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A systematic review of green-aware management techniques for sustainable data center

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ABSTRACT

Cloud computing is one of the powerful engines driving global industrial upgrading and the booming digital economy. However, the explosive growth of cloud data centers (DCs) has resulted in inevitable energy consumption and carbon emission problems. Therefore, constructing energy-efficient and sustainable DCs will be essential for green cloud computing. This review makes several efforts to thoroughly investigate and track the research progress and routes to sustainable DCs. Firstly, we construct a new conceptual model of sustainable DCs to cover cutting-edge research results and indicate future evolutionary directions. Secondly, this review provides a comprehensive survey of five topics from a technical perspective: workload management, virtual resource management, energy management, thermal management, and waste heat recovery. Subsequently, some real-world datasets relevant to the topics, including workload traces, renewable energy data, and electricity price traces, have been specifically collected to support researchers in conducting further research. Finally, based on observations of existing works, we highlight some salient technical challenges and promising solutions to provide sensible energy and carbon reduction suggestions in sustainable DCs.

1. Introduction

Cloud computing is a concentrated expression of digital technology advancement and service model innovation. According to Gartner,[1] the growth rate of the cloud computing market declined significantly in 2022 due to the double impact of inflationary pressure and macroeconomic downturn. However, compared with the global economy's growth of only 3.4%, cloud computing is still a powerful engine to drive the development of new technologies and business models. With the demand stimulated by large models and arithmetic power, the global cloud market will maintain steady growth and exceed one trillion dollars by 2026 (Fig. 1). Due to its computing power, cloud data centers have become an integral part of the modern computing infrastructure. More enterprises increasingly turn to DCs for hosted services and cloud solutions. Meanwhile, the issue of energy consumption and carbon emissions has emerged as a significant challenge for the construction of DCs worldwide. In early 2020 Science reported that the total energy consumption of global DCs reached about 205 TWh in 2018, about 1% of global power usage, an increase of 6% compared to 2010 and a steady growth trend [1]. Consequently, the energy consumption, sustainability, and low-carbon footprint of DCs are a growing concern for society. In general, DCs will play a more significant role in achieving the global dual-carbon goal while being the new engine of future digital economic growth.

With the influence of sustainability concepts, promoting energy efficiency and cost reduction has become an essential evolutionary direction for cloud computing [2]. To gradually achieve carbon neutrality and reduce power usage effectiveness (PUE) in DCs, common international practices include purchasing carbon emission reductions or green energy (including green certificates) and investing in renewable energy [3]. Furthermore, some major global economies have set related emission reduction targets and policies. For example, several European cloud operators have promised a European Green Deal to achieve climate neutrality by 2030, with measurable goals for buying non-carbon energy, water savings, and thermal recycling [4]. The Chinese administration has also declared peak emissions by 2030, adopting more effective policies and measures to achieve carbon neutrality by

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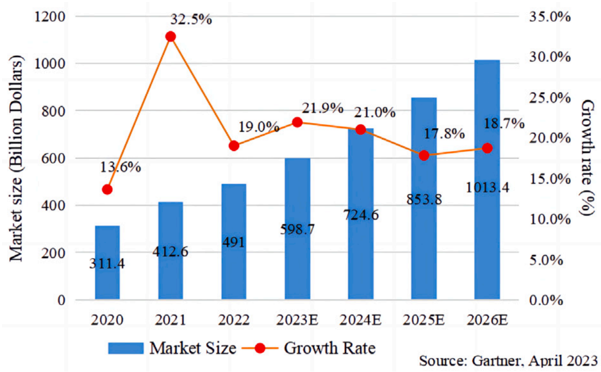

Fig. 1. Global cloud computing market size and growth rate.

2060 [5]. Additionally, California introduced a carbon-neutral law in 2018 to reduce greenhouse gas emissions mainly from power generation facilities. There is no doubt that these green goals and policies are forcing data center owners to urgently promote overall energy efficiency in DCs.

Furthermore, worldwide leading major cloud service providers (CSPs) such as Google, Microsoft, Facebook, and Alibaba have been striving to find new solutions to make cloud computing eco-friendly [6]. For example, Google's 2022 environmental report [7] claims that it operates DCs with an average annual PUE of 1.10, compared to the industry average of 1.573, and has matched 100% of electricity use with renewable energy purchases in its global operations for the fifth year in a row. As another green pioneer, Microsoft established a series of actions, such as increasing renewable energy penetration and charging an internal carbon fee to ensure carbon negativity by 2030 and eliminating its historical carbon emissions by 2050 [8]. Additionally, Facebook is actively pursuing carbon reduction measures such as reforestation and regenerative agriculture. An IT load-balancing scheduler, Autoscale [9], is also being deployed for server consolidation to boost the energy efficiency of IT devices. Simultaneously, Chinese high-tech companies promote their carbon neutrality plans and implement solutions. For example, Alibaba Group, a pioneer in cloud computing in China, adopts advanced AI technology to control cooling systems, immersed liquid cooling technology, power supply systems that integrate green energy and natural cooling sources, etc.[10]. Additionally, Huawei's intelligent cooling solution iCooling [11] has been launched in several large-scale DCs on a commercial scale, realizing intelligent cooling. The solution has been measured to reduce PUE by about 8%–15%, achieving an energy-saving green goal.

Observing previous efforts on sustainable DCs reveals that different entities have put forward different approaches and solutions to enhance DC sustainability. Still, the following five areas are broadly used and accepted: workload management, virtual resource management, energy management, cooling management, and waste heat recovery. In conclusion, driving the shift towards green, low-energy, and sustainable DCs requires multi-dimensional optimization.

