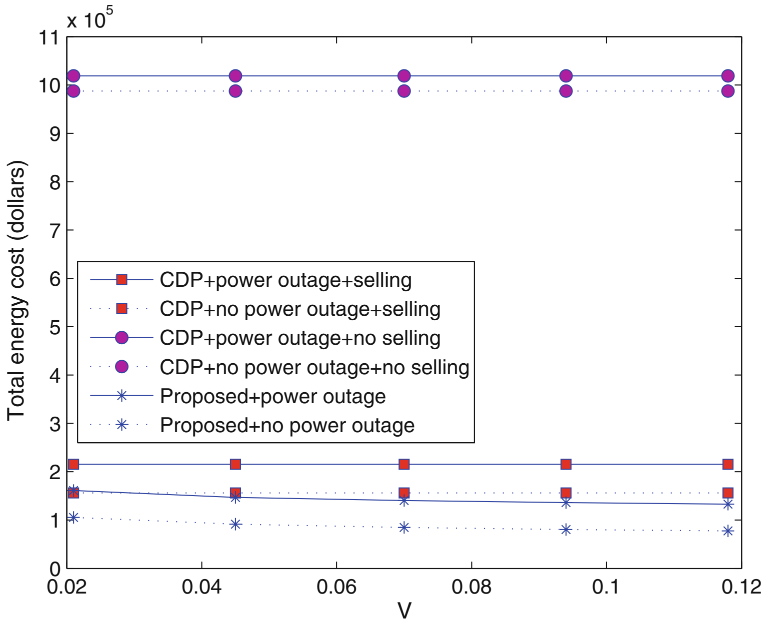

Fig. 2.5 Total energy cost under different algorithms

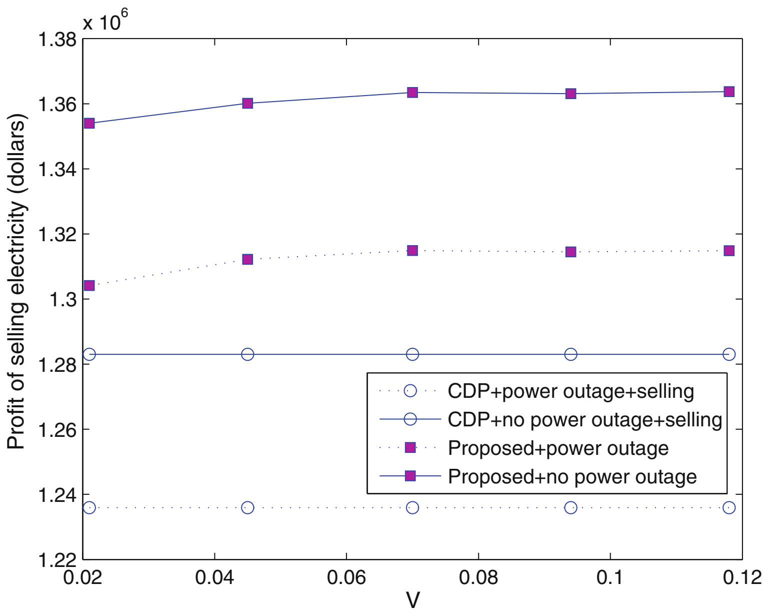

Fig. 2.6 Profit due to the electricity selling

increasing as V increases. In addition, it is obvious that the profit due to electricity selling is lower when there are power outages since power transactions under the above situation are not allowed.

2.5 Summary

In this chapter, we studied the problem of minimizing the long-term energy cost of distributed IDCs in smart microgrids considering power outages. At first, we formulated the problem as a stochastic program by taking SMGs and power outage into consideration. To solve the problem, an operation algorithm was designed based on Lyapunov optimization technique. Moreover, we provided the algorithmic performance guarantee when random parameters are i.i.d. over slots. In addition, the proposed algorithm enables an explicit tradeoff between energy cost saving and battery investment cost. Finally, extensive evaluations based on real-world data showed the effectiveness of the proposed algorithm.

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Chapter 3
Carbon-Aware Energy Cost Minimization for Internet Data Centers

Abstract In Internet data center operations, the operators are faced with high energy cost and carbon emission. Moreover, for socially responsible Internet data center operators, they are expected to minimize energy cost and carbon emission simultaneously. Since smart microgrids have many advantages in supporting the operations of Internet data centers (e.g., low electricity distribution loss, high utilization ratio in renewable energy), we consider the problem of minimizing the long-term weighted summation of energy cost and carbon emission for Internet data center operators in smart microgrids. To achieve the above aim, we propose an efficient operation algorithm considering the uncertainties in renewable generation output, electricity price, workload, and carbon emission rate.

Keywords Internet data centers · Smart microgrids · Carbon-aware · Energy management

3.1 Introduction

With the proliferation of cloud computing and Internet online services, more and more data and computation are migrated to geographically distributed Internet data centers (IDCs) for reliability, management, and cost benefits. For IDC operators, they encounter two major problems in IDC operations: (1) Huge power consumption and electricity bills, e.g., the annual power consumption and electricity cost of Google are larger than 6.3×10^5 MWh and 38 million dollars, respectively [1]. (2) Severe environmental impacts, e.g., carbon emission of data centers was 0.6 % of the global carbon emissions in 2008 and the proportion is expected to reach 2.6 % by 2020 [2]. For socially responsible IDC operators, they expect to mitigate the above problems simultaneously [1].

On the other hand, electrical power system is evolving toward smart grid [3], which is recognized as one of the important applications of Internet of Things (IoT) [4–7]. In smart grid environment, microgrids are evolving toward smart microgrids (SMGs) [8, 9], which have the ability to provide fault isolation and ease of distributed generation handling. When running IDCs in SMGs, there are some benefits: (1) Direct current microgrids can contribute to reduce distribution loss and cooling power consumption, resulting in lower energy cost [10]; (2) Power

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transactions between SMGs and main grids can help to reduce the waste of renewable energy and decrease carbon emission [11]; (3) When there are power outages in main grids [12], SMGs would operate in the islanded mode, the spatial and temporal variations of renewable energy and carbon emission rate could still be exploited to save energy cost and reduce carbon emission [13].

Since socially responsible IDC operators are expected to reduce energy cost and carbon emission simultaneously, we consider a scenario that runs distributed IDCs in SMGs. Specifically, a socially responsible IDC operator has some IDCs geographically distributed in several self-owned SMGs located in independent electric regions (ERs). Moreover, the IDC operator intends to minimize the long-term weighted summation of energy cost and carbon emission with guaranteed quality of service (QoS) for service requests by deciding service request distribution, the number of active servers, the operations of energy storage, the schedule of backup generators, and the quantity of power transactions between SMGs and main grids.

The above problem is challenging since we need to efficiently manage energy storage devices in SMGs considering their time coupling effects. In existing works on data centers [14–20], several schemes have been developed for exploiting energy storage devices. However, these studies do not consider the SMG environment. In this chapter, we focus on jointly minimizing energy cost and carbon emission of distributed IDCs in SMG environment, which makes the design of efficient operation algorithm more difficult.

The main contributions of this chapter are stated as follows:

- By taking smart microgrids into consideration, we formulate an optimization problem to minimize the time-averaged expectation of the weighted summation of energy cost and carbon emission with the uncertainties in electricity price, workload, renewable energy generation, and carbon emission rate.
- We design an operation algorithm to solve the problem based on Lyapunov optimization technique without requiring any statistical knowledge of the system dynamics. Moreover, we analyze the feasibility of the proposed algorithm and its performance guarantee.
- Evaluations based on real-world data show that the proposed algorithm can achieve lower energy cost and carbon emission simultaneously compared with the existing carbon-oblivious algorithm.

The rest of this chapter is organized as follows. Section 3.2 describes the system model. Problem formulation and algorithm design are conducted in Sect. 3.3. Section 3.4 gives the algorithmic performance analysis and simulations. Finally, conclusions are made in Sect. 3.5.

3.2 System Model

In Fig. 3.1, the system model is given, where front-end servers, IDCs, SMGs, and main grids could be identified. A front-end server receives incoming service requests and dispatches them to IDCs that located in multiple ERs for processing. We assume

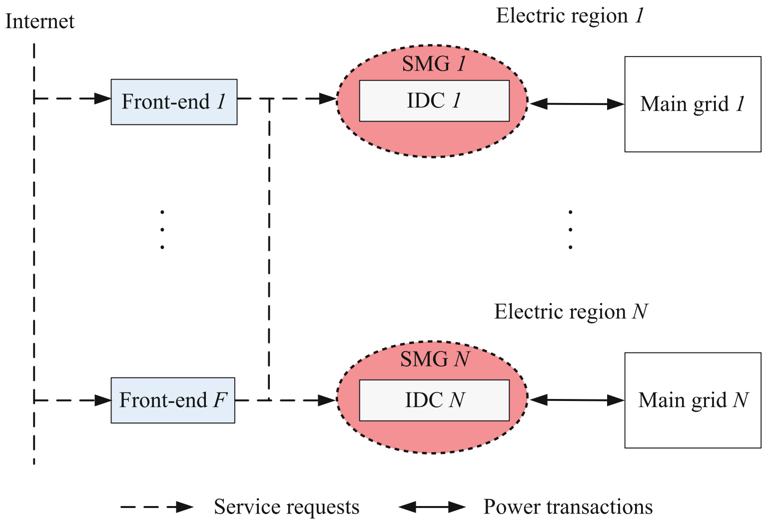

Fig. 3.1 System model

that an IDC operator owns some SMGs located in some independent ERs. The main components in a SMG under study include generators, IDCs, energy storage units, and energy management system. Generators include backup generators (fuel types most common are diesel, natural gas and gasoline [21]), and renewable generators (e.g., solar panels or wind turbines). In this chapter, diesel generators and wind turbines are considered (note that the proposed operation algorithm is also applicable to other kinds of power sources). Diesel generators are fast responding and dispatchable, and they are typically incorporated in data centers for reliability considerations. By contrast, wind turbines are nondispatchable and their generation outputs depend on weather conditions. SMGs have two operation modes, i.e., grid connected and islanded. In the islanded mode, energy management system enables SMGs to take independent decisions from main grids. In the grid-connected mode, power transactions between SMGs and main grids could be conducted.

3.2.1 Models Related to Front-End Servers and Internet Data Centers

3.2.1.1 Workload Allocation Model

We assume there is an IDC operator with N IDCs geographically distributed in N independent electric regions (ERs) to offer Internet services, and each IDC acts as the load in a SMG connected to a main grid, i.e., N SMGs and N main grids are considered. For simplicity, we use the common index i for IDCs, SMGs, and main grids, where $1 \leq i \leq N, i \in \mathscr{Z}^+$. In this chapter, we mainly focus on delay-sensitive workloads (e.g., "request-response" type web services [22]). In IDC i, we assume there are M_i homogeneous servers and $m_i(t)$ of them are turned on to process service requests at slot t. Define $\mathbf{m}(t) = (m_1(t), \ldots, m_N(t))$ as the active server vector. Moreover, $m_i(t)$ is assumed to be unchanged within slot t since activating servers typically costs a nonnegligible amount of time and frequently switching back and forth between active and sleep states can result in reliability problems [23]. We denote the average arrival rate of workload at front-end server f $(1 \leq f \leq F)$ as $R_f(t)$ (in requests per slot, req/slot) and $\mathbf{R}(t) = (R_1(t), \ldots, R_F(t))$ as the workload arrival vector, where F is the total number of front-end servers. Let $\lambda_{f,i}(t)$ (in req/slot) be the workload that assigned from front-end web server f to the servers in IDC i at slot t. $\boldsymbol{\lambda}(t) = (\lambda_{f,i}(t), \ \forall f, i)$ denotes the service request distribution. In order to assure that all service requests would be handled, we have

$$\sum_{i=1}^{N} \lambda_{f,i}(t) = R_f(t). \tag{3.1}$$

3.2.1.2 Service Delay Model

For delay-sensitive requests, their average response delay should be bounded in a certain range that is specified in *service level agreement* (SLA) since SLA violation would result in lost business revenue [24]. In this chapter, the M/M/n queueing model is adopted to process the incoming workload as in the previous work [25]. Note that the queueing model is not necessarily the most accurate for the practical workload, but it will not affect the nature of the carbon-aware energy cost minimization problem and the proposed operation algorithm. General queuing models would be considered in future work. Since the average response delay should be smaller than $D_i^{\max}$ (i.e., the threshold that identifies the revenue/penalty region at IDC i), we have[1]

$$\frac{1}{m_i(t)\mu_i - \sum_{f=1}^{F} \lambda_{f,i}(t)} + \frac{1}{\mu_i} \leq D_i^{\max}, \tag{3.2}$$

where μ_i (in req/slot) is the average service rate of servers in IDC i, $0 \leq m_i(t) \leq M_i$.

3.2.1.3 Power Consumption Model

The energy efficiency of an IDC is always measured by *power usage effectiveness* (PUE), which is defined as the ratio of the total power consumption at an IDC to the power consumption at IT equipment. Let PUE_i be the PUE of IDC i, P_i^{idle}

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[1] Here, a simple SLA is adopted as in [26]. Other more complicated SLAs would be considered in future work.

and P_i^{peak} be the idle power and peak power of a server in IDC i, respectively. Let $u_i(t)$ be the average server utilization at slot t, which is equal to $\lambda_i(t)/(m_i(t)\mu_i)$. Denote the total power consumption at IDC i within slot t as $P_i(t)$ (in MW) and $\mathbf{P}(t) = (P_1(t), \ldots, P_N(t))$ as the power consumption vector. As in previous work [1], $P_i(t)$ can be estimated by

$$P_i(t) = m_i(t)(\varphi_i u_i(t) + \gamma_i), \tag{3.3}$$

where $\varphi_i \triangleq P_i^{\mathrm{peak}} - P_i^{\mathrm{idle}}$, $\gamma_i \triangleq P_i^{\mathrm{idle}} + (\mathrm{PUE}_i - 1)P_i^{\mathrm{peak}}$. Note that servers in each IDC are assumed to be homogeneous in the above power consumption model. For more general situations, the corresponding model can also be incorporated easily.

3.2.2 Models Related to Smart Microgrids

3.2.2.1 Power Supply Model

As mentioned above, wind turbines and diesel generators are considered in each SMG. Based on the wind energy generation model in [27], we can estimate the output of wind turbines at slot t in SMG i, i.e., $G_i^{\mathrm{r}}(t)$ (in MW).

As in [28, 29], the piecewise linear production cost model is adopted to model the energy cost of diesel generators in SMGs. Suppose there are N_B piecewise linear segments in the adopted piecewise linear production cost model, each piecewise linear segment b ($1 \le b \le N_B$) introduces a binary variable $Z_{i,j,b}^{\mathrm{g}}(t)$ and a continuous variable $Q_{i,j,b}(t)$, where $1 \le j \le N_i^{\mathrm{d}}$, N_i^{d} denotes the total number of diesel generators in SMG i. If the energy produced by the diesel generator j in SMG i at slot t falls into the range $g_{i,j,b}^{\min}$ to $g_{i,j,b}^{\max}$, $Z_{i,j,b}^{\mathrm{g}}(t) = 1$; Otherwise, $Z_{i,j,b}^{\mathrm{g}}(t) = 0$. $Q_{i,j,b}(t)$ (in MWh) is adopted to represent the specific energy quantity when the energy generation of the diesel generator j in SMG i at slot t fall into the range above. Then, we have

$$Z_{i,j,b}^{\mathrm{g}}(t) \in \{0, 1\}, \tag{3.4}$$

$$\sum_{b=1}^{N_B} Z_{i,j,b}^{\mathrm{g}}(t) \le 1, \tag{3.5}$$

$$g_{i,j,b}^{\min} Z_{i,j,b}^{\mathrm{g}}(t) \le Q_{i,j,b}(t) \le g_{i,j,b}^{\max} Z_{i,j,b}^{\mathrm{g}}(t), \tag{3.6}$$

where $g_{i,j,b}^{\min}$ and $g_{i,j,b}^{\max}$ (both in MWh) are the lower and upper limit of energy generation of the diesel generator j in SMG i corresponding to the segment b of the piecewise linear production cost model, respectively.

Let $G_i^{\mathrm{a}}(t)$ (in MW) be the total power produced by diesel generators at SMG i at slot t. Then, $G_i^{\mathrm{a}}(t)$ is given as

$$G_i^{\mathrm{a}}(t) = \sum_{j=1}^{N_i^{\mathrm{d}}} \sum_{b=1}^{N_B} Q_{i,j,b}(t)/\Delta T, \tag{3.7}$$

where ΔT (in hour) is the duration of a time slot. Let $H_{i,j,b}$ (in \$/MWh) and $\alpha_{i,j,b}$ (in \$) be the slope and Y-intercept of the segment b associated with the diesel generator j in SMG i. Then, the total energy cost of diesel generators in SMG i at slot t is given by.[2]

$$K_i(t) = \sum_{j=1}^{N_i^{\mathrm{d}}} \sum_{b=1}^{N_B} (H_{i,j,b} Q_{i,j,b}(t) + \alpha_{i,j,b} Z_{i,j,b}^{\mathrm{g}}(t)). \tag{3.8}$$

3.2.2.2 Battery Model

$G_i^{\mathrm{g2}}(t)$ and $G_i^{\mathrm{2g}}(t)$ represent the power purchased from and sold back to the main grid i at slot t, respectively. $G_i^{\mathrm{b2}}(t)$ and $G_i^{\mathrm{2b}}(t)$ are the discharging and charging power for the battery in SMG i at slot t. To balance the power supply and demand in SMG i, we have

$$G_i^{\mathrm{a}}(t) + G_i^{\mathrm{r}}(t) + G_i^{\mathrm{g2}}(t) + G_i^{\mathrm{b2}}(t) = P_i(t) + G_i^{\mathrm{2b}}(t) + G_i^{\mathrm{2g}}(t). \tag{3.9}$$

To indicate whether SMG i is buying or selling power or not at slot t, two binary variables are adopted, i.e., $Z_i^{\mathrm{g2}}(t)$ and $Z_i^{\mathrm{2g}}(t)$. Specifically, $Z_i^{\mathrm{g2}}(t) = 1$ if SMG i is purchasing power from main grid i at slot t; Otherwise, $Z_i^{\mathrm{g2}}(t) = 0$. Similarly, $Z_i^{\mathrm{g2}}(t) = 1$ if SMG i is selling power back to main grid i at slot t; Otherwise, $Z_i^{\mathrm{g2}}(t) = 0$. Since it is not reasonable to purchase and sell energy on the market at the same time, we have the following constraints,

$$Z_i^{\mathrm{g2}}(t), Z_i^{\mathrm{2g}}(t) \in \{0, 1\}, \tag{3.10}$$

$$Z_i^{\mathrm{g2}}(t) + Z_i^{\mathrm{2g}}(t) \le 1, \tag{3.11}$$

$$0 \le G_i^{\mathrm{g2}}(t) \le G_i^{\mathrm{bmax}} Z_i^{\mathrm{g2}}(t), \tag{3.12}$$

$$0 \le G_i^{\mathrm{2g}}(t) \le G_i^{\mathrm{smax}} Z_i^{\mathrm{2g}}(t), \tag{3.13}$$

where G_i^{bmax} and G_i^{smax} denote the maximum purchasing power from main grid i and maximum selling power to man grid i, respectively, and these parameters are

[2] For fast-responding diesel generators, its minimum on/off periods could be regarded as zero and ramping-up/-down rate could be assumed to be ∞ [30]. Thus, some constraints about minimum on/off periods and ramping-up/-down rate are neglected. In addition, due to the lack of public knowledge about start-up cost of diesel generators, we also neglect such cost. More realistic generation cost models would be considered in future work.

determined by the capacity of the transformers and power transmission lines [31]. For simplicity, we assume that the transmission loss is negligible in the process of purchasing or selling electricity [31]. Moreover, we assume that the capacity of the transformers and power transmission lines is large enough, i.e., $G_i^{\text{bmax}} \geq \max_t\{P_i(t) + G_i^{\text{2b}}(t)\}$ and $G_i^{\text{smax}} \geq \max_t\{G_i^{\text{a}}(t) + G_i^{\text{r}}(t) + G_i^{\text{b2}}(t)\}$.

Let $E_i(t)$ be the energy level of the battery in SMG i at slot t. Then, $E_i(t)$ is bounded by

$$E_i^{\min} \leq E_i(t) \leq E_i^{\max}, \tag{3.14}$$

where $E_i^{\max} \geq 0$ is the maximum capacity, and $E_i^{\min} \geq 0$ is the minimum capacity, which may be set by the battery deep discharge protection settings. Assume that there is no conversion loss either in charging or discharging the batteries, noting that this can be easily generalized to the case where a fraction of $G_i^{\text{2b}}(t)$ and $G_i^{\text{b2}}(t)$ is lost. Moreover, we assume that the battery energy leakage is negligible, which is a reasonable assumption when the timescale over which the loss takes place is much larger than that of interest to us [15]. Then, the dynamics over time of $E_i(t)$ can be described as

$$E_i(t+1) = E_i(t) + \Delta T(G_i^{\text{2b}}(t) - G_i^{\text{b2}}(t)). \tag{3.15}$$

To indicate whether the battery in SMG i is charging or not at slot t, two binary variables are introduced, i.e., $Z_i^{\text{bc}}(t)$ and $Z_i^{\text{bd}}(t)$. Specifically, $Z_i^{\text{bc}}(t) = 1$ if that battery is charging; Otherwise, $Z_i^{\text{bc}}(t) = 0$. Similarly, $Z_i^{\text{bd}}(t) = 1$ if that battery is discharging; Otherwise, $Z_i^{\text{bd}}(t) = 0$. Without loss of generality, we assume that charging and discharging cannot be done simultaneously [13]. Then, we have

$$Z_i^{\text{bc}}(t), Z_i^{\text{bd}}(t) \in \{0, 1\}, \tag{3.16}$$

$$Z_i^{\text{bc}}(t) + Z_i^{\text{bd}}(t) \leq 1, \tag{3.17}$$

$$0 \leq G_i^{\text{2b}}(t) \leq G_i^{\text{cm}} Z_i^{\text{bc}}(t), \tag{3.18}$$

$$0 \leq G_i^{\text{b2}}(t) \leq G_i^{\text{dm}} Z_i^{\text{bd}}(t), \tag{3.19}$$

where G_i^{cm} and G_i^{dm} are the maximum charging and discharging power for the battery in SMG i, respectively.

3.2.2.3 Carbon Emission Model

As shown in [2], carbon emission rate shows spatial and temporal variations. By summing the weighted contribution from each fuel type, we can estimate the carbon emission rate in ER i at slot t ($e_i(t)$). Let $\boldsymbol{e}(t) = (e_1(t), \ldots, e_N(t))$ be the carbon emission rate vector. Then, the total carbon emission $A_i(t)$ (in g) in SMG i is given by

$$A_i(t) = \big(e_i(t)G_i^{\mathrm{g2}}(t) + G_i^{\mathrm{r}}(t)a_1 + G_i^{\mathrm{a}}(t)a_2\big)\Delta T, \tag{3.20}$$

where a_1 and a_2 are the carbon emission rate for wind and diesel oil, respectively. Typically, $a_1 = 22.5$, $a_2 = 890$ (both in g/kWh) [2].

3.3 Problem Formulation and Algorithm Design

Let $C(t)$ (in \$) be the total energy cost of IDC operators at slot t, which consists of four parts, namely, the energy cost associated with buying electricity from main grids, the revenue from selling electricity to main grids, the cost due to the negative effect of the charging and discharging power (charging/discharging power too much may reduce the lifetime of the battery), and the generation cost of diesel generators in SMGs. Note that we ignore all fixed costs associated with wind generation (e.g., capital expenditure and fixed operational and maintenance cost) since these parts would not affect the optimization results of the formulated problem as in (3.22a, 3.22b). As a result, the generation cost of wind energy can be assumed to be zero since the variable operational and maintenance costs of wind turbines is negligible [32]. Based on the above analysis, the total energy cost $C(t)$ is given by

$$\begin{aligned} C(t) = &\sum_{i=1}^{N}\{G_i^{\mathrm{g2}}(t)S_i(t) - G_i^{\mathrm{2g}}(t)W_i(t)\}\Delta T + \sum_{i=1}^{N}K_i(t) \\ &+ \sum_{i=1}^{N}(Z_i^{\mathrm{bc}}(t) + Z_i^{\mathrm{bd}}(t))\rho_i^b, \end{aligned} \tag{3.21}$$

where ρ_i^b denotes the cost incurred by battery charging and discharging per time [15]. $S_i(t)$ and $W_i(t)$ (both in \$/MWh) denote the price for purchasing and selling electricity from and to main grid i at slot t, respectively. We assume $S_i(t) \in [S_i^{\min}, S_i^{\max}]$, $W_i(t) \in [W_i^{\min}, W_i^{\max}]$, which are announced by the utility market at the beginning of each time slot and remains constant during the time slot [31]. We assume $S_i(t)$ and $W_i(t)$ are independent of the amount of energy to be purchased or sold in that time slot. Let $\mathbf{S}(t) = (S_1(t), \ldots, S_N(t))$ and $\mathbf{W}(t) = (W_1(t), \ldots, W_N(t))$ be the purchasing and selling price vector, respectively. Moreover, we assume $S_i^{\max} \geq W_i^{\max}$, $S_i^{\min} \geq W_i^{\min}$ and $S_i(t) \geq W_i(t)$ for all t [31]. That is, SMG cannot make profit by greedily purchasing energy from the market and then selling it back to the market at a higher price simultaneously.

As mentioned in Sect. 3.1, socially responsible IDC operators intend to jointly consider the energy cost and carbon emission with guaranteed QoS for service requests. Then, we formulate the carbon-aware energy cost minimization problem as follows,

$$\text{(P3.1)} \ \min \ \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t) + \vartheta \sum_{i=1}^{N} A_i(t)\}, \tag{3.22a}$$

$$\text{s.t. (3.1)–(3.6), (3.9)–(3.19)}, \tag{3.22b}$$

where ϑ (in \$/g) is a scaler (i.e., weighted parameter) that transfers the carbon emission into energy cost. Note that the combination of two performance metrics is a common approach in multi-objective optimization [33]. Moreover, ϑ is equivalent to the corresponding Lagrangian multiplier if we formulate the carbon emission as a constraint. The expectation above is with respect to the stationary distribution of $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^{\mathrm{r}}(t), \boldsymbol{e}(t)\}$ and possibly random control decisions that are made in reaction to the observed $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^{\mathrm{r}}(t), \boldsymbol{e}(t)\}$. Specifically, these control decisions are $\mathbf{m}(t)$, $\boldsymbol{\lambda}(t)$, $\mathbf{G}(t)$, and $\mathbf{Z}(t)$. The definitions of $\mathbf{G}(t)$ and $\mathbf{Z}(t)$ are given as follows:

$$\mathbf{G}(t) = \{G_i^{\mathrm{g2}}(t), G_i^{\mathrm{2g}}(t), G_i^{\mathrm{a}}(t), G_i^{\mathrm{2b}}(t), G_i^{\mathrm{b2}}(t)\}, \tag{3.23}$$

$$\mathbf{Z}(t) = \{Z_i^{\mathrm{g2}}(t), Z_i^{\mathrm{2g}}(t), Z_i^{\mathrm{bc}}(t), Z_i^{\mathrm{bd}}(t)\}. \tag{3.24}$$

To solve P1, we need to know the statistical information about the system parameters, such as electricity price, workload, renewable generation output, and carbon emission rate. However, these parameters are not available or difficult to obtain in practice. In addition, the constraints on energy level of battery bring the "time coupling" property to P3.1, which means that the current decision can impact the future decisions. Previous methods to handle the "time coupling" problem are usually based on dynamic programming, which suffers from the "the curse of dimensionality" problem. Therefore, we propose an operation algorithm to solve P3.1. Before proposing the operation algorithm, we consider the following relaxed problem, which can provide some intuitions to solve P3.1.

3.3.1 Relaxed Problem

Defining the time-averaged expectation of charging and discharging power of the battery at IDC i under any feasible control policy of P3.1 as follows,

$$\overline{G_i^{\mathrm{2b}}} = \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{G_i^{\mathrm{2b}}(t)\}, \tag{3.25}$$

$$\overline{G_i^{\mathrm{b2}}} = \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{G_i^{\mathrm{b2}}(t)\}. \tag{3.26}$$

Since battery energy levels update according to (3.15), summing over all $t \in \{0, 1, 2, \ldots, T-1\}$, taking expectation of both sides and dividing both sides with T and letting $T \to \infty$, we have $\overline{G_i^{\mathrm{2b}}} = \overline{G_i^{\mathrm{b2}}}$. Then, a relaxed problem of P3.1 is given as follows, called P3.2.

$$\text{(P3.2)}\ \min\ \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t) + \vartheta \sum_{i=1}^{N} A_i(t)\}, \tag{3.27a}$$

$$\text{s.t. (3.1)–(3.6), (3.9)–(3.13), (3.16)–(3.19),} \tag{3.27b}$$

$$\overline{G_i^{\mathrm{2b}}} = \overline{G_i^{\mathrm{b2}}}. \tag{3.27c}$$

Let y^* and y^{rel} be the optimal solution of P3.1 and P3.2, respectively. As mentioned before, any feasible solution to P3.1 is also a feasible solution to P3.2. Therefore, we have $y^{\mathrm{rel}} \le y^*$. Obviously, P3.2 is easier to solve than P3.1 due to the removal of "time coupling" property. From the framework of Lyapunov optimization [34], we have the following Theorem for the solution to P3.2:

Theorem 1 *If* $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^r(t), \boldsymbol{e}(t)\}$ *are i.i.d. over slots, then there exists a stationary and randomized policy that takes control decisions* $\hat{\mathbf{m}}(t)$*,* $\hat{\boldsymbol{\lambda}}(t)$*,* $\hat{\mathbf{G}}(t)$ *and* $\hat{\mathbf{Z}}(t)$ *every time slot t as a pure (possibly randomized) function of the observed* $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^r(t), \boldsymbol{e}(t)\}$ *while satisfying the constraints of P3.2 and providing the following guarantees.*

$$\mathbb{E}\{\hat{G}_i^{2b}(t)\} = \mathbb{E}\{\hat{G}_i^{b2}(t)\}, \tag{3.28}$$

$$\mathbb{E}\{\hat{C}(t) + \vartheta \sum_{i=1}^{N} \hat{A}_i(t)\} = y^{\mathrm{rel}}, \tag{3.29}$$

where the expectation operations above are with respect to the stationary distribution of $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^r(t), \boldsymbol{e}(t)\}$ *and randomized control decisions.* $\hat{C}(t)$ *and* $\hat{A}_i(t)$ *are the values defined in* (3.21) *and* (3.20)*, respectively, under the stationary and randomized policy.*

The proof can be obtained according to *Theorem of Optimality over ω-only Policies* in [34]. Thus, it is omitted for brevity. To obtain such a control policy, we need to know the statistical distributions of all combinations of $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^{\mathrm{r}}(t), \boldsymbol{e}(t)\}$, which may be unknown and difficult to obtain. Moreover, the control policy may be infeasible for the original problem P3.1 as it could violate the constraint (3.14). However, the existence of such a control policy ca help us to derive the performance results of the proposed operation algorithm as shown in the part 4 of Theorem 2.

3.3.2 Proposed Operation Algorithm

In this subsection, we propose an online operation algorithm that approximately solves P3.1. The key idea of the proposed operation algorithm is described as follows:

- transforming P3.2 into a queue stability problem according to the framework of Lyapunov optimization technique;
- obtaining the *drift-plus-penalty* term according to the theory of Lyapunov optimization technique;
- minimizing the R.H.S. of the upper bound of the *drift-plus-penalty* term.

According to the above key idea, we introduce battery virtual queues $X(t)$ in order to transform P3.2 into a queue stability problem, where

$$X_i(t) = E_i(t) - E_i^{\min} - \theta_i^{\max} - \Delta T G_i^{\mathrm{dm}}, \tag{3.30}$$

where $\theta_i^{\max}$ is a constant to be explained later. Continually, we have

$$X_i(t+1) = X_i(t) + \Delta T (G_i^{2\mathrm{b}}(t) - G_i^{\mathrm{b}2}(t)). \tag{3.31}$$

According to the framework of Lyapunov optimization in [34], P3.2 can be equivalently transformed to a queue stability problem as follows, named P3.3

$$\text{(P3.3)} \;\; \min \;\; \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t) + \vartheta \sum_{i=1}^{N} A_i(t)\}, \tag{3.32a}$$

$$\text{s.t. (3.1)–(3.6), (3.9)–(3.13), (3.16)–(3.19),} \tag{3.32b}$$

$$\text{Queues } X_i(t) \text{ are mean rate stable.} \tag{3.32c}$$

To obtain the operation algorithm for P3.3, Lyapunov optimization technique is applied. On one hand, the proposed operation algorithm needs to push the queues toward stability. On the other hand, the proposed operation algorithm intends to minimize the objective function. To achieve the trade-off between the aims above, the proposed operation algorithm greedily minimizes the R.H.S. of the upper bound of the *drift-plus-penalty* term (3.37) in every time slot t subjecting to the constraints in P3.3, where the trade-off is implemented by adjusting parameter V. If $V = 0$, it corresponds to the pure system stability problem by minimizing the one-slot conditional Lyapunov drift (3.35). In Theorem 2, we will prove that queues $X_i(t)$ are mean rate stable.

Specifically, we define a Lyapunov function as follows,

$$L(t) \triangleq \frac{1}{2} \sum_{i=1}^{N} \{X_i(t)^2\}. \tag{3.33}$$

Then, the one-slot conditional Lyapunov drift is given by

$$\Delta(t) = \mathbb{E}\{L(t+1) - L(t)|\mathbf{X}(t)\}. \tag{3.34}$$

where $\mathbf{X}(t) = (X_1(t), \ldots, X_N(t))$, the expectation is taken over the randomness of workload, electricity price, renewable generation output, and carbon emission rate, as well as the randomness in choosing the control decisions. We define $\chi_i(t) = G_i^{2\mathrm{b}}(t) - G_i^{\mathrm{b}2}(t)$, then

$$L(t+1) - L(t) \le \omega + \sum_{i=1}^{N} \Big\{X_i(t)\Delta T \chi_i(t)\Big\}, \tag{3.35}$$

where $\omega \triangleq \sum_{i=1}^{N} \frac{(\Delta T \max\{G_i^{\mathrm{cm}}, G_i^{\mathrm{dm}}\})^2}{2}$. Thus, we have

$$\Delta(t) \le \omega + \sum_{i=1}^{N} \mathbb{E}\{X_i(t)\Delta T \chi_i(t)|\mathbf{X}(t)\}. \tag{3.36}$$

Then, following the Lyapunov optimization framework, we add a function of the expected weighted summation of energy cost and carbon emission over one period (i.e., the penalty function) to (3.34) to obtain the following *drift-plus-penalty* expression,

$$\begin{aligned}\Delta Y(t) &= \Delta(t) + V\mathbb{E}\{C(t) + \vartheta \sum_{i=1}^{N} A_i(t)|\mathbf{X}(t)\} \\ &\le \omega + \mathbb{E}\Big\{\sum_{i=1}^{N}[X_i(t)\Delta T \chi_i(t) + \vartheta V A_i(t)] + VC(t)|\mathbf{X}(t)\Big\}.\end{aligned} \tag{3.37}$$

Note that the proposed operation algorithm intends to minimize the R.H.S. of the upper bound of the *drift-plus-penalty* term subject to the constraints in P3.3, which is equivalent to minimize P3.4 as described in Algorithm 1, since the proposed operation algorithm makes scheduling decisions only based on current system states without requiring any statistical knowledge of system parameters. To solve P3.4, which is a MILP, its certain structure can be exploited, i.e., by fixing the discrete variables first, the resulting problem becomes convex for continuous variables. Therefore, Benders decomposition [35] can be adopted to solve P3.4, which can decompose P3.4 into two subproblems. Due to limitations of space, we omit the procedure of Benders decomposition to solve P3.4.

$$\text{(P3.4)} \;\; \min \;\; \sum_{i=1}^{N} \{X_i(t)\Delta T \chi_i(t) + \vartheta V A_i(t)\} + VC(t) \tag{3.38a}$$

$$\text{s.t. } (3.1)\text{–}(3.6),\ (3.9)\text{–}(3.13),\ (3.16)\text{–}(3.19). \tag{3.38b}$$

Algorithm 1 : Operation Algorithm for IDC Operators

1: **For** each time slot t **do**
2: At the beginning of time slot t, obtain system states: $S_i(t)$,$W_i(t)$,$R_f(t)$,$G_i^{\mathrm{r}}(t)$,$e_i(t)$,$X_i(t)$;
3: Choose control decisions $\mathbf{m}(t)$, $\boldsymbol{\lambda}(t)$, $\mathbf{G}(t)$, and $\mathbf{Z}(t)$ as the solution to P3.4;
4: Update $X_i(t)$ according to (3.31).
5: **End**

3.4 Analysis and Simulations

In this subsection, we analyze the feasibility and algorithmic performance of the proposed operation algorithm.

To start with, we define an upper bound $V^{\max}$ on parameter V as follows, i.e.,

$$V^{\max} = \min_i \{V|\theta_i^{\max} - \theta_i^{\min} \leq E_i^{\max} - E_i^{\min} - \ell\}, \tag{3.39}$$

where $\ell = \Delta T(G_i^{\mathrm{cm}}+G_i^{\mathrm{dm}})$, $\theta_i^{\max} = \max\{VH_i^{\max}+\vartheta Va_2, \vartheta Ve_i^{\max}+VS_i^{\max}, VW_i^{\max}\}$, $H_i^{\max} = \max_{j,b}\{H_{i,j,b}\}$, $e_i^{\max} = \max_t\{e_i(t)\}$, $\theta_i^{\min} = \min\{VW_i^{\min}, VS_i^{\min} + \vartheta Ve_i^{\min}, VH_i^{\min} + \vartheta Va_2\}$, $e_i^{\min} = \min_t\{e_i(t)\}$, $H_i^{\min} = \min_{j,b}\{H_{i,j,b}\}$. Note that how to choose the above parameters is the key to design an efficient operation algorithm. In fact, these parameters can be obtained from the proof procedure of the following Lemma and Theorem.

3.4.1 Analysis

Note that the optimal solution to P3.4 has the following properties that are useful for the following analysis of algorithmic performance.