So far, related reviews have analyzed and discussed cutting-edge research advances in sustainable DCs. For instance, Junaid et al. [6] provide multiple case studies from academia and industry to demonstrate that three sustainability technologies – renewable energy integration and utilization, waste heat recycling, and migration of modular DCs – bring promising results. Sukhpal et al. [12] proposed a comprehensive taxonomy of sustainable cloud computing to compare and classify existing technologies. Huang et al. [13] focused on the upstream integration of renewable energy and the downstream use of waste heat in DCs. This work analyzed DC performance and future directions in terms of technology, policy, and economics. Avita et al. [14] investigated software solutions for establishing green DCs, including virtualization, operating system, and application levels. Study cases for integrating and utilizing green energy to reduce brown energy and carbon footprints are also discussed. Table 1 exhibits the comparison between our work and other related reviews. Overall, existing reviews have discussed specific themes of sustainable DCs with their focus and insights, but they are incomplete or have limitations. Additionally, they have not given a blueprint for constructing a sustainable DC. More importantly, as theories and technologies evolve, exploring the path forward for critical topics from historical and cutting-edge work is essential.

Therefore, this review first gives a new conceptual model for sustainable DCs. Then, we present a comprehensive review of green-aware management technologies in the five most promising topics: workload scheduling, virtualization technologies, energy management, thermal management, and waste heat recovery. In addition, considering the positive impact of real-world datasets on simulation performance, we collected real datasets relevant to the topic to drive the research. Finally, we suggest some critical scientific issues and practical solutions for sustainable DCs.

The review method is briefly introduced as follows. We have collected papers from several authoritative electronic libraries (IEEE Xplore,[2] ScienceDirect,[3] SpringerLink,[4] ACM Digital Library,[5] and arXiv[6]). A multi-keyword combined search was conducted based on the following two or more keywords: cloud computing, data center, renewable energy, sustainability, green, energy-aware, cooling system, and waste heat recovery. Additionally, to cover the research progress in energy-saving management technologies for sustainable data centers, we not only focus on the latest published work but also track some long-standing and seminal work. After relevance screening, this review collected 183 papers and industry reports, including 157 journal papers, 16 conference papers, and 10 reports.

The remaining content is structured as follows. Section 2 presents the conceptual model of sustainable DCs. Section 3 is a comprehensive classification and analysis of green-aware management techniques. Section 4 is a collection of real-world datasets related to the topic, with available links. Section 5 presents existing open issues and future research directions. Finally, a conclusion of the review is provided. An overview of this review is shown in Fig. 2.

2. Conceptual model of sustainable data center

As research on sustainable DCs continues to make breakthroughs, new conceptual models must be developed to cover cutting-edge research findings. The early models developed by Gill et al. [12] and Jordi et al. [15] are innovative and cover the critical topics of the data center. However, the conceptual model proposed in [12] describes the composition of the DC from a macro-perspective. In addition, the model presented in the review [15] focuses more on cooling infrastructure and workload management. Therefore, we introduce a new conceptual model that combines the characteristics of existing models to provide a more comprehensive description of sustainable DCs. As shown in Fig. 3, the proposed conceptual model includes essential parts such as the IT system, cooling system, power supply system, waste heat recovery system, and lighting.

The IT system is the core system of the data center, which receives and executes the various requests and workloads from individual users, research institutions, and enterprises. The system identifies the quality of service (QoS) requirements of each workload and subsequently configures physical or virtual machine (VM) resources to execute the workload. **The cooling system** regulates the temperature and humidity

2 http://ieeexplore.ieee.org/Xplore/home.jsp
3 http://www.sciencedirect.com
4 http://link.springer.com
5 http://dl.acm.org
6 https://arxiv.org/

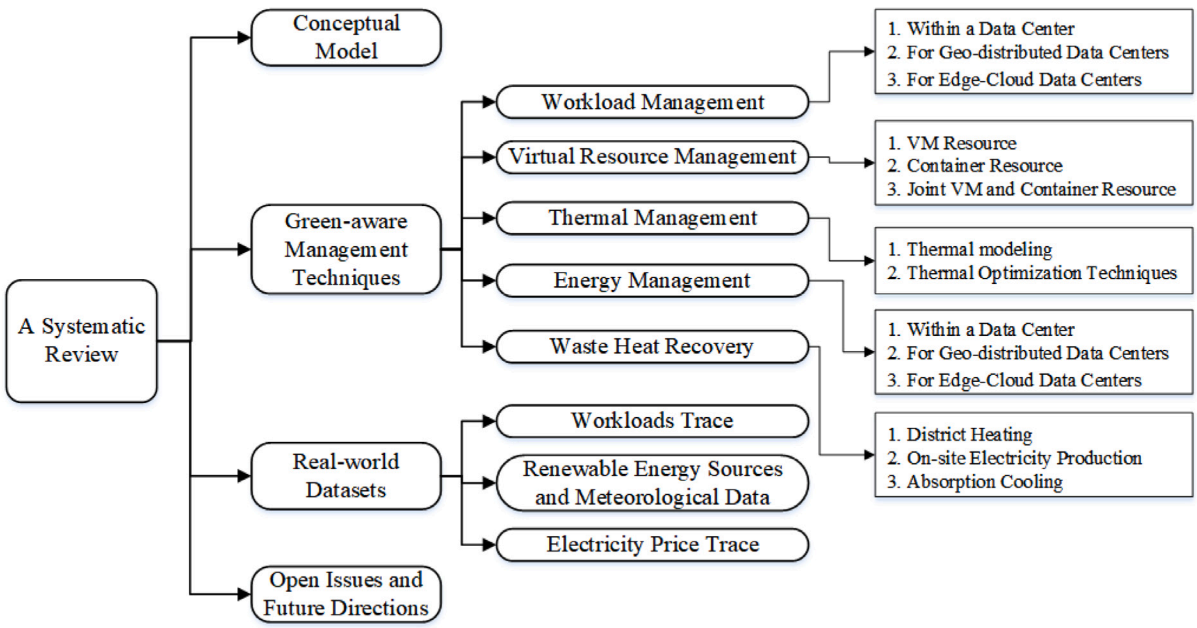

Fig. 2. Overview of the review.

Table 1
Comparison with related reviews.

Ref.	Year	Workload management	Virtual resource management	Thermal management	Energy management	Waste heat recovery	Real-world datasets	Characteristics
[6]	2016		√		√	√		Modular data centers, case studies from both academia and industry
[12]	2019	√	√	√	√	√		A comprehensive taxonomy of sustainable cloud computing
[13]	2020			√	√	√		Renewable energy integration and waste heat reuse in district heating
[14]	2022	√	√		√			Virtualization, operating system and application level software solutions
our work	–	√	√	√	√	√	√	A conceptual model, green-aware management techniques

in the computer room, with the second highest energy consumption after the IT system. The heat released by the IT facilities in the computer room is discharged to the outdoor environment through a twofold thermal cycle consisting of cooling devices such as computer room air conditioning (CRAC), cooling towers, pumps, and chillers. **The power supply system** is designed to provide stable and secure electrical power to the DC infrastructure. The system can adopt multiple energy sources, such as the commercial grid, renewable energy (solar and wind), and energy storage devices (ESDs), to power the data center. Moreover, an automatic transfer switch (ATS) is employed to manage energy sources and redirect power to the uninterruptible power supply (UPS). Distributed UPS power architectures are adopted to avoid single points of failure and to maximize the reliability and availability of the power supply system. Additionally, ESDs are an energy buffer that smooths out intermittent renewable energy sources (RESs). Power distribution units (PDUs) regulate voltage and transmit power to IT equipment, cooling, and lighting systems. **The waste heat recovery system** reuses low-quality waste heat from cooling systems for district heating, absorption cooling, and thermal power plants. Efficient reuse of waste heat significantly reduces carbon emissions and can offset part of the carbon credits.

3. Green-aware management techniques

3.1. Workload management

Effective workload management in DCs is critical to reducing operating costs, energy consumption, and carbon emissions while ensuring QoS. To provide users with low-latency and high-reliability cloud computing services worldwide, large CSPs such as Google, Facebook, and Alibaba usually build distributed DCs in different locations and connect each node through high-speed fiber-optic networks [16]. With the explosive evolution of the mobile Internet, the cloud has become the primary centralized data storage, searching, and management method. A large number of mobile terminals have evolved information destinations and display platforms. Edge computing is a significant extension of cloud computing. As the base station between the cloud and the user, the edge node effectively shortens the physical distance between the user and the cloud. This computing model reduces the communication burden of data transmission and the response delay [17]. Therefore, with the continuous innovation of the cloud computing paradigm, it is challenging to carry out effective workload management among massive heterogeneous computing nodes to ensure the greenness and sustainability of the cloud. Some significant related work is summarized in Table 2.

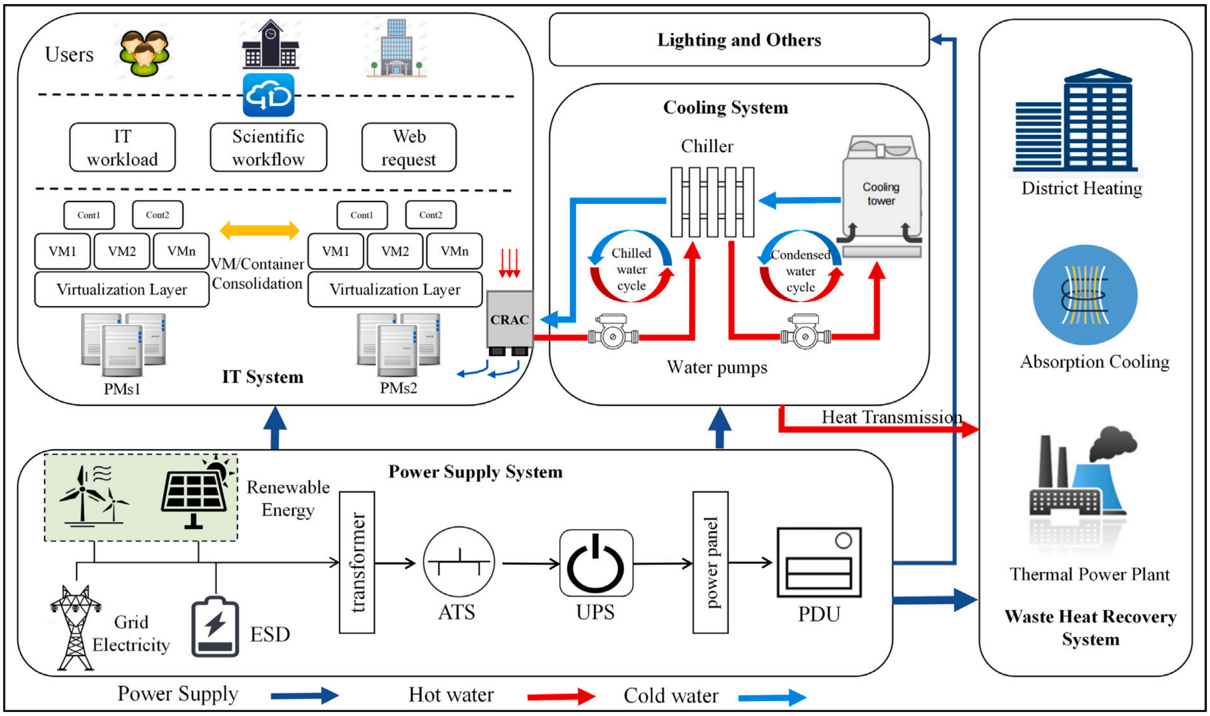

Fig. 3. A Conceptual Model for Sustainable Data Center.