Lemma 1 *The optimal solution to P3.4 has the following properties:*

1. *If $X_i(t) < -\theta_i^{\max}$, the optimal solution always choose $G_i^{b2}(t) = 0$.*
2. *If $X_i(t) > -\theta_i^{\min}$, the optimal solution always choose $G_i^{2b}(t) = 0$.*

Proof

1. For each SMG i, suppose that $X_i(t) < -\theta_i^{\max}$ and $G_i^{\mathrm{b2}}(t) > 0$, then, we have $G_i^{\mathrm{2b}}(t) = 0$. Let $\Gamma_1(t)$ denote the optimal value of the objective in P3.4, which is the summation of $\Gamma_{1,i}(t)$ at all IDCs.
   To prove that the above decision is not optimal, we choose $\tilde{G}_i^{\mathrm{b2}}(t) = 0$, and $\tilde{G}_i^{\mathrm{2b}}(t) = 0$. Let $\Gamma_2(t)$ denote the value of the objective in P3.4, which is the summation of $\Gamma_{2,i}(t)$ at all IDCs. According to (3.9), the decisions about power supply for IDCs given the power demand $P_i(t)$ can be divided into the following cases:

Case **1**: If $G_i^{g2}(t) = G_i^{2g}(t) = 0$, we set $\tilde{G}_i^{g2}(t) = G_i^{g2}(t)$, $\tilde{G}_i^{2g}(t) = G_i^{2g}(t)$, then, we have $G_i^{a}(t) + G_i^{b2}(t) = \tilde{G}_i^{a}(t)$. Continually, we can obtain that $\Gamma_{1,i}(t) > \Gamma_{2,i}(t)$ when $X_i(t) < -(VH_i^{\max} + \vartheta Va_2)$.
Case **2**: If $G_i^{g2}(t) > 0$, $G_i^{2g}(t) = 0$, we set $\tilde{G}_i^{2g}(t) = G_i^{2g}(t)$, $\tilde{G}_i^{a}(t) = G_i^{a}(t)$. Then, we have $G_i^{g2}(t) + G_i^{b2}(t) = \tilde{G}_i^{g2}(t)$. Continually, we can obtain that $\Gamma_{1,i}(t) > \Gamma_{2,i}(t)$ when $X_i(t) < -(VS_i^{\max} + \vartheta Ve_i^{\max})$. Note that if we set $\tilde{G}_i^{2g}(t) = G_i^{2g}(t)$, and $\tilde{G}_i^{g2}(t) = G_i^{g2}(t)$ under this case, the situation is the same as the case 1.
Case **3**: If $G_i^{g2}(t) = 0$, $G_i^{2g}(t) > 0$, we set $\tilde{G}_i^{g2}(t) = G_i^{g2}(t)$, $\tilde{G}_i^{a}(t) = G_i^{a}(t)$. Then, we have $G_i^{2g}(t) - G_i^{b2}(t) = \tilde{G}_i^{2g}(t)$. Continually, we can obtain that $\Gamma_{1,i}(t) > \Gamma_{2,i}(t)$ when $X_i(t) < -VW_i^{\max}$. Note that if we set $\tilde{G}_i^{g2}(t) = G_i^{g2}(t)$, and $\tilde{G}_i^{2g}(t) = G_i^{2g}(t)$ under this case, the situation is the same as the case 1.
Taking three cases into consideration, we know that when $X_i(t) < -\theta_i^{\max}$, the optimal decision always choose $G_i^{b2}(t) = 0$.

2. For each SMG i, if $X_i(t) > -\theta_i^{\min}$ and $G_i^{2b}(t) > 0$, we have $G_i^{b2}(t) = 0$. Let $\Gamma_3(t)$ be the optimal value of the objective of P3.4, which is the summation of $\Gamma_{3,i}(t)$ at all IDCs. To prove the above decision is not optimal, we choose $\tilde{G}_i^{2b}(t) = 0$ and $\tilde{G}_i^{b2}(t) = 0$. Then, the value of the objective of P3.4 $\Gamma_4(t)$ is the summation of $\Gamma_{4,i}(t)$ at all IDCs. According to (3.9), the decisions about power supply for IDCs given the power demand $P_i(t)$ can be divided into the following cases:
Case **1**: If $\tilde{G}_i^{g2}(t) = G_i^{g2}(t)$, $\tilde{G}_i^{2g}(t) = G_i^{2g}(t)$, then, $G_i^{a}(t) - G_i^{2b}(t) = \tilde{G}_i^{a}(t)$. Continually, we can obtain that $\Gamma_{3,i}(t) > \Gamma_{4,i}(t)$ when $X_i(t) > -(VH_i^{\min} + \vartheta Va_2)$.
Case **2**: If $G_i^{g2}(t) > 0$, $G_i^{2g}(t) = 0$, we set $\tilde{G}_i^{2g}(t) = G_i^{2g}(t)$, $\tilde{G}_i^{a}(t) = G_i^{a}(t)$, then $G_i^{g2}(t) - G_i^{2b}(t) = \tilde{G}_i^{g2}(t)$. Continually, we can obtain that $\Gamma_{3,i}(t) > \Gamma_{4,i}(t)$ when $X_i(t) > -(VS_i^{\min} + \vartheta Ve_i^{\min})$.
Case **3**: If $G_i^{g2}(t) = 0$, $G_i^{2g}(t) > 0$, we set $\tilde{G}_i^{g2}(t) = G_i^{g2}(t)$, $\tilde{G}_i^{a}(t) = G_i^{a}(t)$, then $G_i^{2g}(t) + G_i^{2b}(t) = \tilde{G}_i^{2g}(t)$. Continually, we can obtain that $\Gamma_{3,i}(t) > \Gamma_{4,i}(t)$ when $X_i(t) > -VW_i^{\min}$. Taking three cases into consideration, we know that when $X_i(t) > -\theta_i^{\min}$, the optimal decision always choose $G_i^{2b}(t) = 0$.

Theorem 2 *Suppose the initial battery energy level $E_i(0) \in [E_i^{\min}, E_i^{\max}]$. Implementing the proposed operation algorithm with any fixed parameter $V \in (0, V^{\max}]$, we have the following performance guarantees for each IDC i:*

1. *The battery energy level $E_i(t)$ is always in the range $[E_i^{\min}, E_i^{\max}]$ for all time slots.*
2. *All control decisions are feasible.*
3. *Queues $X_i(t)$ are mean rate stable.*
4. *If $\{\mathbf{S}(t), \mathbf{W}(t), \mathbf{R}(t), \mathbf{G}^r(t), \boldsymbol{e}(t)\}$ are i.i.d. over slots, then the time-averaged expectation of objective function under the proposed operation algorithm is within bound ω/V of the optimal value:*

$$\limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t) + \vartheta \sum_{i=1}^{N} A_i(t)\} \leq y^* + \frac{\omega}{V}. \tag{3.40}$$

Proof

1. To show $E_i(t) \in [E_i^{\min}, E_i^{\max}]$, according to the definition of $X_i(t)$, it is equivalent to show that for each IDC i, $-\theta_i^{\max} - \Delta TG_i^{\mathrm{dm}} \leq X_i(t) \leq E_i^{\max} - E_i^{\min} - \theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$, As $E_i^{\min} \leq E_i(0) \leq E_i^{\max}$, the above inequalities hold for $t = 0$. We prove that the above inequalities are satisfied for all periods by induction. Suppose the above inequalities about $X_i(t)$ hold for time slot t, we need to prove that the inequalities are also hold for time slot $t + 1$.
   - If $-\theta_i^{\max} - \Delta TG_i^{\mathrm{dm}} \leq X_i(t) < -\theta_i^{\max}$, then, according to Lemma 1, the optimal decision would choose $G_i^{\mathrm{b2}}(t) = 0$. Thus, $X_i(t+1) \geq X_i(t) \geq -\theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$. If $-\theta_i^{\max} \leq X_i(t) < E_i^{\max} - E_i^{\min} - \theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$, then, according to (3.30), $X_i(t+1) \geq -\theta_i^{\max} - \Delta TG_i^{\mathrm{b2}}(t) > -\theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$.
   - If $-\theta_i^{\min} < X_i(t) \leq E_i^{\max} - E_i^{\min} - \theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$, then, according to Lemma 1, the optimal decision would choose $G_i^{\mathrm{2b}}(t) = 0$. Thus, $X_i(t+1) \leq X_i(t) \leq E_i^{\max} - E_i^{\min} - \theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$. If $-\theta_i^{\max} - \Delta TG_i^{\mathrm{dm}} \leq X_i(t) \leq -\theta_i^{\min}$, then, $X_i(t+1) \leq -\theta_i^{\min} + \Delta TG_i^{\mathrm{cm}} \leq E_i^{\max} - E_i^{\min} - \theta_i^{\max} - \Delta TG_i^{\mathrm{dm}}$, where we have used the following condition, $\theta_i^{\max} - \theta_i^{\min} \leq E_i^{\max} - E_i^{\min} - \Delta T(G_i^{\mathrm{cm}} + G_i^{\mathrm{dm}})$.
2. From the part 1 of Theorem 2, we know that $E_i^{\min} \leq E_i(t) \leq E_i^{\max}$ holds for any time slot t and i. Furthermore, the proposed algorithm makes decision to satisfy all constraints in P3.4. Considering the definition of $X_i(t)$, we know that all constraints of P3.1 could be satisfied. Therefore, the control decisions are feasible to P3.1.
3. According to the part 1 of Theorem 2, we have

$$\limsup_{T\to\infty} \frac{1}{T} \mathbb{E}\{|X_i(T)|\} = 0. \tag{3.41}$$

   Thus, queues $X_i(t)$ are mean rate stable.
4. By plugging the policy mentioned in Theorem 1 into the R.H.S. of (3.37), then we have

$$\Delta Y(t) \leq \omega + V\mathbb{E}\{\hat{C}(t) + \vartheta \sum_{i=1}^{N} \hat{A}_i(t)\} = \omega + Vy^{\mathrm{rel}} \leq \omega + Vy^*. \tag{3.42}$$

   Taking the expectation of both sides, using the law of iterative expectation. Then, summing the result over $t \in \{0, 1, 2, \ldots, T-1\}$, we have

$$V\sum_{t=0}^{T-1}\mathbb{E}\{C(t)+\vartheta\sum_{i=1}^{N}A_i(t)\}\leq \omega T+VTy^*-\mathbb{E}\{L(T)\}+\mathbb{E}\{L(0)\}. \quad (3.43)$$

Dividing both side by VT, and taking a lim sup of both sides. Let $T\rightarrow\infty$, and using the facts that $E\{L(0)\}$ is finite and $E\{L(T)\}$ is nonnegative, we obtain the result as in (3.40).

3.4.2 Simulations

In this section, we describe the system parameters and real-world data used in simulations. The carbon-oblivious algorithm in [22] is chosen as the baseline, which only consider buying electricity from the grid. For fair comparison, renewable energy is incorporated in the baseline.

3.4.2.1 Real-World Traces and Experimental Setup

We consider a scenario that the total workload from one front-end web portal server is forwarded to two back-end IDCs located in two independent ERs, i.e., $F=1, N=2$. Some parameters about servers in IDCs are set as follows: $P_1^{\text{peak}}=250\,\text{W}$, $P_2^{\text{peak}}=240\,\text{W}$, $P_1^{\text{idle}}=175\,\text{W}$, $P_2^{\text{idle}}=168\,\text{W}$, $\text{PUE}_1=2.5$, $\text{PUE}_2=2.4$ [1], $M_1=$22,000, $M_2=$35,000, $\mu_1=2$ requests/second, $\mu_2=1.75$ requests/second, $D_i^{\max}=0.7\,\text{s}$, $\Delta T=1\,\text{h}$. In this chapter, we assume that generators in each IDC have the capacity to power the whole IDC, which is quite common in industry. Specifically, each IDC has 10 diesel generators with model TP-C2000-T2-60 (2 MW) and 5 diesel generators with model TP-C100-T1-60 (100 kW) [36], where the parameters $H_{i,j,b}$ and $\alpha_{i,j,b}$ can be estimated as in [29, 37]. According to the recent empirical experiments, we assume that the limits of battery charging/discharging rates are $P^{\text{cm}}=P^{\text{dm}}=0.5\,\text{MW}$, and charging/discharging cost is $\rho_i^b=0.1$ dollars [15], $V=V^{\max}$. As in [22], we assume that two IDCs are located in California and Houston, respectively. Then, the corresponding carbon emission rates in these locations are [200–399] g/kWh and [400–599] g/kWh, respectively [2]. For simplicity, we assume that carbon emission rate follows a uniform distribution. The wind speed information is obtained from the dataset published by the National Renewable Energy Laboratory. In addition, V90 wind turbine is adopted in this chapter.[3] The real-time electricity price traces of the U.S. NYISO and ERCOT markets in 2012 are used. Based on the traces, we calculate the average electricity price during the disjoint hour. Moreover, we set $W_i(t)=0.9S_i(t)$ [38]. The real-world workload data is taken from FIFA's 1998 World Cup web traces. Moreover, the original workload is enlarged by 60 times taking into

[3] http://www.vestas.com/en/wind-power-plants/, Sept. 2013.

account the increase of Internet traffic in the past decade.[4] In simulations, we choose $E_i^{\min} = 0$, $E_1^{\max} = 6.875$ MWh, $E_2^{\max} = 10.08$ MWh. Note that the storage capacity can power the peak demand of two IDCs for 30 min, which is the duration that UPS units can usually support in existing data centers [15].

3.4.2.2 Simulation Results

In Fig. 3.2, $V^{\max}$ and the weighted summation of energy cost and carbon emission with varying ϑ are depicted. It can be observed that $V^{\max}$ increases with the increase of ϑ, which leads to the increased weighted summation as shown by the part 4 of Theorem 2. Though the part 4 of Theorem 2 holds when future random parameters are i.i.d. over slots, the simulation results based on real-world traces (without any specific distribution assumption) show that the proposed algorithm is robust to non-i.i.d. and nonergodic cases (note that the theoretical basis for such robustness can be found in [34]).

As shown in Figs. 3.3 and 3.4, with the increase of ϑ, there is a trade-off between energy cost and carbon emission under the proposed algorithm. The rationale of such a trade-off is that larger ϑ would lead to a larger weight on minimizing carbon

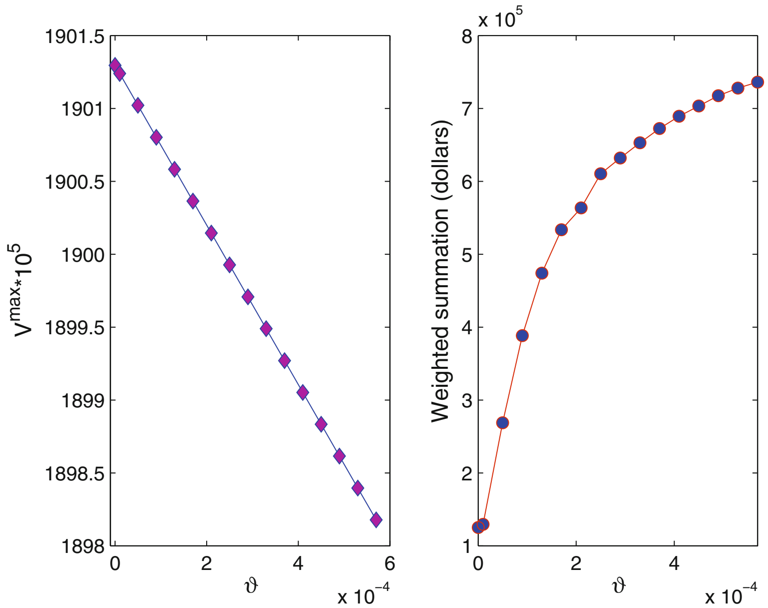

Fig. 3.2 $V^{\max}$ and weighted summation under different ϑ

[4] E.g., the average workload is smaller than 2 million requests/h, while the average workload of Google search is 121 million requests/h.

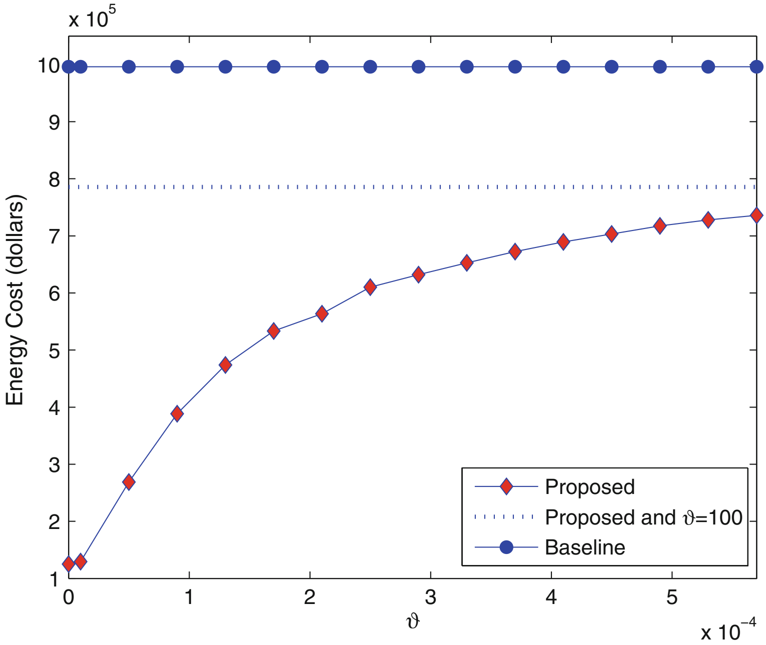

Fig. 3.3 Energy cost versus ϑ under different algorithms

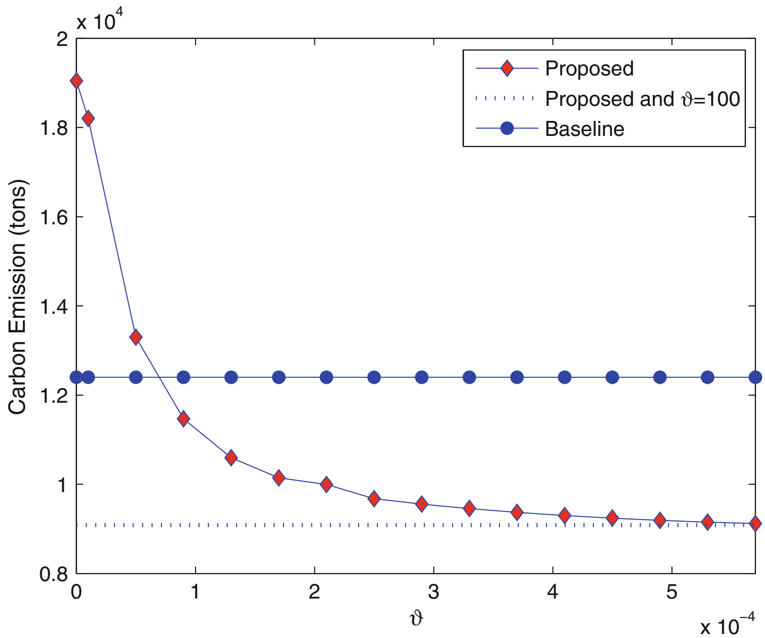

Fig. 3.4 Carbon emission versus ϑ under different algorithms

emission. As a result, the proposed algorithm would migrate an appropriate amount of workload from the IDCs in low-price ERs to the IDCs in low-carbon ERs, leading to both carbon emission reduction and energy cost rise.

The proposed algorithm can achieve lower energy cost and lower carbon emission than the benchmark when ϑ is larger than 9×10^{-5}. Specifically, compared with the benchmark, the proposed algorithm can reduce the energy cost by 6×10^5 dollars without increasing carbon emission when $\vartheta = 9 \times 10^{-5}$. When $\vartheta = 100$, the proposed algorithm can reduce carbon emission and energy cost by 3,316 tons and 210,610 dollars, respectively. The reason can be explained as follows: the surplus renewable energy in a SMG can be stored into the battery for future use or sold to the main grid for profit under the proposed algorithm, but it would be wasted under the benchmark.

3.5 Summary

In this chapter, we investigated the problem of minimizing carbon-aware energy cost for distributed IDCs in smart microgrids. First, we formulated the problem as a stochastic optimization problem to minimize the time-averaged expectation of the weighted sum of energy cost and carbon emission with the uncertainties in electricity price, workload, renewable energy output, and carbon emission rate. To solve the formulated problem, we designed an operation algorithm based on Lyapunov optimization technique without requiring any system statistics. Finally, evaluations based on real-world data showed that the effectiveness of the proposed algorithm.

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Chapter 4
Joint Workload and Battery Scheduling for Data Center Energy Cost Minimization

Abstract In practice, some workloads are delay-tolerant, which can be adopted to reduce energy cost of Internet data centers by utilizing the temporal diversity of electricity prices, i.e., executing the workloads when prices are low and delay the workloads when prices are high. To avoid the penalty for violating the service level agreements, heterogeneous service delay guarantees must be provided by Internet data center operators. Moreover, to fully utilize the temporal diversity of electricity prices, energy storage devices are incorporated. Thus, in this chapter, we focus on designing a joint workload and energy storage scheduling with heterogeneous service delay guarantees for data center energy cost minimization and propose an effective algorithm to save energy cost.

Keywords Internet data center · Energy cost · Heterogeneous service delay guarantees · Energy storage

4.1 Introduction

With the proliferation of cloud computing and Internet online services, massive Internet data centers (IDCs) have been built to meet the skyrocketing demand. In IDC operations, a critical issue is the energy cost. According to a recent study, many IDC operators (e.g., Microsoft and Google) spend more than $30 million on their annual electricity costs, which contribute to a large portion of IDC operational expenditure [1].

To reduce energy cost for IDCs, lots of work have been done that exploit the temporal and spatial variations of electricity price in deregulated electricity markets [2–6]. When minimizing energy cost, IDC operators should guarantee service level agreements (SLAs) for all requests since SLA violation would result in lost business revenue [7]. For different requests, their SLA requirements may be very different [8]. For example, average delay (or 95th percentile delay) is usually adopted as the SLA metric for delay-sensitive requests (e.g., web search requests) [2, 5], while service delay deadline (or completion time) is used as the SLA metric for delay-tolerant requests (e.g., batch jobs) [9, 10]. In most existing work on delay-tolerant requests, average delay [6, 11] (or the same worst-case delay [4, 12], or the same service delay guarantee [3]) is considered in IDC operations, which may lead to SLA violations for

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delay-tolerant requests. Moreover, IDC operators could reduce energy cost by fully exploiting the temporal diversity of electricity price when heterogeneous service delay guarantees are provided. Thus, it is necessary for IDC operators to provide heterogeneous service delay guarantees for delay-tolerant requests.

Based on the above observations, we investigate the problem of minimizing the energy cost for an IDC in deregulated electricity markets considering heterogeneous service delay guarantees for delay-tolerant requests. Moreover, batteries (which are usually incorporated in an IDC for reliability considerations [4, 5]) are adopted to fully exploit the temporal diversity of electricity price. Specifically, we consider an IDC operator who intends to minimize the long-term energy cost for an IDC by scheduling workload and battery jointly.

To achieve the above target, the challenge is how to efficiently manage the battery operation and simultaneously provide heterogeneous service delay guarantees for admitted requests. In existing works on data centers [4–6, 12–16], several schemes have been developed to exploit battery based on Lyapunov optimization technique [17]. However, these schemes can only provide the same worst-case service delay, rather than heterogeneous service delay guarantees. Thus, we need to design a new operation algorithm.

In this chapter, we propose a novel three-stage decision framework shown in Fig. 4.1 to deal with the above challenge. Specifically, in the first stage, admission control module decides to accept or reject the incoming requests based on available capacity. In the second stage, workload scheduling module allocates capacity to the accepted requests (which are enqueued into a FIFO queue), so that their service delays could be guaranteed and the energy cost of finishing each request is minimized. In the third stage, battery scheduling module decides the optimal battery operation with obtained energy demand information. To obtain the optimal decisions in above stages, we design a low-complexity operation algorithm based on Lyapunov optimization technique.

The main contributions of this chapter can be listed below:

- By taking heterogeneous service delay guarantees and battery management into consideration, we formulate a stochastic optimization problem to minimize the total energy cost of an IDC.

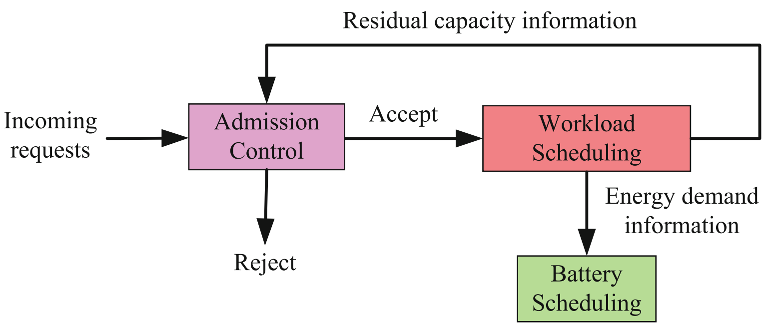

Fig. 4.1 The proposed three-stage decision framework

- We design a low-complexity operation algorithm to solve the problem based on Lyapunov optimization technique. Moreover, we analyze the feasibility of the proposed algorithm and its performance guarantee.
- Extensive evaluations based on real-world data show that the proposed algorithm can achieve lower energy cost than the existing schemes.

The rest of this chapter is organized as follows. Section 4.2 describes the system model. Problem formulation and algorithm design are conducted in Sect. 4.3. Section 4.4 gives the algorithmic performance analysis and simulations. Finally, conclusions are made in Sect. 4.5.

4.2 System Model

In this section, we model an IDC system and formulate a long-term energy cost minimization problem. First, we describe IDC capacity, workload model, and battery model. Then, we formulate a stochastic optimization problem to minimize the total energy cost for an IDC.

4.2.1 Internet Data Center Capacity

We consider a discrete-time system evolving over a sequence of equal-length time slots. As in [3], we quantify the capacity of an IDC by the maximum amount of work that can be done with all IDC resources in a time slot. All IDC resources are quantified in unit of *basic resource unit*. A *basic resource unit* may include a number of microprocessor cores, an amount of memory and so on. Thus, an IDC capacity is in unit of *basic resource unit·time slot*. When an IDC receiving service requests, it needs to allocate a certain amount of capacity for them. Generally, there are two type of service requests in an IDC, i.e., delay-sensitive and delay-tolerant requests [3]. In this chapter, we focus on the jobs in delay-tolerant requests, assuming that the management of delay-sensitive requests has been determined by previous schemes [2]. As many-core computing and massive-scale deployment of commodity computers become the norm in data centers, interest in parallelizing applications keeps growing. Target parallelized applications, we assume that a service request can be decomposed into several tasks that are small enough to finish in one time slot [3].

4.2.2 Workload Model

Let $\mathscr{N}(t)$ represent the set of jobs or requests that arrive in time slot t, while $n(t)$ represents the number of jobs in $\mathscr{N}(t)$, i.e., $n(t) = |\mathscr{N}(t)|$, where $|\cdot|$ denotes the cardinality of a set. Suppose that there are N types of jobs, and each type may correspond to a specific application. Assume that all jobs are computation-intensive, and CPU resource is the bottleneck resource. For simplicity, we assume that all jobs arrive at the beginning of each slot. A job i with type f $(1 \le f \le N)$ arrives in time slot t could be represented by a tuple: $(i, t, f, a_i(t), d_i(t), D_i(t), \mathbf{A}_i(t))$, where $i \in \mathcal{N}(t)$, $a_i(t)$ is an indicator variable to show whether job i is admitted or not, $d_i(t)$ denotes the computation demand[1] (in *basic resource unit·time slot*), $D_i(t)$ denotes the maximum number of time slots allowed for finishing the job i from its arrival time t, i.e., the job i must be served before the beginning of time slot $t + D_i(t)$. Let $D^{\max}$ be the maximum completion time allowed for any job, i.e., $D^{\max} \triangleq \max\limits_{i,t} D_i(t)$. Let $\mathbf{A}_i(t)$ be the capacity allocation vector for job i that arrives in time slot t, which can be expressed by $\big(e_i(0), \ldots, e_i(j), \ldots, e_i(D_i(t) - 1)\big)$, where $e_i(j)$ denotes the allocated capacity in slot $t + j$ $(0 \le j \le D_i(t) - 1)$. If a job i arrives at slot t is admitted into the system, then, we have

$$\sum_{j=0}^{D_i(t)-1} e_i(j) = d_i(t), \tag{4.1}$$

$$0 \le e_i(j) \le \Lambda(t + j), \tag{4.2}$$

where $\Lambda(t+j)$ represents the residual IDC capacity in time slot $t+j$ $(0 \le \Lambda(t+j) \le M$, M denotes IDC capacity). Then, the total residual IDC capacity for job i is $\sum_{j=0}^{D_i(t)-1} \Lambda(t + j)$.

4.2.3 Battery Model

Let $G(t)$ be the power purchased from the main grid at slot t. $G^{\mathrm{b2}}(t)$ and $G^{\mathrm{2b}}(t)$ are the discharging and charging power for the battery at slot t, respectively. Let $P(t)$ be total power consumption of servers at time slot t. Then, according to the power balance, we have

$$G(t) + G^{\mathrm{b2}}(t) = P(t) + G^{\mathrm{2b}}(t), \tag{4.3}$$

where $G(t) \le G^{\mathrm{bmax}}$, G^{bmax} denotes the maximum purchasing power from the main grid, which is determined by the capacity of transformers and power transmission lines [18]. For simplicity, we assume that the transmission loss is negligible and the capacity of transformers and power transmission lines is large enough [18], i.e., $G^{\mathrm{bmax}} \ge \max\limits_{t}\{P(t) + G^{\mathrm{2b}}(t)\}$.

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[1] In this study, we neglect the job's service demands in terms of memory, storage, network for simplicity. Note that they can also be considered if we extend the service demand from a scalar to a vector in which each element corresponds to one type of demand.

Let $E(t)$ be the energy level of the battery at the beginning of slot t. Then, we have

$$E^{\min} \leq E(t) \leq E^{\max}, \tag{4.4}$$

where $E^{\max} \geq 0$ is the maximum capacity, and $E^{\min} \geq 0$ is the minimum capacity, which may be set by the battery deep discharge protection settings. As in [4], we do not explicitly consider some practical issues, such as energy leakage in the battery or DC/AC conversion loss, which can be readily incorporated. Then, the energy dynamics of the battery can be described as follows:

$$E(t+1) = E(t) + \Delta T(G^{2b}(t) - G^{b2}(t)), \tag{4.5}$$

where ΔT denotes the length of a time slot.

To indicate whether the battery is charging or not at slot t, two binary variables are introduced, i.e., $Z^{bc}(t)$ and $Z^{bd}(t)$. Specifically, $Z^{bc}(t) = 1$ if that battery is charging; Otherwise, $Z^{bc}(t) = 0$. Similarly, $Z^{bd}(t) = 1$ if that battery is discharging; Otherwise, $Z^{bd}(t) = 0$. Without loss of generality, we assume that charging and discharging cannot be done simultaneously [5]. Then, we have

$$Z^{bc}(t), Z^{bd}(t) \in \{0, 1\}, \tag{4.6}$$

$$Z^{bc}(t) + Z^{bd}(t) \leq 1, \tag{4.7}$$

$$0 \leq G^{2b}(t) \leq G^{cm} Z^{bc}(t), \tag{4.8}$$

$$0 \leq G^{b2}(t) \leq G^{dm} Z^{bd}(t), \tag{4.9}$$

where G^{cm} and G^{dm} are the maximum charging and discharging power for the battery, respectively.

4.2.4 Energy Cost Model

Let $C(t)$ be the total energy cost of the data center at slot t. Then, $C(t)$ is composed of two parts, i.e., the energy cost associated with buying electricity and the cost due to the negative effect of the charging and discharging power [4]. Based on the above analysis, $C(t)$ is given by

$$C(t) = G(t)S(t)\Delta T + (Z^{bc}(t) + Z^{bd}(t))\rho^b, \tag{4.10}$$

where ρ^b denotes the cost incurred by battery charging and discharging per time, which are assumed to be the same [4, 5]. $S(t)$ denotes the electricity price at slot t. We suppose that $S(t) \in [S^{\min}, S^{\max}]$, and $S(t)$ is independent of the amount of energy to be purchased at slot t. As in [19], we assume that the short-term estimated electricity price can be accurately forecasted, i.e., we know $\mathbf{S}(t) = (S(t), S(t+1), \ldots, S(t + D^{\max} - 1))$. Meanwhile, in later parts, we will discuss the case that $\mathbf{S}(t)$ is not accurately estimated.

4.3 Problem Formulation and Algorithm Design

In this chapter, we are interested in minimizing the time-averaged expected energy cost (i.e., the expected energy cost averaged over the infinite time horizon). Compared with existing work on energy cost reduction for data centers [3, 4], we formulate the minimization problem (i.e., P4.1) by jointly considering heterogeneous service delay guarantees for delay-tolerant requests and battery management.

$$\text{(P4.1)} \quad \min \ \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)\}, \tag{4.11a}$$

$$\text{s.t. } (4.1)-(4.9), \tag{4.11b}$$

where the expectation above is with respect to the stationary distribution of $\{n(t), d_i(t), S(t+k), k \geq D^{\max}\}$ and possibly random control decisions that are made in reaction to the observed system states. Specifically, these control decisions are $e_i(j)$, $G^{2b}(t)$, $G^{b2}(t)$, $G(t)$, $Z^{bc}(t)$, $Z^{bd}(t)$.

According to (4.3) and (4.10), we can rewrite P4.1 as follows:

$$\min \ \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{(G^{2b}(t) - G^{b2}(t))S(t)\Delta T$$

$$+ P(t)S(t)\Delta T + (Z^{bc}(t) + Z^{bd}(t))\rho^{b}\}, \tag{4.12a}$$

$$\text{s.t. } (4.1), (4.2), (4.4)-(4.9). \tag{4.12b}$$

Notice that $\limsup_{T\to\infty} \sum_{t=0}^{T-1} P(t)S(t)\Delta T$ represents the total energy cost, which is equal to the summation of the energy cost for executing all jobs. That is,

$$\limsup_{T\to\infty} \sum_{t=0}^{T-1} P(t)S(t)\Delta T = \limsup_{T\to\infty} \sum_{t=0}^{T-1} \sum_{i=1}^{\tilde{n}(t)} \sum_{j=0}^{D_i(t)-1} e_i(j)S(t+j)\eta, \tag{4.13}$$

where η denotes the amount of consumed energy to execute one unit of computation demand [3], and $\tilde{n}(t)$ denotes the number of jobs that are admitted into the system, i.e., $0 \leq \tilde{n}(t) \leq n(t)$. Obviously, IDC operators expect that $\tilde{n}(t) = n(t)$, i.e., there is no workload drop. To evaluate the extent of workload drop, we define workload drop ratio (WDR) as the ratio of the total workload dropped to the total workload arriving at the IDC:

$$\text{WDR} = 1 - \frac{\sum_{t=0}^{T-1} \sum_{i=1}^{\tilde{n}(t)} d_i(t)}{\sum_{t=0}^{T-1} \sum_{i=1}^{n(t)} d_i(t)}. \tag{4.14}$$

Now, we can reformulate P4.1 as follows:

$$\text{(P4.2)}\ \min\ \limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{F(t)\}, \tag{4.15a}$$

$$\text{s.t. } (4.1), (4.2), (4.4)-(4.9), \tag{4.15b}$$

where $F(t) \triangleq \sum_{i=1}^{\tilde{n}(t)} \sum_{j=0}^{D_i(t)-1} e_i(j)S(t+j)\eta + (G^{2\mathrm{b}}(t) - G^{\mathrm{b}2}(t))S(t)\Delta T + (Z^{\mathrm{bc}}(t) + Z^{\mathrm{bd}}(t))\rho^b$.

There are two challenges to solve P4.2. On one hand, the future random parameters are not known. On the other hand, the constraints on the energy level of battery bring the "time coupling" property to P4.2, which means that the current decision can impact the future decisions. Previous methods to handle the "time coupling" problem are usually based on dynamic programming, which suffers from the "the curse of dimensionality" problem.

In this section, we design a joint workload and battery scheduling algorithm based on Lyapunov optimization technique. Because of the time coupling constraint (4.5), we first consider a relaxed problem, which fits into the framework of Lyapunov optimization. Then, we design our algorithm based on the insights provided by the relaxed problem.

4.3.1 Relaxed Problem

In this subsection, a relaxed problem of P4.2 is considered. Defining the time-averaged expectation of charging and discharging power of the battery at the IDC under any feasible control policy of P4.2 as follows,

$$\overline{G^{2\mathrm{b}}} = \limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{G^{2\mathrm{b}}(t)\}, \tag{4.16}$$

$$\overline{G^{\mathrm{b}2}} = \limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{G^{\mathrm{b}2}(t)\}. \tag{4.17}$$

Since battery energy levels update according to (4.5), summing over all $t \in \{0, 1, 2, \ldots, T-1\}$, taking expectation of both sides and dividing both sides with T and letting $T \to \infty$, we have $\overline{G^{2\mathrm{b}}} = \overline{G^{\mathrm{b}2}}$. Then, a relaxed problem is given as follows, called P4.3.

$$\text{(P4.3)}\ \min\ \limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{F(t)\}, \tag{4.18a}$$

$$\text{s.t. } (4.1), (4.2), (4.6)-(4.9), \tag{4.18b}$$

$$\overline{G^{2b}} = \overline{G^{b2}}. \tag{4.18c}$$

Let y^* and y^{rel} be the optimal solution of P4.2 and P4.3, respectively. As mentioned before, any feasible solution to P4.2 is also a feasible solution to P4.3. Therefore, we have $y^{rel} \le y^*$. Obviously, P4.3 is easier to solve than P4.2 due to the removal of "time coupling" property. From the framework of Lyapunov optimization [17], we have the following Theorem for the solution to P4.3:

Theorem 1 *If $\{n(t), d_i(t), S(t+k), k > D^{\max}, \forall i,\ t,\ k\}$ are i.i.d. over slots, then there exists a stationary and randomized policy that takes control decisions every slot t as a pure (possibly randomized) function of the observed system states, while satisfying the constraints of P4.2 and providing the following guarantees.*

$$\mathbb{E}\{\hat{G}^{2b}(t)\} = \mathbb{E}\{\hat{G}^{b2}(t)\}, \tag{4.19}$$

$$\mathbb{E}\{\hat{F}(t)\} = y^{rel}, \tag{4.20}$$

where the expectation operations above are taken with respect to the randomness in $\{n(t), d_i(t), S(t+k), k > D^{\max}, \forall i,\ t,\ k\}$ and (potentially) randomized control decisions. $\hat{F}(t)$ denotes the value of $F(t)$ under the stationary and randomized policy.

The proof can be obtained according to *Theorem of Optimality over ω-only Policies* in [17]. Thus, it is omitted for brevity.

To obtain such a control policy, we need to know the statistical distribution of $\{n(t), d_i(t), S(t+k), k > D^{\max}, \forall i,\ t,\ k\}$, which may be unknown and difficult to obtain. Moreover, the control policy may be infeasible for P4.2 as it could violate the constraint (4.4). However, the existence of such a control policy can help us to derive the performance guarantee of the proposed operation algorithm as shown in the part 3 of Theorem 2.

4.3.2 Proposed Operation Algorithm

The key idea of the proposed operation algorithm is described as follows:

- transforming P4.3 into a queue stability problem according to the framework of Lyapunov optimization technique;
- obtaining the *drift-plus-penalty* term according to the theory of Lyapunov optimization technique;
- minimizing the R.H.S. of the upper bound of the *drift-plus-penalty* term.

According to the above key idea, we introduce battery virtual queues $X(t)$ in order to transform P4.3 into a queue stability problem, where

$$X(t) = E(t) - \theta, \tag{4.21}$$

where θ is a constant to be explained later. Continually, we have

$$X(t+1) = X(t) + \Delta T(G^{\text{2b}}(t) - G^{\text{b2}}(t)). \tag{4.22}$$

Then, according to the framework of Lyapunov optimization in [17], P4.3 can be equivalently transformed to a queue stability problem as follows, named P4

$$\text{(P4)} \;\; \min \;\; \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{F(t)\}, \tag{4.23a}$$

$$\text{s.t. (4.1), (4.2), (4.6)}-\text{(4.9)}, \tag{4.23b}$$

$$\text{Queues } X(t) \text{ are mean rate stable.} \tag{4.23c}$$

To solve P4, we develop an operation algorithm based on Lyapunov optimization technique. First, we define a Lyapunov function as follows:

$$\Gamma(t) = \frac{1}{2}[X(t)]^2 = \frac{1}{2}[E(t) - \theta]^2, \tag{4.24}$$

Now, we define a one-slot conditional Lyapunov drift as follows:

$$\triangle(t) \triangleq \mathbb{E}\{\Gamma(t+1) - \Gamma(t)|E(t)\}. \tag{4.25}$$

Here, the expectation is taken over the randomness of job arrival, computation demand, electricity price as well as the randomness in choosing the control actions. Then, following the Lyapunov optimization framework, we add a function of the expected cost over one slot (i.e., the penalty function) to (4.25) to obtain the following *drift-plus-penalty* term:

$$\Delta Y(t) = \Delta(t) + V\mathbb{E}\{F(t)|E(t)\}, \tag{4.26}$$

where V is a positive control parameter to be specified later. Then, we have the following lemma regarding the *drift-plus-penalty* term:

Lemma 1 *For any feasible action under constraints* (1), (2), (6)–(9) *that can be implemented at slot t, we have*

$$\Delta Y(t) \le \mathbb{E}\{X(t)\triangle T\chi(t) + VF(t)|E(t)\} + \omega, \tag{4.27}$$

where $\chi(t) = G^{2b}(t) - G^{b2}(t)$, ω is the constant given by the following:

$$\omega \triangleq \left[\frac{(\Delta T)^2 \max\{(G^{\text{cm}})^2, (G^{\text{dm}})^2\}}{2}\right]. \tag{4.28}$$

Proof From $E(t+1) = E(t) + \Delta T(G^{2b}(t) - G^{b2}(t))$, subtracting both sides by θ, and squaring both sides, we obtain

$$\begin{aligned} &\frac{[E(t+1)-\theta]^2 - [E(t)-\theta]^2}{2} \\ &= \frac{[\Delta T\chi(t)]^2}{2} + (E(t)-\theta)\Delta T\chi(t) \\ &\leq \omega + X(t)\Delta T\chi(t). \end{aligned} \tag{4.29}$$

Taking the expectation with respect to $E(t)$ on both sides, adding penalty term $V\mathbb{E}\{F(t)|E(t)\}$ to both sides of the above inequality, we obtain the conclusion as in (4.27).