Table 2
Comparison of workload management techniques.

Ref.	Workload	Cluster	Methods and strategies	Optimization objective and effect
[18]	HPC workload	HPC DCs	DVFS, Spatio-temporal thermal model	Minimize the makespan of workloads subjected to temperature constraints
[19]	Communication-intensive workload	HPC DCs	The binary quadratic programming method.	Communication cost and cooling energy consumption
[20]	High-priority job	HPC DCs	A thermal-aware resource allocation optimizer; an economic model predictive controller;	power consumption, equipment life, and QoS
[21]	Request	DC	Karush–Kuhn–Tucker optimality conditions	Minimize the power consumption
[22]	Soft real-time task	DC	A novel smart green energy-efficient scheduling strategy	Utilization of renewable energy, system running cost and task satisfaction rate
[23]	Delay-tolerant workload	DC	Lyapunov optimization framework	Reduce the electricity cost, while guaranteeing the performance constraint
[24]	Batch workload	DC	A new algorithm with several variants for scheduling batch tasks with awareness of renewable energy and electricity cost.	Reduce brown energy consumption and cost
[25]	Mixed workload	DC	A self-adaptive approach for managing applications and harnessing renewable energy	Reduce the usage of brown energy and maximizing the usage of renewable energy
[26]	Service and batch job	DC	A three-step algorithm is proposed to schedule heterogeneous workloads	Green energy production, cooling power, and distributed UPS power supply
[27]	Web application	Geo-distributed DCs	A reactive load balancing algorithm	Reduce costs and brown energy
[28]	Transactional and batch workload	Geo-distributed DCs	a heterogeneity-aware cloud workload placement and migration approach	Green energy availability and QoS
[29]	Interactive and batch workload	Geo-distributed DCs	A Receding Horizon Control based online algorithm	Trade-off cost benefits and scheduling penalties
[30]	Interactive request	Geo-distributed DCs	An online algorithm for interactive workload distribution	Minimize the energy cost
[31]	Application or VM	Geo-distributed DCs	A hierarchical framework	Reduce the energy costs, load balancing, and carbon emission
[32]	computation-intensive and latency-sensitive task	Edge-cloud DCs	Intelligent learning classifier systems (LCS) and evolutionary algorithms	Reduce the workload's processing delay and energy consumption
[33]	Mobile applications	Edge-cloud DCs	Then the long short-term memory model (LSTM) and RL technology	Reduce the execution time and energy consumption
[34]	computation-intensive and latency-sensitive task	Edge-cloud DCs	Multi-agent RL method	Minimize the average completion time of tasks under migration energy budget

3.1.1. Within a data center

Workload management significantly influences the QoS and operating costs of DCs. Following a comprehensive survey, cutting-edge work focuses on thermal-aware, renewable-aware, and hybrid-aware workload scheduling.

Thermal-aware workload scheduling is to minimize the heat emitted by active servers to reduce thermal gradient and cooling load [35]. Thermal-aware scheduling differs from efficiency-aware scheduling, which reduces the number of active hosts. The efficiency-aware scheduling strategy is to consolidate the workload on as few active servers as possible and shut down the idle servers. In this case, most active servers are overloaded and prone to high regional temperatures or hot spots. As a result, the cooling devices will consume more energy to push colder air to cool the hot spots [36]. In addition, servers overloaded for a long time are more prone to hardware failures, which can degrade service performance. Nevertheless, the thermal-aware strategy fully considers IT and cooling energy consumption, looking for computing resources with minor energy consumption to execute workloads. This scheduling strategy can reduce the frequency of hot spots and the cooling load [37]. Thermal-aware management has been well acknowledged as an essential technology to optimize system performance and energy efficiency in modern DCs [18]. After investigation, the thermal sensing workload scheduling is divided into three categories: QoS-based, optimization-based, and thermal constraint-based scheduling.

QoS-based workload scheduling ensures QoS while controlling temperature and reducing the cooling load. The conflicts between QoS and thermal scheduling may be caused by the constraints such as task completion deadline, task priority, and server resource availability. Therefore, some novel solutions have been proposed to solve this issue. For example, for the trade-off problem of cooling efficiency and performance during workload scheduling in high-performance computing (HPC) DCs, Meng et al. [19] formulated and solved a joint optimization thermal-aware workload scheduling problem that took into account the latency of communication-intensive parallelized applications and the cooling capacity of the DC. Additionally, Sun et al. [18] designed a thermal-aware online scheduling heuristic to minimize the makespan of HPC workloads subjected to temperature constraints. The innovation of this work is that a concept of the thermal-aware load is introduced into the scheduling decision, which can more accurately capture the server's load under thermal constraints to achieve load balancing in the sense of thermal-aware. Fang et al. [20] developed a thermal-aware optimal control framework to solve high-priority job scheduling in the HPC data center. The framework aims to save energy for idle servers and cooling systems while maintaining job scheduling and execution efficiency, thus balancing power consumption, equipment life, and QoS.

The optimization goals of workload scheduling vary, as do the solutions adopted. For example, the server-based approach aims to minimize the increase in peak inlet temperature due to thermal disturbances [38]. Some commonly used methods to reduce thermal cycling are reducing the workload on the underlying servers or migrating the IT load from hot servers to cold servers [39]. Furthermore, it is worth noting that most previous works focused on promoting the energy efficiency of either the IT or the cooling subsystem, ignoring the relationship between the power consumption of these two systems [40]. Consequently, the cold supply of the cooling system does not match the cold demand of the IT equipment. Therefore, it is necessary to consider joint optimization of cooling operating parameters and workload distribution when performing energy-saving optimization. Damme et al. [21] developed an optimized thermal-aware job scheduling and control model to explore the optimal set point of workload distribution and cooling parameters to minimize power consumption. This model assumes that the servers on the rack are all homogeneous. Thus, the complex general energy minimization optimization problem is transformed into a simple equivalent problem for homogeneous DCs. Subsequently, the authors demonstrate that an optimal air-conditioning supply temperature and workload distribution can be uniquely determined to obtain a minimum total energy consumption in a DC.