Note that our proposed scheduling algorithm intends to minimize the R.H.S. of the upper bound of the *drift-plus-penalty* term subject to the constraints in P4, which is equivalent to minimize P4.5 based on the instant system states at the beginning of slot t.

$$\text{(P4.5)} \ \min \ \{X(t)\triangle T\chi(t) + VF(t)\}, \tag{4.30a}$$

$$\text{s.t. (4.1), (4.2), (4.6)–(4.9).} \tag{4.30b}$$

The objective function of P5 can be written as follows: $V\sum_{i=1}^{\tilde{n}(t)}\sum_{j=0}^{D_i(t)-1} e_i(j) S(t+j)\eta + (X(t) + VS(t))\triangle T\chi(t) + V(Z^{bc}(t) + Z^{bd}(t))\rho^b$. To provide service delay guarantees for each admitted job, admission control is required, i.e., admitting a job when there is enough capacity, and rejecting it otherwise. Therefore, the proposed operation algorithm comprises of three parts, i.e., admission control, workload scheduling, and battery scheduling. The relationships among these parts can be illustrated by Fig. 4.1. Specifically, the incoming jobs are firstly accepted or rejected by the admission control module according to the residual IDC capacity information. Then, the accepted jobs are scheduled to be executed in the future. Next, the residual IDC capacity is updated and used as the input of admission control module. At the beginning of a time slot, after all incoming jobs are processed by the admission control module and workload scheduling module, the energy demand in the current slot is determined. Finally, based on the energy demand information and price information, battery scheduling module decides the optimal battery operation.

Proposed Operation Algorithm: At the beginning of slot t, $n(t)$ and $d_i(t)$ are observed. For each incoming job, steps (1) and (2) are executed. After all incoming jobs are processed, the proposed algorithm goes to steps (3) and (4).

1. *Admission Control*: Admission control module decides to accept or reject an incoming job based on the present and future resource availability. Specifically, if the residual capacity for job i at slot t exceeds the required computation demand $d_i(t)$, then, job i would be accepted. Otherwise, job i would be rejected.

Suppose $a_i(t) = 1$ if job i arrives at slot t is accepted. Otherwise, $a_i(t) = 0$. Then, we have

$$a_i(t) = \begin{cases} 1, \ d_i(t) \le \sum\limits_{j=0}^{D_i(t)-1} \Lambda(t+j), \\ 0, \ \text{Otherwise}. \end{cases} \tag{4.31}$$

2. *Workload Scheduling*: Every admitted job will be enqueued into a FIFO queue. For each job i in the queue, workload scheduling module allocates capacity for it with the aim of minimizing the energy cost, i.e.,

$$\text{(P4.6)} \ \min_{\mathbf{A}_i(t)} \sum_{j=0}^{D_i(t)-1} e_i(j)S(t+j)\eta, \tag{4.32a}$$

$$\text{s.t. (4.1), (4.2).} \tag{4.32b}$$

Then, the residual IDC capacity in each time slot will be updated, i.e., $\Lambda(t+j) = \Lambda(t+j) - e_i(j)$ $(0 \le j \le D_i(t) - 1)$. Next, admission control module will process the next job until all incoming jobs are processed. Note that $S(t+j)$ $(0 \le j \le D^{\max} - 1)$ is assumed to be accurately predicted in P4.6 as mentioned in Sect. 4.2.4. In fact, we do not need a precisely estimated electricity price sequence $\mathbf{S}(t)$ to yield the optimal solution of P4.6. As long as the sort order of each element in $D^{\max}$-term sequence $\mathbf{S}(t)$ is the same as that of each element in $\tilde{\mathbf{S}}(t)$, where $\tilde{\mathbf{S}}(t) = (\tilde{S}(t), \ \tilde{S}(t+1), \ldots, \ \tilde{S}(t+D^{\max}-1))$ ($\tilde{S}(t)$ is the actual electricity price), then the proposed operation algorithm can achieve the optimal solution. In other words, the proposed algorithm has a moderate requirement for accuracy in electricity price estimation.

3. *Battery Scheduling*: With obtained energy demand at slot t, battery scheduling module decides the optimal operation of battery based on the solution of the following optimization problem:

$$\text{(P4.7)} \ \min \ (X(t) + VS(t))\triangle T\chi(t) + V(Z^{\text{bc}}(t) + Z^{\text{bd}}(t))\rho^b, \tag{4.33a}$$

$$\text{s.t. (4.6)–(4.9),} \tag{4.33b}$$

where the decision variables are $G^{\text{2b}}(t)$, $G^{\text{b2}}(t)$, $Z^{\text{bc}}(t)$, and $Z^{\text{bd}}(t)$.

4. *Queue Update*: Updating $X(t)$ according to the dynamics (4.22).

Note that P4.6 is a linear programming problem, which can be solved by in polynomial time. Moreover, the optimal solution to P4.7 has the following simple threshold structure.

1. If $X(t) + VS(t) > 0$, then $G^{\text{2b}}(t) = 0$. Moreover, if $-(X(t) + VS(t)) * (\min\{G^{\text{dm}}, E(t), P(t)\}) + V\rho^b < 0$, we have $G^{\text{b2}}(t) = \min\{G^{\text{dm}}, E(t), P(t)\}$. Otherwise, $G^{\text{b2}}(t) = 0$.
2. If $X(t) + VS(t) \le 0$, then $G^{\text{b2}}(t) = 0$. Moreover, if $(X(t) + VS(t)) * (\min\{G^{\text{cm}}, E^{\max} - E(t)\}) + V\rho^b < 0$, we have $G^{\text{2b}}(t) = \min\{G^{\text{cm}}, E^{\max} - E(t)\}$. Otherwise, $G^{\text{2b}}(t) = 0$.

We will prove that the above solution is feasible and does not violate the finite battery constraint (4.4) in Sect. 4.2.3.

4.4 Analysis and Simulations

In this section, we analyze the feasibility of the proposed operation algorithm. Moreover, we provide the performance guarantees of the proposed operation algorithm when $\{n(t), d_i(t), S(t+k), k > D^{\max}, \forall i, t, k\}$ are i.i.d. over slots. Note that according to the framework of Lyapunov optimization [17], the performance guarantees can also be extended to the more general settings, for example $\{n(t), d_i(t), S(t+k), k > D^{\max}, \forall i, t, k\}$ evolves according to some finite state irreducible and aperiodic Markov chain.

4.4.1 Analysis

Firstly, we present a lemma that is useful for the analysis of algorithmic performance.

Lemma 2 *The optimal solution to P4.5 has the following properties:*

1. *If $X(t) < -VS^{\max}$, the optimal solution always choose $G^{b2}(t) = 0$,*
2. *If $X(t) > -VS^{\min}$, the optimal solution always choose $G^{2b}(t) = 0$.*

Proof 1. Suppose that $X(t) < -VS^{\max}$ and $G^{\mathrm{b2}}(t) > 0$, then we have $G^{\mathrm{2b}}(t) = 0$. Let $\Theta_1(t)$ denote the optimal value of the objective in P4.5, i.e.,

$$\Theta_1(t) = -\,(X(t) + VS(t))G^{\mathrm{b2}}(t)\triangle T + V\rho^b + V\sum_{i=1}^{\tilde{n}(t)}\sum_{j=0}^{D_i(t)-1} e_i(j)S(t+j)\eta. \tag{4.34}$$

To prove that the above decision is not optimal, we choose $\tilde{G}_i^{\mathrm{b2}}(t) = 0$, and $\tilde{G}_i^{\mathrm{2b}}(t) = 0$. Let $\Theta_2(t)$ denote the value of the objective in P4.5, i.e.,

$$\Theta_2(t) = V\sum_{i=1}^{\tilde{n}(t)}\sum_{j=0}^{D_i(t)-1} e_i(j)S(t+j)\eta. \tag{4.35}$$

Obviously, $\Theta_1(t) > \Theta_2(t)$. Thus, the optimal solution always choose $G^{\mathrm{b2}}(t) = 0$ when $X(t) < -VS^{\max}$.

2. Suppose that $X(t) > -VS^{\min}$ and $G^{\mathrm{2b}}(t) > 0$, then, we have $G^{\mathrm{b2}}(t) = 0$. Let $\Theta_3(t)$ denote the optimal value of the objective in P4.5, i.e.,

$$\Theta_3(t) = (X(t) + VS(t))G^{\mathrm{2b}}(t)\triangle T + V\rho^b + V\sum_{i=1}^{\tilde{n}(t)}\sum_{j=0}^{D_i(t)-1} e_i(j)S(t+j)\eta. \tag{4.36}$$

To prove that the above decision is not optimal, we choose $\tilde{G}_i^{\mathrm{b2}}(t) = 0$, and $\tilde{G}_i^{\mathrm{2b}}(t) = 0$. Let $\Theta_4(t)$ denote the value of the objective in P4.5, i.e.,

$$\Theta_4(t) = V \sum_{i=1}^{\tilde{n}(t)} \sum_{j=0}^{D_i(t)-1} e_i(j) S(t+j)\eta. \tag{4.37}$$

Obviously, $\Theta_3(t) > \Theta_4(t)$. Thus, the optimal solution always choose $G^{\mathrm{2b}}(t) = 0$ when $X(t) > -VS^{\min}$.

Theorem 2 *Suppose the initial battery energy level $E(0) \in [E^{\min}, E^{\max}]$. Implementing the proposed operation algorithm with any fixed parameter $V \in (0, V^{\max}]$, $V^{\max}$ will be explained later, $\theta = E^{\min} + VS^{\max} + \Delta TG^{dm}$, we have the following properties:*

1. *The battery energy level $E(t)$ is always in the range $[E^{\min}, E^{\max}]$ for all slots.*
2. *The decisions of the proposed operation algorithm are feasible to P4.2, i.e., the proposed operation algorithm can operate without requiring any statistical knowledge about system dynamics.*
3. *If $\{n(t), d_i(t), S(t+k), k > D^{\max}, \forall i, t, k\}$ are i.i.d. over slots, then the time-averaged expected energy cost under the proposed operation algorithm is within bound ω/V of the optimal value:* $\limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{F(t)\} \le y^* + \frac{\omega}{V}$.

Proof 1. To show $E(t) \in [E^{\min}, E^{\max}]$, according to the definition of $X(t)$, it is equivalent to show

$$X(t) \ge -VS^{\max} - \Delta TG^{\mathrm{dm}}, \tag{4.38}$$

and

$$X(t) \le E^{\max} - E^{\min} - VS^{\max} - \Delta TG^{\mathrm{dm}}. \tag{4.39}$$

As $E^{\min} \le E(0) \le E^{\max}$, the above inequalities hold for $t = 0$. We prove that the constraints are satisfied for all periods by induction. Suppose inequalities (4.38), (4.39) hold for slot t, we need to prove that they also hold for slot $t+1$.

- If $-VS^{\max} - \Delta TG^{\mathrm{dm}} \le X(t) < -VS^{\max}$, then, according to Lemma 2, the optimal decision would choose $G^{\mathrm{b2}}(t) = 0$. Thus, $X(t+1) \ge X(t) \ge -VS^{\max} - \Delta TG^{\mathrm{dm}}$. If $-VS^{\max} \le X(t) < E^{\max} - E^{\min} - VS^{\max} - \Delta TG^{\mathrm{dm}}$, then according to (4.22), $X(t+1) \ge -VS^{\max} - \Delta TG^{\mathrm{b2}}(t) > -VS^{\max} - \Delta TG^{\mathrm{dm}}$.
- If $-VS^{\min} < X(t) \le E^{\max} - E^{\min} - VS^{\max} - \Delta TG^{\mathrm{dm}}$, then, According to Lemma 2, the optimal decision would choose $G^{\mathrm{2b}}(t) = 0$. Thus, $X(t+1) \le X(t) \le E^{\max} - E^{\min} - VS^{\max} - \Delta TG^{\mathrm{dm}}$. If $-VS^{\max} - \Delta TG^{\mathrm{dm}} \le X(t) \le -VS^{\min}$, then, $X(t+1) \le -VS^{\min} + \Delta TG^{\mathrm{cm}} \le E^{\max} - E^{\min} - VS^{\max} - \Delta TG^{\mathrm{dm}}$, where we have used the following condition,

$$V \le \frac{E^{\max} - E^{\min} - \Delta T(G^{\mathrm{cm}} + G^{\mathrm{dm}})}{S^{\max} - S^{\min}}. \tag{4.40}$$

Continually, the upper bound of parameter V is given by

$$V^{\max} = \frac{E^{\max} - E^{\min} - \Delta T(G^{\mathrm{cm}} + G^{\mathrm{dm}})}{S^{\max} - S^{\min}}. \tag{4.41}$$

2. The proposed operation algorithm can make decisions to satisfy all constraints in P4.5 and update $X(t)$ normally (i.e., update $E(t)$)). Meanwhile, taking the part 1 of Theorem 2 into consideration, we know that all constraints in P4.2 can be satisfied by the decisions of the proposed algorithm. That is, the proposed algorithm can operate without requiring any statistical knowledge.
3. As we have mentioned before, the proposed operation algorithm is always trying to greedily minimize the R.H.S. of the upper bound of the *drift-plus-penalty* term at slot t over all possible feasible control policies including the optimal and stationary policy given in Lemma 1. By plugging this policy into the R.H.S. of the inequality of the *drift-plus-penalty* term, we have

$$\Delta Y(t) \leq \omega + V\mathbb{E}\{\hat{F}(t)\} \leq \omega + Vy^*. \tag{4.42}$$

Taking the expectation of both sides, using the law of iterative expectation, we have

$$\mathbb{E}[\Delta Y(t)] = \mathbb{E}[\Delta(t)] + V\mathbb{E}[F(t)] \leq \omega + Vy^*. \tag{4.43}$$

Then, summing the above equations over $t \in \{0, 1, 2, \ldots, T-1\}$, we have

$$V\sum_{t=0}^{T-1} \mathbb{E}\{F(t)\} \leq \omega T + VTy^* - \mathbb{E}\{L(T)\} + \mathbb{E}\{L(0)\}. \tag{4.44}$$

Dividing both side by VT, and taking a lim sup of both sides. Let $T \to \infty$, and using the facts that $E\{L(0)\}$ is finite and $E\{L(T)\}$ is nonnegative, we arrive at the following performance guarantee,

$$\limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{F(t)\} \leq y^* + \frac{\omega}{V}. \tag{4.45}$$

4.4.2 Simulations

In this section, we evaluate the performances of the proposed operation algorithm in aspects of total energy cost (TEC), completion delay, and workload drop ratio (WDR).

4.4.2.1 Experimental Setup

System parameters. We consider an IDC with 20,000 servers, the peak power consumption of a server in the IDC is 300 W. Suppose IDC can support 100 units of

computation demand when servers are busy, i.e., $M = 100$. The length of a time slot is set to 5 min and the time horizon in the evaluations is 2,880 slots. Then, we have $\eta = 0.005$ MWh/unit of computation demand. We use the 5 min locational marginal prices (LMP) in real-time electricity market,[2] and the time horizon we consider in this chapter is from February 1 to February 10, 2013. As in [6], we assume that the number of jobs arrive in each slot $n(t)$ follows a Poisson distribution with parameter 4 and the computation demand follows a uniform distribution with parameters 5 and 10. We assume that the limits of battery charging/discharging rates are $P^{\text{cm}} = P^{\text{dm}} = 3$ MW, and charging/discharging cost is $\rho_i^b = 0.1$ dollars [4]. In addition, we set $V = V^{\max}$.
Algorithms for comparison. We consider the following six algorithms in this chapter:

- *Baseline-1* (B1): no completion delay is incurred and no battery is considered.
- *Baseline-2* (B2): no completion delay is incurred and battery is considered.
- *Baseline-3* (B3): homogeneous service delay guarantee is considered and battery is not adopted. This scheme is similar to the Algo-3 in [3].
- *Baseline-4* (B4): homogeneous service delay guarantee is considered and battery is adopted. This scheme is modified from the proposed algorithm by setting the service delay guarantees provided for all requests to be the same.
- *Baseline-5* (B5): heterogeneous service delay guarantees are considered and battery is not adopted.
- *Proposed algorithm* (Proposed): heterogeneous service delay guarantees are considered and battery is adopted.

Since battery scheduling lags behind job scheduling, B1 and B2 (or B3 and B4, or B5 and Proposed) have the same completion delay and workload drop ratio.

4.4.2.2 Simulation Results

Without loss of generality, we consider three types of jobs and their completion times are 5, 7, and 9 (i.e., their completion delays are 4, 6, and 8.), respectively. We set $V = 0.1983$. Moreover, we plot the cumulative distribution function (CDF) of completion delay under the proposed algorithm in the upper part of Fig. 4.2, where we can find that the proposed algorithm indeed provides the heterogeneous service delay guarantees for different types of jobs. If homogeneous service delay guarantee is considered, the maximum completion delay would be 4 slots, so that there is no SLA violation, and the CDF of completion delay under such case is shown in the lower part of Fig. 4.2.

In addition, the TEC under different algorithms is illustrated in Fig. 4.3 (note that WDR of all algorithms under this scenario is zero, and workload intensity $\xi = 0.303$, where ξ is defined as the ratio of the time-averaged computation demand over the given time horizon to the IDC capacity), where the proposed algorithm achieves the lowest TEC. The reason is that the proposed algorithm can fully exploit the temporal

[2] http://www.nyiso.com/, Sept. 2013.