Thermal constrain-based scheduling methods are broadly divided into proactive and reactive scheduling. Proactive scheduling is to plan workload scheduling in advance to avoid thermal anomalies, while reactive scheduling takes dynamic thermal management measures after thermal anomalies occur. Although the energy-saving effect of reactive scheduling is less than that of proactive scheduling, it has the advantages of low complexity and rapid response. Therefore, there is a trade-off when choosing a scheduling type. Zhao et al. [41] introduced a scheduling strategy based on model predictive control called ThermoRing to reduce the cooling costs of DCs. ThermoRing adopted an online feedback control mechanism to improve the thermal management of the server cluster. The advantages of this method are that, on the one hand, the maximum inlet temperature of nodes can be adjusted in real-time under the red line temperature limit. On the other hand, it can handle the thermal emergency by dynamically balancing the load between the nodes to ensure the high performance and stability of the DC. Yao et al. [42] formulated a joint optimization problem for the total power consumption of the server and air-conditioning equipment under unknown thermodynamic conditions. An adaptive power control method is proposed to minimize the gap between the inlet and the required temperature of the server rack.

Renewable energy-aware workload scheduling is also another promising solution to solve the DC carbon footprint. Lei et al. [22] proposed an intelligent green energy-saving scheduling method, which considers the generation of renewable energy, time-varying power prices, and the task satisfaction rate of DC. The model inputs the forecast generation of RESs and power price and then outputs the task scheduling strategy. Dynamic matching of task load and renewable energy generation can maximize renewable energy utilization and save total energy costs. Given the performance constraints of delay-tolerant workloads and the limited future information (time-dependent power prices, carbon footprint, and on-site RESs generation), Dou et al. [23] designed an online workload scheduling algorithm to reduce overall power bills and carbon taxes. The algorithm can make trade-offs between electricity charges and workload performance without considering future information. Grange et al. [24] developed a method for scheduling batch workloads under deadline constraints, considering using green energy to reduce the demand for grid energy. Compared with a traditional scheduler without considering green energy, this scheduler can reduce brown energy consumption by 49% and cost by 51%. To minimize the carbon footprint generated by executing workloads in DCs, Bahreini et al. [43] designed an LP-based approximation algorithm to determine the execution order of workloads to accommodate carbon intensity uncertainty.

Hybrid-aware workload scheduling (thermal and renewable energy-aware) is a novel perspective energy-saving approach for sustainable DCs. This approach aims to fully use non-carbon energy by configuring and shifting workloads while considering IT and cooling power consumption. Xu et al. [44] proposed an adaptive scheduling model for mixed workloads in a hybrid-powered DC, which considers a variety of devices' energy consumption affected by the workload. Moreover, the work [45] designed a low-complexity heterogeneous workload scheduling algorithm considering green energy production, cooling power, and distributed UPS power supply. The work also investigated the impact of weather on the efficiency of the proposed method.

3.1.2. For geo-distributed data centers

Dynamically allocating and migrating workloads among geo-distributed DCs are opportunities to reduce costs. CSPs follow the "follow the moon" paradigm, deploying or shifting workloads to places with more abundant renewable energy, cheaper electricity prices, and lower cooling costs than the original location. In addition, with the enhancement of logical functions of communication technology (for example, the adoption of software-defined network, SDN [25]), high network capacity can ensure the timeliness of workload migration between distributed sites.

Guo et al. [16] considered the load-balancing mechanism of geo-distributed DCs, the opportunistic scheduling of delay-insensitive workloads, and thermal energy storage (TES) to promote the integration and utilization of RES. Subsequently, the author formulated a stochastic optimization model and then applied the Lyapunov optimization technique to solve it. Extensive numerical evaluations prove that the designed online control algorithm balances energy costs and QoS of workload. Considering the availability of RESs for each node, Toosi et al. [26] proposed a reactive load-balancing framework for interactive workloads between multiple clouds. Note that the work was validated on a realistic testbed with real-world workload traces and a real-time monitoring system. Numerical experiments prove that the method can effectively use green energy without knowing the incoming workloads, the generation of RES, and the market power price in advance, thereby reducing costs and reducing the use of brown energy. To address the challenge of using green energy with intermittency in distributed DCs, Cheng et al. [46] developed a holistic heterogeneity-aware cloud workload deployment and migration method, sCloud, while considering the green energy availability and QoS. An adaptive optimization algorithm adaptively assigns transactional workloads in geo-distributed DCs according to its on-site green energy production. Furthermore, an additional online algorithm is integrated to migrate batch workloads over multiple clouds to extend the system throughput. In addition, for the carbon emission problem, Xu et al. [27] developed a workload shift method that considered the shift of workload between multiple remote clouds to minimize the average response time and greenhouse gas emissions. Compared with relevant benchmarks, the proposed method meets the average response time of microservices and reduces carbon emissions by about 40%. Similarly, the work [47] considers carbon-aware workload scheduling in geo-distributed DCs. The authors exploit the temporal and spatial flexibility of batch workload scheduling to maximize the computational resource usage when the power supply carbon intensity is low, effectively reducing the total carbon footprint.