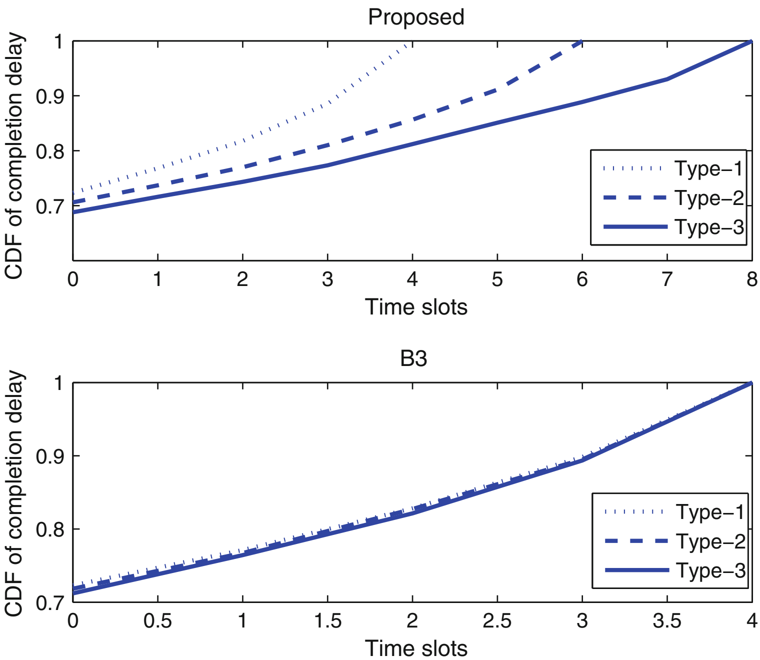

Fig. 4.2 CDF of completion delay under the B3 and the proposed algorithm

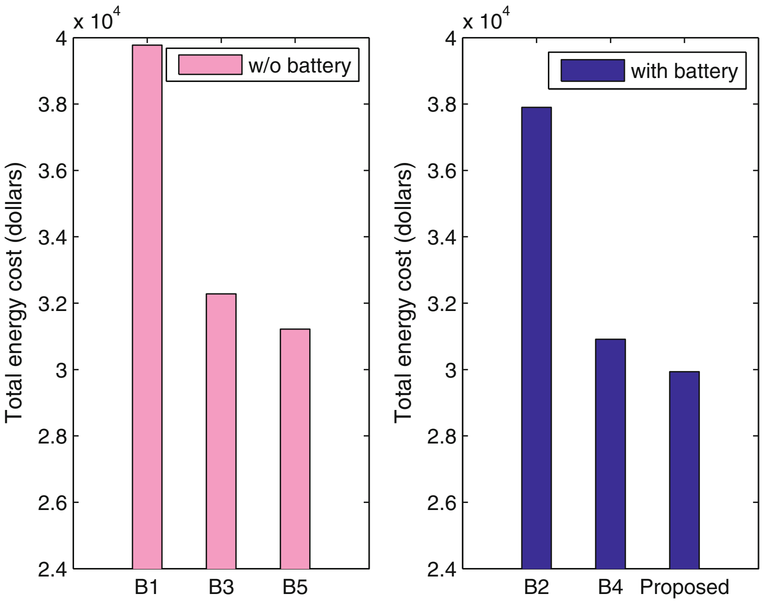

Fig. 4.3 Total energy cost under different algorithms

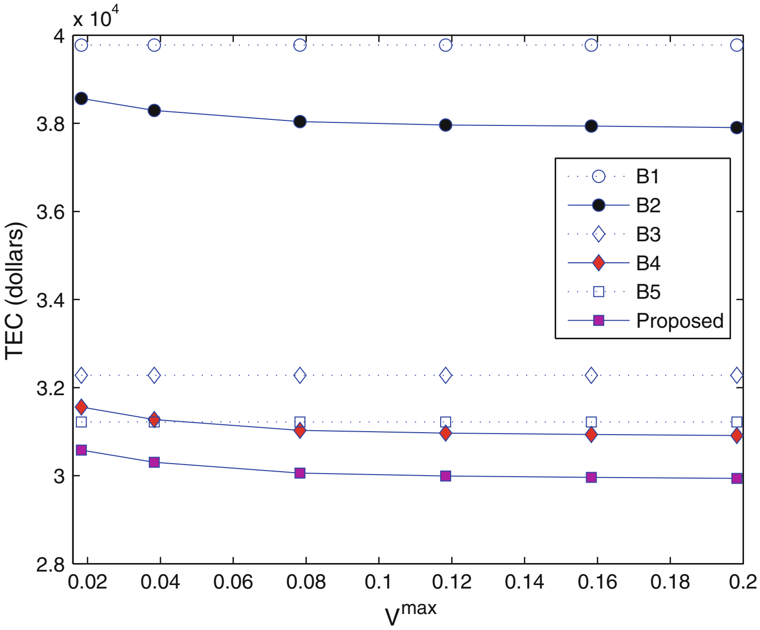

Fig. 4.4 Total energy cost versus V

diversity of electricity price by jointly scheduling workload and battery. Specifically, the proposed algorithm can reduce TEC by 24.74, 21.02, 7.25, 3.15 and 4.11 % when compared with the B1, the B2, the B3, the B4 and the B5, respectively. Furthermore, it can be seen that there is a trade-off between completion time and TEC given the same WDR, which is obvious since larger completion time would result in more opportunities of exploiting the temporal diversity of electricity price.

We evaluate the impact of varying parameter V on TEC as shown in Fig. 4.4, where we make the following observations: (1) As V increases, the TEC becomes lower under the proposed algorithm, the B2 and the B4, which validates the part 3 of the Theorem 2. Though the part 3 of Theorem 2 holds when $\{n(t), d_i(t), S(t+k), k > D^{\max}, \forall i,\ t,\ k\}$ are i.i.d. over slots, the simulation results based on real-world traces show that the proposed algorithm is robust to non-i.i.d. and nonergodic cases (note that the theoretical basis for such robustness can be found in [17]); (2) According to the definition of $V^{\max}$, we know that larger V requires larger investment on battery capacity, which would result in larger investment cost since batteries are expensive currently. Therefore, there is a trade-off between energy cost saving and battery investment cost. In Fig. 4.5, we plot the CDF of energy level when $V = 0.1983$ (i.e., the battery capacity is 60 MWh). It can be found that the battery energy level is always fluctuating in the normal range, which validates the parts 1 and 2 of Theorem 2.

In this subsection, we evaluate the impact of different workload intensities and completion times on WDR. To this end, we enlarge the values of completion time by 1, 1.5, 2, 2.5, and 3 times to simulate the variations of completion time.

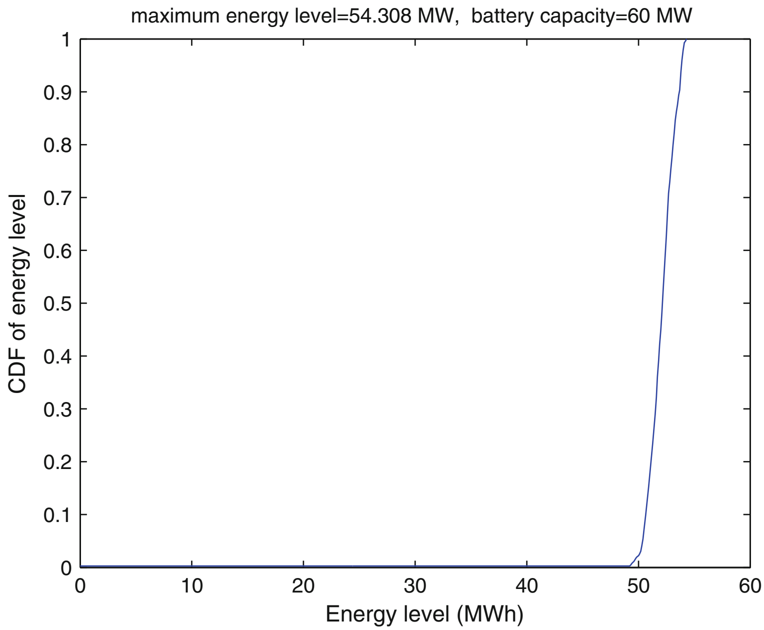

Fig. 4.5 CDF of energy level

Moreover, by adjusting the arrival rate of jobs, we can obtain different workload intensities. As shown in Fig. 4.6, larger completion times would result in lower WDRs, because more jobs are admitted into the system due to the increase of residual capacity for each incoming job.

In the right-hand side of Fig. 4.6, we can find that the B3 achieves lower WDR than the proposed algorithm when completion time is small. This phenomenon can be explained as follows: given a large workload intensity (e.g., $\xi = 0.745$), the capacity allocation for the jobs with larger completion times are more likely to make the residual capacity for the future jobs with smaller completion times to be zero when compared with the situation that all jobs have the same completion time. However, given a large workload intensity, if the completion times are sufficiently large, the WDR under above two algorithms would be the same, i.e., zero. At this time, by providing heterogeneous service delay guarantees, the proposed algorithm can achieve lower TEC than the B3.

Based on the above observations, we know that the proposed algorithm is very suitable for the scenario with small workload intensity (as shown in the left-hand side of Fig. 4.6) or large completion time (as shown in the right-hand side of Fig. 4.6). When workload intensity is large and completion time is small, the B4 would be the best choice since it achieves lower energy cost than the B3 without sacrificing WDR and completion delay. Note that the B4 is a modified version of the proposed algorithm (i.e., by setting service delay guarantees provided for all requests to be the same), we can summarize that the proposed algorithm is applicable to the general scenarios.

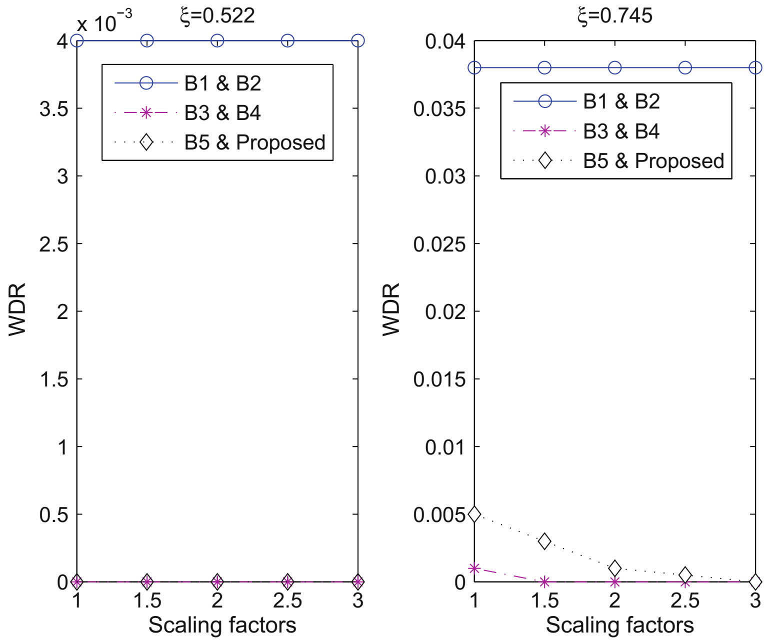

Fig. 4.6 WDR under different algorithms

4.5 Summary

In this chapter, we studied the problem of minimizing the long-term energy cost for an IDC in deregulated electricity markets. First, we formulated a time-averaged expected energy cost minimization problem taking into account heterogeneous service delay guarantees and battery management. Then, we designed a low-complexity operation algorithm to solve the problem based on Lyapunov optimization technique. Moreover, we analyzed the feasibility of the proposed operation algorithm and its performance guarantee. Finally, extensive evaluations based on real-world data showed the effectiveness of the proposed operation algorithm.

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Chapter 5
Risk-Constrained Operation for Internet Data Centers in Deregulated Electricity Markets

Abstract In deregulated electricity markets, there exist multiple markets of different time scales, e.g., forward markets and spot markets. When Internet data center operators only procure energy from spot markets, they can save energy cost by fully exploiting the temporal and spatial variations of spot prices. Meanwhile, prices in spot markets and workloads are volatile, and forecasted prices and workloads tend to be less accurate with the increase of planning horizon, consequently, the future energy cost of Internet data centers is full of uncertainty (or randomness), which is a risk for Internet data center operators since they may experience high probability of having high energy cost in the future. Thus, in this chapter, we consider the risk-constrained operation for Internet data centers in deregulated electricity markets and propose a stochastic programming-based decision framework to decide the optimal quantity of electricity that should be purchased in forward markets given the risk preference of Internet data center operators.

Keywords Internet data center · Deregulated electricity markets · Uncertainty · Operation risk · Energy cost

5.1 Introduction

The past decade has witnessed tremendous growth of online applications and services. Together with the recent trend of cloud computing, more and more data and computations are migrated to or hosted on Internet data centers (IDCs), for reliability, management, and cost benefits. In IDC operations, a critical issue is the energy consumption. According to a recent study, many IDC operators spend more than \$30 million on their annual energy costs, which occupies 30–50 % of total operational expenses [1, 2]. On the other hand, the deregulation of electricity markets provides the opportunity for IDC operators to reduce energy cost since the spatial and temporal price variations could be utilized [1]. Based on the price characteristics in deregulated electricity markets, lots of research has been done to reduce energy cost for IDC operators [2–10].

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Though several schemes have been proposed to reduce energy cost for IDC operators, few attention has been paid to manage the uncertainties in IDC operations in deregulated electricity markets, where multiple markets of different time scales exist, such as forward markets and spot markets (including day-ahead and real-time spot markets) [11, 12]. When IDC operators only procure electricity from spot markets to supply IDCs, the spatial and temporal diversities of prices in deregulated electricity markets could be fully utilized to reduce energy cost. Meanwhile, prices in spot markets and workloads are volatile, and forecasted prices and workloads tend to be less accurate with the increase of planning horizon [13, 14] (e.g., from days to months/years), consequently, the future energy cost of IDCs is full of uncertainty (or randomness), which is a risk for IDC operators since they may experience high probability of having high energy cost in the future. To manage the risk mentioned above, purchasing electricity from forward markets is an effective way since IDC operators can buy a certain amount of electricity at a pre-specified contract price, at certain time in the future, reducing the level of exposure to price risk [15]. However, buying electricity from forward markets could increase the *expected energy cost* of IDC operators due to the positive risk premium (i.e., the difference between forward price and expected spot price during the delivery period) in short-term forward contracts (e.g., daily/weekly/monthly forward contracts) [16, 17]. Moreover, it is important to highlight that such short-term forward contracts are needed if IDC operators are very risk averse since the long-term power demands of distributed IDCs are difficult to forecast accurately due to the workload and price volatility and cannot be perfectly covered by long-term forward contracts (e.g., quarterly/yearly forward contracts). Thus, IDC operators face a tradeoff between *operation risk* (i.e., the risk associated with energy cost) and *expected energy cost* when managing the uncertainties in IDC operations in deregulated electricity markets.

As motivated, we study the problem of risk-constrained operation for IDCs in deregulated electricity markets. Specifically, we consider an IDC operator, which has some IDCs geographically distributed in several independent electric regions. Moreover, the IDC operator needs to meet the power demand of distributed IDCs from multiple energy sources, such as forward markets and spot markets. The objective of an IDC operator is to achieve the optimal tradeoff between *operation risk* and *expected energy cost* according to the given risk preferences.

To achieve the target above, the challenge is how to optimally decide the energy procurement strategy for IDCs with the uncertainties in spot price and workload. In existing works, several energy procurement strategies have been developed for large consumers [18, 19]. In these works, no distributed systems (e.g., distributed IDCs) are considered and power demand in the future is assumed to be known since some consumers may have precise knowledge about their own consumption. However, for distributed IDCs, the power demand depends on price and workload, both of which cannot be controlled by IDC operators. Thus, the power demand of distributed IDCs in the future is more difficult to be accurately predicted. In [20], uncertainties in IDC operations were first considered and electricity forward contracts (EFCs) [15] in forward markets were adopted to minimize *operation risk* in IDC operations. However, merely minimizing the *operation risk* would lead to the highest *expected energy cost* for IDC operators when the tradeoff between *operation risk* and *expected energy cost* is not considered. In addition, variance is adopted as the risk metric for IDCs in [20]. However, when IDC operators are managing the risk for IDCs, they may only care about reducing the upside deviations from *expected energy cost*, rather than reducing downside and upside deviations simultaneously because downside deviations are desirable. Thus, variance is not very suitable for measuring the *operation risk*.

In this chapter, we propose a risk-constrained stochastic programming decision framework for IDC operators, which can achieve the optimal tradeoff between *operation risk* and *expected energy cost* according to the risk preferences of IDC operators. First, a risk-constrained *expected energy cost* minimization problem under the proposed decision framework is formulated based on a two-stage stochastic programming model with recourse. Specifically, the first-stage decisions are made about signing EFCs in forward markets under the uncertainties of future spot price and workload, with the aim of minimizing the weighted sum of *expected energy cost* and *operation risk* (note that *operation risk* in this study is measured by the conditional value-at-risk (CVaR) methodology [21], which can measure the risk just associated with upside deviations from *expected energy cost*); while the second-stage decisions are made to minimize *energy cost* after uncertain spot price and workload are unveiled. Moreover, we solve the formulated problem using a decomposition-based cutting plane algorithm, which can decompose the original large-scale optimization problem into independent smaller subproblems by exploiting the block structure of the original problem.

The main contributions of this chapter are summarized as follows:

1. We present a risk-constrained stochastic programming decision framework for IDC operators to achieve the optimal tradeoff between *operation risk* and *expected energy cost* according to the risk preferences of IDC operators, where *operation risk* is measured by the CVaR methodology which has better characteristics than variance as mentioned in Sect. 5.3.4.
2. We formulate a risk-constrained *expected energy cost* minimization problem under the proposed decision framework based on a two-stage stochastic programming model with recourse.
3. We solve the formulated problem using a decomposition-based cutting plane algorithm, which exploits the block structure of the problem.
4. Extensive evaluations based on real-life data are conducted to show the effectiveness of the proposed decision framework.

The rest of this chapter is organized as follows. Section 5.2 describes the proposed decision framework. Section 5.3 gives system model. Problem formulation and algorithm design are conducted in Sect. 5.4. Simulations are given in Sect. 5.5. Finally, conclusions are made in Sect. 5.6.

5.2 Proposed Decision Framework

In this section, we propose a risk-constrained stochastic programming decision framework as in Fig. 5.1, where two kinds of energy sources are considered, that is forward markets and spot markets. In forward markets, IDC operators should decide the optimal quantity of EFCs to be purchased so that *operation risk* could be controlled. Thus, we briefly introduce electricity forward markets. Then, the decision framework under uncertainty is described. Finally, the uncertainty characterization is given.

5.2.1 Electricity Forward Markets

In electricity forward markets, there are some electricity derivatives, such as EFCs, electricity future/option contracts [15]. In this study, we focus on EFCs since they are primary instruments used in electricity price risk management [15]. EFCs represent the obligation to buy or sell a fixed amount of electricity at a pre-specified contract price (i.e., forward price), at certain time in the future (call maturity or expiration time) [15]. That obligation is discharged in one of two ways depending on contract specification, i.e., physical delivery and financial settlement. For the physical delivery, the seller must deliver a certain amount of electricity to the buyer at a fixed forward price. By contrast, financial settlement only requires the exchange of cash based on the difference between the agreed forward price and spot price. Generally, EFCs with short maturity like 1 h or 1 day are often physical contracts, and those with maturity of weeks or months can be either physical contracts or financial contracts [15].

5.2.2 Risk-Constrained Decision Framework

In this subsection, we propose a risk-constrained stochastic programming decision framework as shown in Fig. 5.1, where two different decisions can be distinguished,

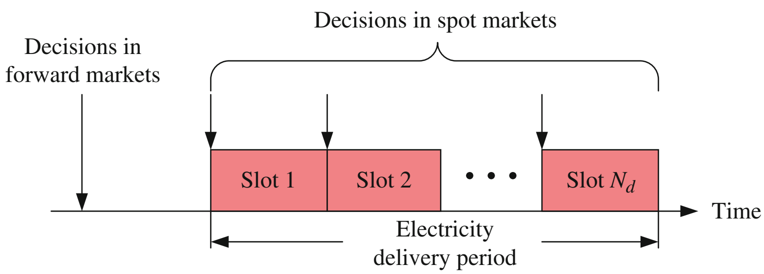

Fig. 5.1 Decision framework under uncertainty

i.e., decisions in forward markets and decisions in spot markets.[1] Specifically, in forward markets, IDC operators should decide the quantity of EFCs under the uncertainties of spot price and workload. In spot markets, with the unknown parameters gradually revealed in the delivery period, IDC operators would accordingly minimize the energy cost in each time slot.[2] Since uncertainties in future spot price and workload are only involved in the decisions in forward markets, the above decision-making problem under uncertainty can be cast as a two-stage stochastic programming model with recourse [24]. Specifically, the decisions in forward markets are the first-stage decisions, with the aim of minimizing the weighted sum of *expected energy cost* and *operation risk* according to a given risk preference of IDC operators, while the decisions in spot markets are the second-stage decisions, with the purpose of minimizing the energy cost at each slot based on gradually unveiled spot price and workload. Note that the decision variables of the first-stage decisions are the quantities of different EFCs, while the decision variables of the second-stage decisions are service request distribution, the number of active servers, and power purchasing/selling in spot markets.

5.2.3 Uncertainty Characterization

In stochastic programming, each uncertain parameter constitutes a random variable [24]. A random variable whose value evolves over time is known as a stochastic process. In this study, the spot price and workload over the delivery period are stochastic processes, which can be represented by a set of scenarios. Each scenario represents a realization of spot price and workload over the delivery period. Let Ω be the set of scenarios and N_Ω be the number of scenarios considered. Let N and F be the number of IDCs and front-end web servers, respectively, and N_d be number of time slots in the delivery period, and $S_i^t(\omega)$ (in \$/MWh) be the spot price at slot t ($1 \leq t \leq N_d$, in hour) and scenario ω at IDC location i ($\omega \in \Omega$), $R_f^t(\omega)$ (in requests per slot, req/slot) be the total workload arrived at the front-end web server f ($1 \leq f \leq F$) at slot t and scenario ω. Then, each scenario ω in this chapter comprises a vector of spot prices at all IDC locations and a vector of workloads at all front-end web servers, i.e.,

$$\omega = \{S_1^t, S_2^t, \ldots, S_N^t, R_1^t, R_2^t, \ldots, R_F^t\}_{t=1,\ldots,N_d}. \tag{5.1}$$

In addition, each scenario ω has a probability of occurrence $\pi(\omega)$, and $\sum_{\omega \in \Omega} \pi(\omega) = 1$. To generate scenarios for optimization problems, some techniques could be adopted, such as path-based methods [25], scenario reduction methods [26], and

[1] In this study, we focus on day-ahead spot markets and assume that prices and workloads in the next day can be accurately predicted [22, 23].

[2] A time-slotted system is considered in this chapter, where each slot represents a time interval in a given delivery period of EFCs, e.g., 1 h.

moment matching [27]. In this chapter, a procedure in [28] is adopted to generate scenarios, which combines both path-based methods and scenario reduction techniques: (1) a large enough number of scenarios are generated by time series models (e.g., ARIMA model) and (2) a scenario-reduction technique is used to obtain a sufficiently small number of scenarios. As to model the uncertainty of workload, the similar time series models could be adopted.

5.3 System Model

In this section, we first introduce the system model. Then, we describe the models related to three components in the system model. Finally, the risk-constrained expected energy cost minimization problem is formulated. The system model we considered in this chapter is shown in Fig. 5.2, where several components could be identified, namely front-end servers, IDCs, spot markets and forward markets. A front-end server acts as a load balancer that receives incoming service requests and dispatches them to geographically distributed IDCs that located in multiple electric regions (ERs) for processing. To satisfy the power demand of distributed IDCs, two energy sources are considered, i.e., spot markets and forward markets.

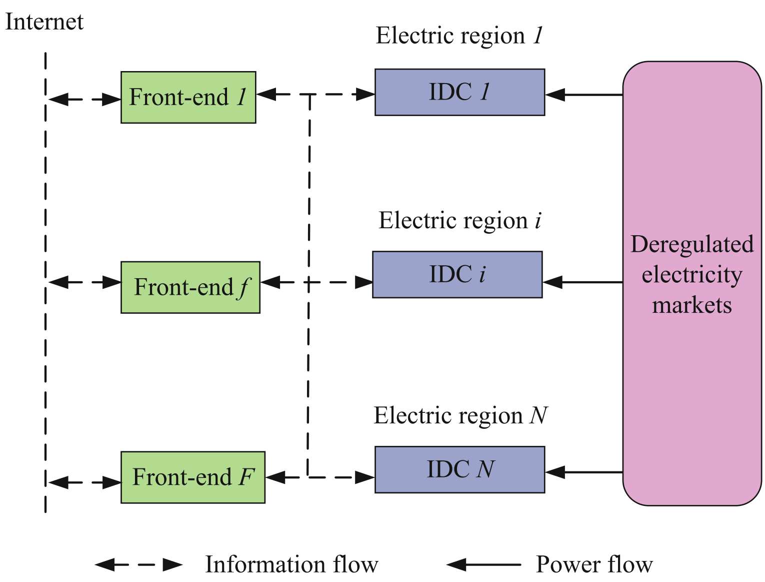

Fig. 5.2 System model

5.3.1 Models Related to Front-End Servers and Internet Data Centers

5.3.1.1 Workload Allocation Model

We consider an IDC operator with N IDCs geographically distributed in N independent electric regions (ERs) to offer Internet services. In this chapter, we mainly focus on delay-sensitive workloads (e.g., "request-response" type web services [5]). The consideration of delay-tolerant workloads (e.g., compute-intensive or data-intensive requests [29]) would be considered in future work. IDC i ($1 \leq i \leq N$) with M_i homogeneous servers and $m_i^t(\omega)$ of them are turned on to process service requests at slot t and scenario ω ($0 \leq m_i^t(\omega) \leq M_i$). Moreover, $m_i^t(\omega)$ is assumed to be unchanged at slot t since activating servers typically cost a non-negligible amount of time and frequently switching back and forth between active and sleep states can result in reliability problems [4, 9]. Let $\lambda^t_{f,i}(\omega)$ (in req/slot) be the workload that assigned from front-end web server f to the servers at IDC i at slot t and scenario ω. For simplicity, we assume that the workload allocation would not alter spot price and market behavior [1], i.e., workload and spot prices are independent. In order to assure that all service requests will be handled, we have the following constraints

$$\sum_{i=1}^{N} \lambda^t_{f,i}(\omega) = R^t_f(\omega). \tag{5.2}$$

5.3.1.2 Power Consumption Model

The total power consumption at an IDC is obtained by adding the total power consumption at IT equipment (e.g., servers, storage and network devices) to the total power consumption at the facility (e.g., cooling, lighting, power distribution) [30]. Moreover, the ratio of the total power consumption at an IDC to the power consumption at IT equipment is referred to as *power usage effectiveness* (PUE), which is a measure of energy efficiency. Currently, the typical value of PUE is 2 [1, 31]. Let PUE_i be the PUE at IDC i, $P_{\mathrm{idle},i}$ and $P_{\mathrm{peak},i}$ (both in Watt) represent the idle power and peak power of a server at IDC i, respectively. Let $U_i^t(\omega)$ be the average server utilization at slot t and scenario ω, which is equal to $\lambda_i^t(\omega)/(m_i^t(\omega)\mu_i)$, where μ_i (in req/slot) denotes the average service rate of servers at IDC i. As in previous work [1, 32], the total power consumption of IDC i at slot t and scenario ω ($P_i^t(\omega)$, in MW) can be estimated by

$$P_i^t(\omega) = m_i^t(\omega)[\varphi_i U_i^t(\omega) + \gamma_i], \tag{5.3}$$

where

$$\varphi_i \triangleq P_{\text{peak},i} - P_{\text{idle},i}, \tag{5.4}$$

$$\gamma_i \triangleq P_{\text{idle},i} + (\text{PUE}_i - 1)\,P_{\text{peak},i}. \tag{5.5}$$

Note that servers in each IDC are assumed to be homogeneous in the above power consumption model. For more general situations (e.g., each IDC with heterogeneous servers and servers with dynamic service rate [4]), the corresponding model can also be incorporated easily.

5.3.1.3 Service Delay Model

To satisfy the quality-of-service requirements, the average response delay for incoming service requests should be limited within a certain range that is determined by the *Service Level Agreement* (SLA). Otherwise, penalties would be incurred [32–34]. In this study, M/M/n queueing model is adopted to process the incoming workload as in previous works [20, 23, 33]. Note that this queueing model is not necessarily the most accurate for the practical workload, but it will not affect the nature of the proposed risk-constrained stochastic programming decision framework. Let $D_i^{\max}$ (in seconds) be the threshold that identifies the revenue/penalty region at IDC i. To avoid the penalty for violating the SLA, the following constraints should be satisfied,[3] i.e.,

$$\frac{1}{m_i^t(\omega)\mu_i - \sum_{f=1}^{F} \lambda_{f,i}^t(\omega)} + \frac{1}{\mu_i} \le D_i^{\max}. \tag{5.6}$$

5.3.2 *Model Related to Electricity Forward Contracts*

Let $q_{i,x}$ (in MW) be the quantity of electricity purchased via EFC x (with forward price $F_{i,x}$ in \$/MWh) in a given delivery period, $q_{i,x}^{\max}$ (in MW) be the upper limits of power that can be purchased via EFC x over the given delivery period. Then, we have the following constraint,

$$0 \le q_{i,x} \le q_{i,x}^{\max}, \tag{5.7}$$

where the lower limits of power that can be purchased via EFC x are assumed to be zero, which is not always hold in practice. However, the assumption only affects

[3] Here, a simple SLA is adopted as in [33, 35]. Other more complicated SLAs would be considered in future work.

the achievable tradeoff range between *expected energy cost* and *operation risk*, and does not change the tradeoff nature of the proposed decision framework.

Let B_i be the number of EFCs available at IDC i during the given delivery period. Then, the total quantity of electricity q_i^t (in MW) purchased via EFCs for slot t at IDC i is given by

$$q_i^t = \sum_{x=1}^{B_i} q_{i,x}. \tag{5.8}$$

Let Z_1^t (in \$) be the cost associated with the purchasing of energy via EFCs for slot t, Δt be the duration of a time slot (in hour). Then, we have

$$Z_1^t = \sum_{i=1}^{N} \sum_{x=1}^{B_i} q_{i,x} F_{i,x} \Delta t. \tag{5.9}$$

In spot markets, the cost of purchasing (selling) electricity at slot t and scenario ω ($Z_2^t(\omega)$, in \$) is computed by

$$Z_2^t(\omega) = \sum_{i=1}^{N} [P_i^t(\omega) - q_i^t] S_i^t(\omega) \Delta t. \tag{5.10}$$

Note that if $P_i^t(\omega)$ is larger (smaller) than q_i^t, it indicates that the IDC operator would purchase (sell) $|P_i^t(\omega) - q_i^t|$ units of electricity from (to) spot markets, $|\varsigma|$ denotes the absolute value of ς.

5.3.3 Expected Energy Cost

Let $Z(\omega)$ (in \$) be the total energy cost of IDC operators under scenario ω. Then, we have

$$Z(\omega) = \sum_{t=1}^{N_d} [Z_1^t + Z_2^t(\omega)]. \tag{5.11}$$

Then, the *expected energy cost* (in \$) in the delivery period is $\sum_{\omega \in \Omega} \pi(\omega) Z(\omega)$.

5.3.4 Operation Risk

In existing work [20], variance is adopted as the risk metric in IDC operations. However, when IDC operators are managing the risk, they may only care about reducing the upside deviations from *expected energy cost*, rather than reducing downside and upside deviations simultaneously because downside deviations are desirable. Therefore, variance is not very suitable for measuring the *operation risk* since it reduces downside and upside deviations simultaneously. Compared with variance, conditional value-at-risk (CVaR) [36] can measure the weighted average value of the tail events, for a given fractile, for example CVaR can measure the risk just associated with the upside deviations from *expected energy cost*. Moreover, CVaR is a positively homogeneous and convex coherent risk measure [21]. Hence, we use CVaR as the risk measure in this chapter. The definition of CVaR of a random variable $A(\omega)$ at the confidence level α is given by

$$\mathrm{CVaR}_\alpha(A(\omega)) = \inf_{\eta \in \mathscr{R}} \{\eta + \frac{1}{1-\alpha}\mathbb{E}[(A(\omega) - \eta)_+]\}, \tag{5.12}$$

where we let $(\cdot)_+ = \max(0, \cdot)$, $\mathbb{E}[\cdot]$ denotes usual mathematical expectation operator. It is well known that the infimum in (5.12) is attained at a α-quantile of $A(\omega)$. Note that for discrete distributions of $A(\omega)$, $\mathrm{CVaR}_\alpha(A(\omega))$ is approximately as the expected value of the $(1-\alpha) \times 100\,\%$ scenarios with the highest energy cost.

5.4 Problem Formulation and Algorithm Design

As described in Sect. 5.2.2, the decisions faced by IDC operators can be cast as a two-stage stochastic programming problem with recourse, where the first-stage decisions take place in forward markets, with the aim of minimizing the weighted sum of *expected energy cost* and *operation risk*, while the second-stage decisions are made in spot markets to minimize the energy cost.

5.4.1 The First-Stage Problem

As explained in Sect. 5.2.3, the future spot price and workload over the delivery period are random processes, which can be represented by a set of scenarios. Let Ω be the sample space (i.e., the set of scenarios), $\mathcal{F}$ be a σ-algebra on Ω (i.e., a set of subsets of Ω), Π be a probability measure on Ω. Let $\tilde{\omega}$ be a random vector (comprising future spot price and workload) defined on a probability space $(\Omega, \mathcal{F}, \Pi)$. Suppose scenario ω is a realization of $\tilde{\omega}$, then, the event $\{\omega\} \subseteq \Omega$ with probability $\Pi(\{\omega\}) = \pi(\omega)$. Let $\mathbb{E}[\cdot]$ denote the usual mathematical expectation operator taken with respect to the probability distribution of the random vector $\tilde{\omega}$. In the first stage, the minimization problem is formulated by

$$\begin{aligned}\text{(P5.1)}\quad &\min\{\mathbb{E}[Q(\tilde{\omega})] + \beta \mathrm{CVaR}_\alpha(Q(\tilde{\omega}))\}\\ &= \min\{\mathbb{E}[Q(\tilde{\omega})] + \beta(\eta + \frac{1}{1-\alpha}\mathbb{E}[(Q(\tilde{\omega}) - \eta)_+])\}\end{aligned} \tag{5.13a}$$

$$\text{s.t. } 0 \le q_{i,x} \le q_{i,x}^{\max}, \tag{5.13b}$$

$$\eta \in \mathscr{R}, \tag{5.13c}$$

where $Q(\tilde{\omega})$ denotes the recourse cost function, which is the objective function of the second-stage problem. The objective function to be minimized in P5.1 consists of two parts, the first term is *expected energy cost*, and the second term is a scaled *operation risk* measure (CVaR). The tradeoff between *expected energy cost* and *operation risk* is enforced through the weighting factor β $\in$[0,+∞). If risk is not considered (risk-neutral IDC operators), the value of β is set to 0. The more risk averse the IDC operators are, the higher the value of β is. In practice, β is specified according to the risk preferences of IDC operators. The detailed discussion on how to select the optimal β is beyond the scope of this chapter. The decision variables of P5.1 are $q_{i,x}$ and η.

5.4.2 The Second-Stage Problem

In the second stage, IDC operators intend to minimize energy cost under a given realization ω of $\tilde{\omega}$. Moreover, q_{i_x} and η are known in this stage. Then, the second-stage problem is cast as follows, named P5.2:

$$\text{(P5.2)} \quad Q(\omega) = \min Z(\omega) \tag{5.14a}$$

$$\text{s.t. } m_i^t(\omega) \le M_i, \ m_i^t(\omega) \in \mathscr{N}, \tag{5.14b}$$

$$m_i^t(\omega) \ge \frac{1}{\mu_i}[(D_i^{\max} - \frac{1}{\mu_i})^{-1} + \sum_{f=1}^{F} \lambda_{f,i}^t(\omega)], \tag{5.14c}$$

$$\sum_{i=1}^{N} \lambda_{f,i}^t(\omega) = R_f^t(\omega), \tag{5.14d}$$

$$m_i^t(\omega) \ge 0, \lambda_{f,i}^t(\omega) \ge 0. \tag{5.14e}$$

The decision variables of P5.2 are $m_i^t(\omega)$ and $\lambda_{f,i}^t(\omega)$. Basically, the second-stage decisions represent the operational decisions for IDCs, which change depending on the realized values of random spot price and workload.

5.4.3 Deterministic Equivalent Programming Problem

Suppose $\tilde{\omega}$ has a finite support on Ω, then, the two-stage stochastic programming problem in (5.13a–5.13c)–(5.14a–5.14e) can be equivalently expressed by the following problem [24], named P5.3:

$$
\begin{aligned}
\text{(P5.3)}\ \ \min &\sum_{\omega\in\Omega}\pi(\omega)Z(\omega)+\beta\eta+\frac{\beta}{1-\alpha}\sum_{\omega\in\Omega}\pi(\omega)(Z(\omega)-\eta)_{+} && (5.15a)\\
\text{s.t. } & m_i^t(\omega)\le M_i,\ \ m_i^t(\omega)\in\mathscr{N}, && (5.15b)\\
& m_i^t(\omega)\ge\frac{1}{\mu_i}[(D_i^{\max}-\frac{1}{\mu_i})^{-1}+\sum_{f=1}^{F}\lambda_{f,i}^t(\omega)], && (5.15c)\\
& \sum_{i=1}^{N}\lambda_{f,i}^t(\omega)=R_f^t(\omega), && (5.15d)\\
& 0\le q_{i,x}\le q_{i,x}^{\max}, && (5.15e)\\
& m_i^t(\omega)\ge 0,\lambda_{f,i}^t(\omega)\ge 0,\eta\in\mathscr{R}. && (5.15f)
\end{aligned}
$$

where decision variables are $q_{i,x}$, η, $m_i^t(\omega)$, and $\lambda_{f,i}^t(\omega)$. To make P5.3 more easy to solve, the linear formulation of CVaR is usually adopted [18]. Then, P5.3 can be transformed to P5.4 as follows:

$$
\begin{aligned}
\text{(P5.4)}\ \ \min &\sum_{\omega\in\Omega}\pi(\omega)Z(\omega)+\beta[\eta+\frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi(\omega)\chi(\omega)] && (5.16a)\\
\text{s.t. } & Z(\omega)-\eta-\chi(\omega)\le 0, && (5.16b)\\
& \chi(\omega)\ge 0, && (5.16c)\\
& (5.15b)-(5.15f). && (5.16d)
\end{aligned}
$$

5.4.4 Algorithm Design

P5.4 could be input to an off-the-shelf mixed integer programming (MIP) solver. However, due to the large number of scenarios in practical problem, P5.4 can be a large-scale mixed-integer programming problem, which imposes large memory and computational burden on the solver. One approach to deal with this difficulty is to work with smaller problems by decomposing P5.4 into a first-stage problem and a collection of second-stage scenario problems, which can be solved independently. In addition, considering that there are huge number of servers in IDCs and a large proportion of them are active, we can relax the integer constraint on $m_i^t(\omega)$ without significant energy cost penalties [10, 37]. Based on the above discussions, P5.4 can be approximately described by P5.5 as follows, where the integer constraint on $m_i^t(\omega)$ in P5.4 is relaxed and the translation-equivariant property of CVaR is used (i.e., $\mathrm{CVaR}_\alpha(A+h)=\mathrm{CVaR}_\alpha(A)+h$, where h is a constant [21]),

$$
\text{(P5.5)}\ \ \min\ \ (1+\beta)\sum_{t=1}^{N_d}Z_1^t+\sum_{\omega\in\Omega}\pi(\omega)\sum_{t=1}^{N_d}Z_2^t(\omega)+\beta[\eta+\frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi(\omega)\chi(\omega)] \qquad (5.17a)
$$

$$\text{s.t. } m_i^t(\omega) \le M_i, \tag{5.17b}$$
$$Z(\omega) - \eta - \chi(\omega) \le 0, \tag{5.17c}$$
$$\chi(\omega) \ge 0, \tag{5.17d}$$
$$\text{(5.16c)–(5.16f)}. \tag{5.17e}$$

In this chapter, we adopt the decomposition-based cutting plane algorithm in [38] to solve P5.5. The key idea of the decomposition-based cutting plane algorithm is similar to the L-shaped algorithm [24], which is widely used in stochastic programming. In the L-shaped algorithm, the expected recourse function in the two-stage model is represented by a single variable θ, whose optimal value is determined iteratively by using linear programming duality to construct a piecewise linear outer approximation of the expected recourse function as well as its effective domain. To achieve this aim, optimality cuts and feasibility cuts are generated, respectively. Different from the L-shaped algorithm, the decomposition-based cutting plane algorithm needs to generate cuts to approximate the optimal expected value function and CVaR of the recourse cost, instead of just expected value function.