Moreover, considering the revenue loss due to power load fluctuations in DCs, the work [28] proposed a collaborative workload scheduling and smart grid approach for geo-distributed DCs to trade off cost benefits and scheduling penalties. Precisely, the power loads of various DCs are effectively smoothed by allocating interactive workloads and deferring the execution of batch workloads. Khalil et al. [48] modeled the energy cost minimization problem in DCs as a two-stage optimization problem. Firstly, the Black–Scholes model determines the call option's value and whether to purchase the power call option. In the second phase, an online algorithm for interactive request allocation is proposed, called OptionGLB, which considers the battery power, option pricing, and time-varying electricity price. OptionGLB dramatically diminishes the overall expense of the DC but ignores the origin of clean energy and bandwidth costs.

Due to the time-varying of electricity prices, intermittency of renewable energy, heterogeneity of infrastructure, diversity of workload, and other elements, the workload scheduling decision of geo-distributed DCs becomes particularly complex [29]. The multi-cloud node workload management is typically modeled as a constrained multi-objective optimization problem, and a centralized method is adopted to solve it. The advantages of centralized management are affordability, reliability, and efficiency. However, centralized management also has some limitations, including (1) Large system scale and many parameters leading to poor scalability. (2) Risk of a single point of failure. (3) Unified management policies to limit the autonomy of child nodes [30]. Therefore, decentralized management will be another potential solution for multi-datacenter workload management. Forestiero et al. [29] proposed a hierarchical framework, EcoMultiCloud, for efficiently distributing workloads among multiple computing nodes. The framework allows centralized management of heterogeneous platforms but also gives sufficient autonomy to individual compute nodes. On the one hand, each node adopts its unique strategy to distribute and consolidate workloads. On the other hand, a set of centralized management algorithms is adopted to assess the state of the individual nodes and allocate and migrate workloads between them based on global optimization goals.

3.1.3. For edge data centers

Edge data centers provide localized interaction and low-latency IoT services. Further, the central cloud provides centralized services that integrate transactional applications that require large-scale computing. Nevertheless, the limitations of edge computing nodes in computing power, memory, storage, communication, and energy make it challenging to handle computing-intensive tasks locally. Thus, delay-tolerant requests can be forwarded to a more capable cloud for centralized processing, thus achieving edge-cloud collaborative scheduling. Significant differences exist between the edge nodes and the cloud regarding infrastructure structure and service goals, increasing the workload distribution complexity in the edge-cloud DC.

In recent years, much research has been carried out on this unresolved problem and achieved good results. Deng et al. [17] studied the conflict between the edge-cloud system's operating costs and service quality. The original issue of workload distribution is roughly decomposed into three sub-problems, which are solved in corresponding subsystems. Extensive numerical simulations show that fog-cloud computing can reduce bandwidth costs and transmission delays by sacrificing appropriate computing resources. Borylo et al. [31] explored the possibility of processing fog-related traffic in a delayed sensing method. To this end, a wide-area software-defined network (WA-SDN) was introduced to support the energy-aware interaction between fog and cloud. Wu et al. [49] developed a novel framework for edge computing, called GLOBE, to optimize the distribution of computing workload between distributed base stations and the performance of mobile edge computing (MEC). In addition, GLOBE works in a distributed manner, so it has good scalability and is suitable for large networks.

The MEC network includes three computing nodes with different computing and communication capabilities: local mobile terminals, edge nodes, and the central cloud. Additionally, the available resources of the computing nodes in the running state constantly change, so optimizing the task offload in the heterogeneous and changeable MEC network is a considerable challenge. Abbasi et al. [50] took the lead in using intelligent learning classifier systems (LCS) to achieve the optimal workloads configuration in fog computing. LCS, a particular reinforcement learning (RL) model, learns by continuously interacting with the environment to obtain rewards to select the best action according to the current state. The LCS-based method reduces the workload's processing delay and saves energy consumption by 18% compared with the most advanced method. Shahidinejad et al. [51] developed a joint task offloading and resource provisioning approach for edge-cloud DCs. First, the learning automaton (LA) technology provides an efficient computing offloading mechanism to offload the incoming dynamic workload to the edge server or cloud server. Then the long short-term memory model (LSTM) is adopted to predict the incoming workload. Finally, RL technology was adopted to make an appropriate scaling decision to deal with fluctuations in dynamic workloads.

Most of the above works solve the problem of computing offloading in quasi-static scenarios, and a few works [32,33] focus on migration management issues related to user mobility. All of them are based on perfectly predicted user movement trajectory information to carry out offloading migration. Nevertheless, in a realistic scenario, predicting the user's movement information accurately is not practical. Therefore, Liu et al. [52] designed a distributed task migration algorithm based on the counterfactual multi-agent (COMA) reinforcement learning method to solve the energy-aware task migration problem. The innovation of this method is that multi-agent RL is adopted to realize multi-user collaborative decisions, and the computational complexity is low. The framework includes a centralized critic and multiple actors corresponding to multiple users.

3.2. Virtual resource management

The advancement of virtualization technology has brought more diversified service models to cloud computing while also increasing the complexity of resource management issues. Therefore, how to conduct efficient resource management to save energy in the DCs while ensuring QoS is one of the significant challenges cloud computing faces. Virtual resource management consists of two parts: resource allocation and resource consolidation. The goal of resource allocation is to achieve a high level of matching between workload and system resources, in other words, to implement high-quality services to clients based on the available resources of the cloud system. Consolidating and migrating virtual resources allows the system to shift from a specific state to a more optimized state and avoid underloading and overloading resources while ensuring performance and minimizing operating costs [53]. VMs and containers are the most commonly used virtual resource instances to provide services to users. Containers are lightweight VMs that make consolidating and migrating virtual resources more flexible and efficient [34]. The overall idea of virtual resource management is to map VMs/Containers to servers or DC nodes based on resource matching and performance metrics. This section presents existing solutions and works for virtual resource management, listed in Table 3.

3.2.1. VM resource

VM Allocation. Multi-dimensional VM allocation problem can be represented as a vector bin-packing problem. The energy-aware VM allocation strategy reduces energy consumption by minimizing the number of active PMs while considering resource requirements and QoS. For example, Mishra et al. [71] focus on the problem of adaptively allocating VMs to PMs under unpredictable dynamic workloads. The proposed VM allocation scheme first searches for suitable VMs for tasks with different resource requirements, then deploy the selected VMs to as few PMs as possible. The proposed method can start the least PMs to meet VM resource requirements while reducing task completion time and rejection rate. Similarly, Saxena et al. [54] proposed a highly efficient resource supply and allocation framework, which adopted a novel online multi-resource feed-forward neural network predictor model to evaluate the demand for multiple resources. Accurate resource demand forecasting provides a solid basis for resource management operations such as VM consolidation and cluster scaling to solve excessive power consumption, resource waste, and performance loss due to frequent changes in user resource requirements.

For VM allocation in heterogeneous DCs, Peng et al. [55] developed an evolutionary energy-saving VM allocation method, which relies on the energy optimization model of sustainable DC with renewable energy. First, the genetic algorithm (GA) is used to explore a nearly optimal solution for VM allocation while considering the cost of renewable energy and traditional grids. Subsequently, a new metric, powerMark, was proposed, which quantified the power efficiency by measuring the server's power consumption at each resource utilization level and then determined the allocation priority of each cloud data center. Similarly, Mergenci et al. [72] proposed two parameterized metrics to measure the current state of VM allocation and proposed a multi-dimensional resource allocation heuristic algorithm based on the new metrics. Numerical simulation shows that the proposed metrics can accurately measure the resource utilization state to place the VM more effectively. Peng et al. [56] modeled the dynamic VM placement problem as a markov decision process (MDP) and proposed a multi-objective trade-off cloud resource scheduling framework based on deep reinforcement learning (DRL) technology, considering the makespan and energy consumption. This method can capture the dynamic variations of the task requirements and resource status of the cloud system and make the VM placement strategy in real-time, reducing the long-term energy overhead of the system while ensuring the task deadline. Not coincidentally, Zeng et al. [57] introduced an impact factor to measure the VM impact on host overload and to select VMs to be migrated. Subsequently, DRL with a prediction mechanism was used to learn the optimal policy for VM placement. The experimental results validate that DRL is an effective method for solving the VM dynamic consolidation problem.

VM Consolidation and Migration. Many VM instances are deployed on PMs serving various applications, and they have different life cycles and resource requirements. System resources constantly change dynamically as the VM's life cycle begins and ends. Dynamic VM consolidation and migration facilitate improved system resource utilization. The VM consolidation and migration is divided into four sub-problems, including (1) detecting overloaded hosts and determining the number of VMs to be migrated, (2) detecting underloaded hosts and then migrating all VMs on it, subsequently shutting down or hibernating the host. (3) determine which VMs in the overloaded host need to be migrated, and (4) select a target host for those migrated VMs. Additionally, virtualization technology supports VM migration between geo-distributed DCs, and more consideration is given to green energy and grid power prices.

Many works have proposed solutions to various sub-problems of VM consolidation and migration. For example, Arianyan et al. [58] developed a novel comprehensive cloud resource management method that considers power consumption, the number of VM migrations, and SLA violations. Additionally, a new heuristic approach based on multi-criteria decision-making is proposed to solve two sub-problems, including (1) underloaded host detection and (2) VMs allocation. To solve the trade-off between reliability and energy efficiency during the dynamic VM consolidation process, Sayadnavard et al. [59] developed an innovative method for dynamic VM consolidation. The technique first adopts a Markov model to evaluate the reliability of PM and then classifies PM according to the load rate of the CPU. Finally, this method considers utilization and reliability when selecting the source and target PMs for VM migration.

In response to VM migration leading to the extra power and performance loss, Jiang et al. [60] designed an adaptive resource allocation method to boost energy efficiency and decrease SLA violations in DCs. All servers in the DC are clustered according to the path length of the given DCN topology. After that, the VMs are preferably placed on servers with large capacity and substantial computing power to minimize the number of activated servers. If some servers are overloaded, the proposed scheme will preferentially select servers in the same cluster as the target host of VM migration, thus shortening the length of the migration path. Simulation experiments show that the proposed method effectively reduces dynamic power consumption, migration times, and path length. Moreover, Dulaimy et al. [73] developed a distributed dynamic VM integration method. This method first determines which VMs need to be migrated and then models the selected VMs allocation problem as a multi-choice knapsack problem to minimize energy consumption. Extensive data analysis shows that the dynamic threshold technique proposed in underload/overload host detection is better than static threshold technology, especially for those cloud scenarios that lack future workload information. Meanwhile, placing VMs with different resource requirements on the same PM can avoid the overuse and underuse of a particular resource, thus improving resource utilization.

In addition, the integration and utilization of renewable energy [61], the temperature distribution of the machine room, and the cooling supply [62] have become significant considerations for VMs consolidation and migration. Wang et al. [61] developed a green-aware VM migration method for DCs that takes into account both server and air conditioning power consumption. The goal is to take full advantage of non-carbon energy by migrating VMs to reduce brown energy consumption while ensuring service level agreement (SLA) violations. In addition, Esfandiarpoor et al. [63] also proposed a novel VM consolidation method, taking into account the data center's network topology, server racks, and cooling equipment to reduce energy consumption without affecting

Table 3
Comparison of resource management techniques.