In the decomposition-based cutting plane algorithm, additional variables $\nu_l(\omega)$ and η_l are introduced to construct optimality cuts associated with CVaR of the recourse cost. The procedure of solving P5.5 is described as follows,

1. Initialization. Set $a = 0$ (optimality cut number), $b = 0$ (iteration number).
2. Set $b = b + 1$. Solve the following problem, named P5.6:

$$\text{(P5.6)} \quad \min \quad (1+\beta)\sum_{t=1}^{N_d} Z_1^t + \theta_1 + \beta\theta_2 \tag{5.18a}$$
$$\text{s.t. } 0 \le q_{i,x} \le q_{i,x}^{\max}, \tag{5.18b}$$
$$\Phi_l(\theta_1, q_{i,x}) \ge 0, \tag{5.18c}$$
$$\theta_2 \ge \eta_l + \frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi(\omega)\nu_l(\omega), \tag{5.18d}$$
$$\Psi_l(\nu_l(\omega), q_{i,x}, \eta_l) \ge 0, \tag{5.18e}$$
$$\nu_l(\omega) \ge 0, \ \ \eta_l \in \mathscr{R}, \tag{5.18f}$$

where $0 \le l \le a$. Let $(q_{i,x}^b, \theta_1^b, \theta_2^b)$ be the optimal solution of P5.6 at the iteration b. Then, the optimal value $\theta^b = (1+\beta)\sum_{t=1}^{N_d} Z_1^t + \theta_1^b + \beta\theta_2^b$. If $a = 0$, θ_1^b and θ_2^b are set equal to $-\infty$ and are not considered in the computation of $q_{i,x}^b$. Note that $\Phi_l(\theta_1, q_{i,x})$ denotes the optimality cuts for expected value function, while $\Psi_l(\nu_l(\omega), q_{i,x}, \eta_l)$ describes the relationship between $\nu_l(\omega)$ and η_l in computing the optimality cuts for CVaR, and the specific expressions of $\Phi_l(\theta_1, q_{i,x})$ and $\Psi_l(\nu_l(\omega), q_{i,x}, \eta_l)$ would be given in the step 8). Similar to the existing work about stochastic programming, we give the computational complexity of P5.5 and P5.6 in Table 5.1 from the perspective of problem sizes. In Table 5.1, it can be seen that the computational complexity of P5.6 is far smaller than that of P5.5 (note that the empirical results in the simulations showed that the value of a is 2 or 3), i.e., the decomposition-based cutting plane algorithm can greatly reduce the computational complexity of P5.5.

3. For $\omega \in \Omega$, solve the following problem, named P5.7:

$$\text{(P5.7)}\ \max\ \sum_{i=1}^{N}\sum_{t=1}^{N_d} M_i v_i^t + \sum_{i=1}^{N}\sum_{t=1}^{N_d} y_i^t[(D_i^{\max} - \frac{1}{\mu_i})^{-1}] + \sum_{f=1}^{F}\sum_{t=1}^{N_d} e_f^t R_f^t(\omega) \tag{5.19a}$$

$$\text{s.t.}\ \ v_i^t + \mu_i y_i^t \le \gamma_i S_i^t(\omega)\Delta t, \tag{5.19b}$$

$$- y_i^t + e_f^t \le \frac{\phi_i}{\mu_i} S_i^t(\omega)\Delta t, \tag{5.19c}$$

$$v_i^t \le 0,\ y_i^t \ge 0,\ e_f^t \in \mathscr{R}, \tag{5.19d}$$

where v_i^t, y_i^t, and e_f^t are simplex multipliers. In P5.7, the number of variables is $(2N + F)N_d$, and the number of constraints is $(F + 1)NN_d$. Thus, the size of P5.7 is independent of the number of scenarios. Let $\Gamma(\omega)$ be the optimal value of P5.7. Then, we define $\Gamma_1(\omega) = \Gamma(\omega) + \sum_{t=1}^{N_d}\sum_{i=1}^{N}\sum_{x=1}^{B_i} q_{i,x}^b (F_{i,x} - S_i^t(\omega))\Delta t$.

4. Using the definition of CVaR to obtain CVaR_α, where $A(\omega)$ is replaced by $\Gamma_1(\omega)$.
5. Let CVaR_α^b be the optimal CVaR_α. Since the translation-equivariant property of CVaR is used, the actual CVaR_α is computed by $\text{CVaR}_\alpha^b + \sum_{t=1}^{N_d}\sum_{i=1}^{N}\sum_{x=1}^{B_i} q_{i,x}^b F_{i,x}\Delta t$.
6. Denote θ^* as the mean-risk function value of the recourse cost at iteration b. Then, we have

$$\theta^* = \sum_{\omega\in\Omega} \pi(\omega)\Gamma_1(\omega) + \beta\text{CVaR}_\alpha.$$

7. If $\theta^b > \theta^*$, then, stop the algorithm. $q_{i,x}^b$ is the optimal first-stage decision vector.
8. If $\theta^b \le \theta^*$, then, add optimality cuts into P5.6. Specifically, $\Phi_{a+1}(\theta_1, q_{i,x})$ is given by

$$\Phi_{a+1}(\theta_1, q_{i,x}) = \theta_1 + \sum_{\omega\in\Omega} \pi(\omega)\{\sum_{t=1}^{N_d}\sum_{i=1}^{N}\sum_{x=1}^{B_i} q_{i,x} S_i^t(\omega)\Delta t\}$$

Table 5.1 Computational size comparison between P5.5 and P5.6

Number of variables in P5.5	$(2N+F)N_{\Omega}N_d + N_{\Omega} + \sum_{i=1}^{N} B_i + 1$
Number of constraints in P5.5	$(2N+F)N_{\Omega}N_d + N_{\Omega} + \sum_{i=1}^{N} B_i$
Number of variables in P5.6	$N_{\Omega}a + a + \sum_{i=1}^{N} B_i + 2$
Number of constraints in P5.6	$3a + \sum_{i=1}^{N} B_i$

$$
\begin{aligned}
&-\sum_{i=1}^{N}\sum_{t=1}^{N_d} M_i v_{i,b}^t - \sum_{i=1}^{N}\sum_{t=1}^{N_d} y_{i,b}^t[(D_i^{\max} - \frac{1}{\mu_i})^{-1}] \\
&-\sum_{\omega\in\Omega} \pi(\omega)\{\sum_{f=1}^{F}\sum_{t=1}^{N_d} e_{f,b}^t R_f^t(\omega)\}.
\end{aligned}
$$

where $v_{i,b}^t, y_{i,b}^t, e_{f,b}^t$ are the optimal decisions of P5.7 at the iteration b. Moreover, $\Psi_{a+1}(\nu_{a+1}(\omega), q_{i,x}, \eta_{a+1})$ is described by

$$
\begin{aligned}
\Psi_{a+1}(\nu_{a+1}(\omega), q_{i,x}, \eta_{a+1}) = \nu_{a+1}(\omega) &+ \sum_{t=1}^{N_d}\sum_{i=1}^{N}\sum_{x=1}^{B_i} q_{i,x} S_i^t(\omega)\Delta t \\
&-\sum_{i=1}^{N}\sum_{t=1}^{N_d} M_i v_{i,b}^t - \sum_{i=1}^{N}\sum_{t=1}^{N_d} y_{i,b}^t[(D_i^{\max} - \frac{1}{\mu_i})^{-1}] \\
&-\sum_{f=1}^{F}\sum_{t=1}^{N_d} e_{f,b}^t R_f^t(\omega) + \eta_{a+1}.
\end{aligned}
$$

9. $a = a + 1$. Go to step (2).

5.5 Simulations

In this section, extensive simulations are conducted to evaluate the optimal tradeoff performance between *expected energy cost* and *operation risk* under different risk preferences of IDC operators. For comparison, the scheme in [20] is adopted as the baseline, which intends to minimize *operation risk*.

5.5.1 Simulation Settings

Suppose the total workload from one front-end web server is forwarded to two IDCs in two independent ERs, i.e., $F = 1$, $N = 2$. To reduce *operation risk*, IDC operators can participate in forward markets by signing EFCs. In this chapter, monthly EFCs with financial settlement are considered. The delivery period is set to be $N_d = 744\,\text{h}$, $\Delta t = 1$. In the delivery period, three monthly EFCs are available in two ERs, and the parameters defining each EFC are provided in Table 5.2, where forward price $F_{i,x}$ is the summation of $\bar{S}_i$ and ΔS_i, $\bar{S}_i$ denotes the expected spot price in the delivery period, and ΔS_i represents the positive risk premium [16]. Some parameters related to IDCs are summarized in Table 5.3 [1, 7, 20]. Confidence level α is set to 0.95 [18]. To generate scenarios, the day-ahead spot prices in U.S. NYISO (N.Y.C. bus is considered)[4] and ERCOT markets (HUDSON-8 bus is considered)[5] are adopted to construct time series models as in Sect. 5.3. Then, we use the fast-forward scenario reduction algorithm in [39] to obtain the price scenarios in two ERs and their corresponding probability distributions. For workload, we use the data of 1998 World Cup during June 10, 1998 to June 30, 1998[6] and modify the original workload by enlarging 60 times considering the increase of Internet traffic in the past decades, for example the average workload of World Cup 1998 is smaller than 2 million requests/h [40], while the average workload of Google search is 121 million

Table 5.2 Forward contract data

i	x	$F_{i,x}$ (\$/MWh)	$q_i^{\max}$ (MW)
1	1	$\bar{S}_1 + \triangle S_1$	10.93
	2	$\bar{S}_1 + \triangle S_1$	23.4
	3	$\bar{S}_1 + \triangle S_1$	6.778
2	1	$\bar{S}_2 + \triangle S_2$	10.93
	2	$\bar{S}_2 + \triangle S_2$	23.4
	3	$\bar{S}_2 + \triangle S_2$	6.778

Table 5.3 Simulation parameters

Parameter	Value		Unit
i	1	2	–
M_i	2.2×10^4	3.5×10^4	–
$P_{\text{peak},i}$	250	240	Watt
$P_{\text{idle},i}$	175	168	Watt
PUE_i	2.5	2.4	–
$D_i^{\max}$	0.7	0.7	s
μ_i	2	1.25	Req/s

4 http://www.nyiso.com/public/index.jsp, Sept. 2013.

5 http://www.ercot.com/mktinfo/, Sept. 2013.

6 http://ita.ee.lbl.gov/html/contrib/WorldCup.html, Sept. 2013.

requests/h [41]. In this chapter, 200 workload scenarios are generated. Using the scenario reduction algorithm, the generated scenarios are reduced to 20 for spot prices in two ERs and workload. Thus, there are totally 8,000 joint scenarios since prices in two ERs and workload. Moreover, the probability of each resulting scenario is equal to the joint probability of price scenario in two ERs and workload scenario at the front-end web server. Note that we focus on the method to implement the tradeoff between *expected energy cost* and *operation risk* given a set of scenarios and their probability distributions, instead of obtaining a reduced scenario set that can yield a good approximation to the optimal value of the original problem (corresponding to the situation that no scenario is reduced). For more details about yielding a good approximation, refer to [42].

5.5.2 Simulation Results

In Fig. 5.3, the tradeoff curves between *expected energy cost* (EEC) and *operation risk* (two risk metrics are adopted, i.e., CVaR and standard deviation) are shown under different risk preferences of IDC operators, where risk preference β is decreasing with the increase of CVaR and standard deviation. Since the impact of β on the tradeoff performance may be quite different under different combinations of ΔS_1 and ΔS_2,

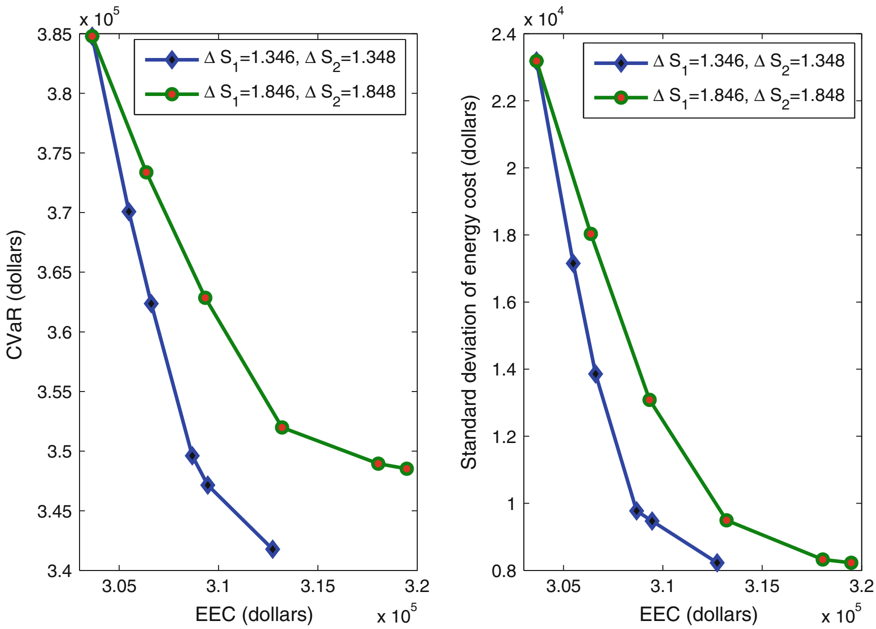

Fig. 5.3 Expected energy cost versus operation risk

we choose different β for different combinations of ΔS_1 and ΔS_2. Specifically, {1 0.5 0.18 0.15 0.12 0} (corresponding to $\Delta S_1 = 1.346$ and $\Delta S_2 = 1.348$) and {5 3 1 0.3 0.25 0} (corresponding to $\Delta S_1 = 1.846$ and $\Delta S_2 = 1.848$) are chosen as the value of β in simulations. Taking into account positive risk premiums, IDC operators would experience the increase of *expected energy cost* and the decrease of *operation risk* when signing EFCs in forward markets. Therefore, it is expected that *expected energy cost* attains the lowest and *operation risk* achieves the highest (i.e., largest CVaR and standard deviation) when $\beta = 0$. In existing work [20], the tradeoff between *operation risk* and *expected energy cost* is not considered. Thus, minimizing the *operation risk* would incur the highest *expected energy cost*, for example compared with one risk-neutral situation, ($\beta = 0$, $\Delta S_1 = 1.846$ and $\Delta S_2 = 1.848$), minimizing *operation risk* would lead to a reduction of 9.42 % (64.51 %) in the CVaR (standard deviation) and an increase of 5.21 % in the *expected energy cost*. Similarly, compared with another risk-neutral situation, ($\beta = 0$, $\Delta S_1 = 1.346$ and $\Delta S_2 = 1.348$), minimizing *operation risk* would lead to a reduction of 11.18 % (64.52 %) in the CVaR (standard deviation) and an increase of 2.99 % in the *expected energy cost*. By contrast, under the proposed decision framework, the flexible tradeoff between *expected energy cost* and *operation risk* could be achieved according to the risk preferences of IDC operators.

In Fig. 5.4, it can be seen that larger β would lead to the increased quantity of electricity purchased via EFCs. This is due to the fact that IDC operators tend to procure more electricity from forward markets to reduce *operation risk* if they are

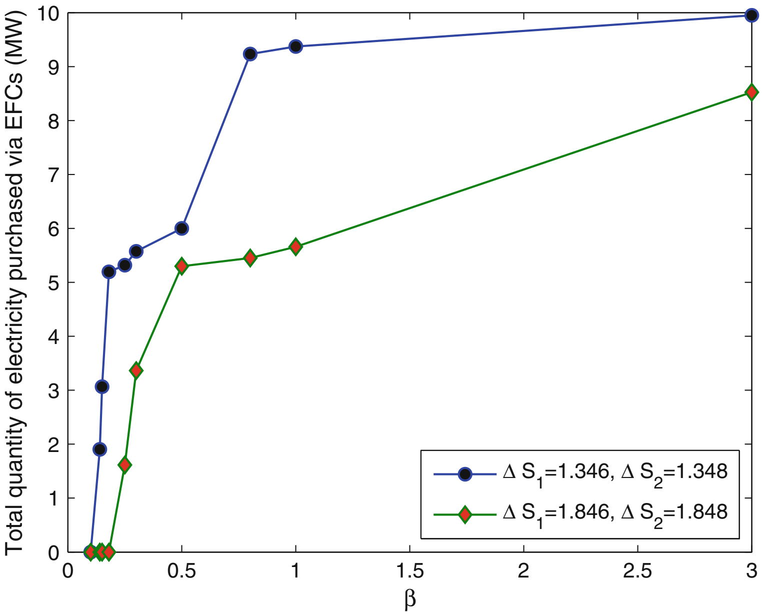

Fig. 5.4 Quantity of EFCs versus β

more risk averse. Moreover, with the increase of risk premiums, the quantity of electricity purchased vias EFCs is decreasing for a given β. The reason is that higher risk premiums would lead to higher *expected energy cost* if the quantity of electricity purchased via EFCs remains unchanged, which is equivalent to reduce the importance weight on minimizing CVaR in the objective function as in (5.13a–5.13c), resulting in the decreased quantity of electricity purchased via EFCs.

5.6 Summary

In this chapter, we investigated the risk-constrained operation for distributed Internet data centers in deregulated electricity markets. First, a risk-constrained decision framework was proposed to achieve the flexible tradeoff between *operation risk* and *expected energy cost* according to the risk preferences of IDC operators. Note that the proposed decision framework in this study can be easily extended to the scenarios that take into account other kinds of energy sources, such as future/option contracts in future markets and self-generation. Second, a risk-constrained *expected energy cost* minimization problem was formulated based on a two-stage stochastic programming model with recourse. Third, we proposed a solution to solve the problem. Extensive simulation results based on real-life data showed the effectiveness of the proposed decision framework.

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Chapter 6
Conclusions

In this book, we have studied the energy management of Internet data centers in smart grid from several perspectives, which can be described as follows.

1. In Chap. 2, we investigated the problem of minimizing energy cost for distributed IDCs in smart microgrids considering power outages. We designed an operation algorithm based on the Lyapunov optimization technique, which enables an explicit tradeoff between energy cost saving and battery investment cost. Finally, the effectiveness of the proposed algorithm was evaluated.
2. In Chap. 3, we investigated the problem of minimizing carbon-aware energy cost for distributed IDCs in smart microgrids. We designed an operation algorithm based on Lyapunov optimization technique without requiring any knowledge about system statistics. Finally, evaluations showed that the proposed algorithm can achieve lower energy cost and carbon emission simultaneously compared with the carbon-oblivious algorithm.
3. In Chap. 4, we investigated the problem of minimizing the long-term energy cost for an IDC in deregulated electricity markets taking heterogeneous service delay guarantees into account. We designed a joint workload and battery scheduling algorithm based on Lyapunov optimization technique. Meanwhile, we analyzed the feasibility and performance guarantee of the proposed algorithm. Finally, extensive simulation results show the effectiveness of the proposed algorithm.
4. In Chap. 5, we investigated the problem of achieving the optimal tradeoff between operation risk and expected energy cost for IDC operators in deregulated electricity markets. We proposed a risk-constrained stochastic programming decision framework. To solve the formulated problem, we used a decomposition-based cutting plane algorithm. Finally, extensive evaluations showed the effectiveness of the proposed decision framework.

Though some works have been done, there are some directions deserved for further research.

1. In this book, we have assumed that IDCs are price-takers, i.e., IDC power consumption and electricity prices are independent. However, there are two clear

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cases where IDC power consumption will affect electricity prices. First, IDCs have very high power densities compared to homes. This concentrated consumption can cause transmission congestion in the power grid and if IDCs were to rapidly ramp their power up or down, they could cause localized disturbances that affect electricity prices. Second, electricity prices would be affected if the power-demand being shifted represents the marginal load in the electric region, i.e., if adding that load to the electric region will require the activation of an additional power plant or if removing it will allow a running plant to be shut down. Furthermore, if many IDCs in a electric region implement load balancing, even one operator's power-demand is not enough to affect electricity prices, the aggregate demand from multiple operators could be large enough to affect electricity prices. Therefore, IDCs could be price-markers, i.e., IDC power consumption could change the electricity prices. In this situation, the algorithms proposed in this book should be redesigned.

2. IDCs represent large loads for the power grid and the power consumption of IDCs can be adjusted flexibly by scheduling workloads or changing the state of IT equipments (e.g., servers, storage and networking devices) and cooling facility. Therefore, IDCs are particularly suitable for participation in demand response programs to obtain financial benefits. However, there are some challenges that limit IDC participation in demand response, namely (1) price-based demand response programs require predicting the flexibility of IDCs accurately in order to set prices efficiently, which is especially difficult for distributed IDCs; (2) participation in incentive-based demand response programs is highly regulated and the bidding necessary to extract profits is typically difficult to automate and incorporate into IDC management system; and (3) how to design new demand response programs that can efficiently extract IDC flexibility?