Ref.	Resource management	Methods and strategies	Optimization objective	Characteristics or limitation
[54]	VM Allocation	A proactive autoscaling and energy-efficient VM allocation framework	Power consumption, resource waste, and performance loss	Using online multi-resource feed-forward neural network to forecast the multiple resource demands
[55]	VM Allocation	Genetic algorithm	Energy efficiency and performance	A novel metric which diagnoses the power efficiency of each DC
[56]	VM Allocation	DQN algorithm	Energy consumption and task makespan	Make a trade-off of the energy and task makespan
[57]	VM Allocation	A Prediction aware DRL-based VM placement method	Energy consumption and SLA violation	VM selection and placement
[58,59]	VM Allocation	A novel multi criteria resource allocation method	Power consumption, the number of VM migrations, and SLA violations.	Multiple resource criteria
[60]	VM Consolidation and Migration	An online self-adaptive resource allocation algorithm	Energy efficiency and SLA violations	Consider the network-side migration cost
[61]	VM Consolidation and Migration	Joint optimal planning strategy	Reduce brown energy consumption while ensuring SLA violation	hybrid energy supplies for DCs
[62]	VM Consolidation and Migration	A power and thermal-aware VM consolidation algorithm	Minimizing energy consumption	Jointly considers the VM consolidation and cooling system
[59]	VM Consolidation and Migration	A VM placement algorithm that improves the MBFD algorithm	Reduce energy consumption without affecting SLA	considers the cooling and network structure
[63]	VM Consolidation and Migration	A communication efficient framework and a suboptimal algorithm	Minimize the application deployment cost and the operation cost	Docker, good expansibility
[64]	Container Allocation	A new container-aware application scheduling strategy with an auto-scaling policy	A new container-aware application scheduling strategy with an auto-scaling policy	Evaluated the performance of the proposed algorithm using real-time datasets
[65]	Container Allocation	A Cooperative Coevolution Genetic Programming hyper-heuristic approach	Energy consumption	CCGP is based on a cooperative coevolution framework
[66]	Container Allocation	Accelerated particle swarm optimization technique	Minimize the overall energy consumptions and computational time of the tasks	Multi-objective optimization
[67]	Container Allocation	Whale optimization algorithm	Power consumption and resources utilization	The two placement problems are framed as a single optimization problem
[68]	Container Allocation	A renewable energy-aware multi-indexed job classification and scheduling scheme using Container as-a-Service	Renewable Energy Sources, energy consumption	Container as-a-Service, two types of controllers global and local are used
[69]	Container Consolidation and Migration	A new cloud resource management procedure based on a multi-criteria decision-making method	Energy consumption, SLA violation, and number of migrations	The joint management of VM and containers solution performs better than a single VM or container in energy-efficient
[70]	VM and Container Resource Management	An energy-performance efficient consolidation algorithm.	Energy consumption and performance	VM migration has higher performance efficiency, but container migration is more energy-saving than VM

SLA. This method is a two-stage VM placement technology considering racks, cooling devices, and network topology. This method aims to migrate selected VMs in overloaded servers and all VMs in underutilized rack servers to other suitable servers. Subsequently, those idle servers, racks, cooling systems, and network components will be turned off to save energy. Considering the undesirable effects of thermal recirculation patterns, Chen et al. [62] proposed a power and thermal-aware dynamic VM integration scheme. The authors designed a history-based host overload monitoring algorithm and a particle swarm optimization (ACO) algorithm-based VM placement method to reduce holistic energy consumption while ensuring thermal constraints.

3.2.2. Container resource

As lightweight VMs, Containers make deploying microservices/applications easier while also making it harder to manage fine-grained applications. Online resource allocation is a widely used operation in the cloud, but it is new and challenging in a container-based cloud. As shown in Fig. 4 below, container-based resource allocation is a task responsible for allocating a set of containers to a group of VMs with different types and then allocating the created VMs to a set of PMs.

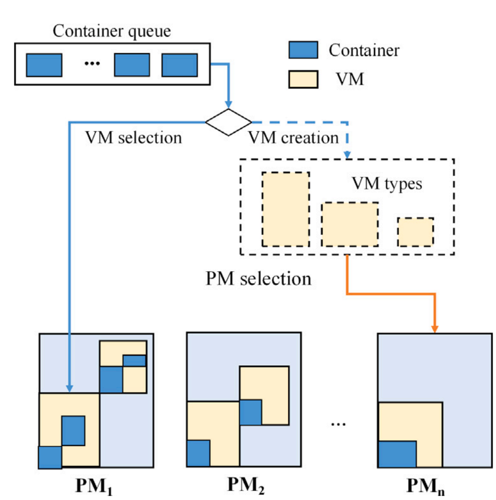

Fig. 4. Schematic diagram of container-based resource allocation [65].

Container Allocation. Existing container resource allocation methods mainly rely on mathematical approaches [64,74,75], heuristic algorithms [65,76], and meta-heuristic algorithms [66,67,77] classified as follows.

Mathematical approaches: Wan et al. [64] proposed a practical communication framework and sub-optimal approach to execute container allocation and task scheduling. Distributed and incremental manner is one of the most notable features of the method. Precisely, it adaptively adjusts the resources allocated to each application in a distributed manner. In addition, the proposed framework divides the source problem into multiple sub-problems and solves these sub-problems independently. Similarly, Srirama et al. [74] proposed a novel container placement method with an automatic expansion function. The proposed method deploys the requested application on the most suitable container with the shortest deployment time according to resource requirements. Then, a dynamic container boxing strategy was designed to efficiently deploy the application to a minimum number of PMs using computing resources. Finally, a heuristic-based automatic scaling strategy is adopted to minimize the waste of computing resources. Kaur et al. [75] proposed a scalable and comprehensive container management controller, KEIDS, based on the Kubernetes platform. The author modeled the container placement problem with carbon emissions, performance interference, and energy consumption into a multi-objective optimization problem and adopted the integer linear programming method to solve it. In detail, KEIDS minimizes edge nodes' brown energy utilization rate to achieve the best green energy utilization rate.

Heuristic Approaches: Tan et al. [65] developed a novel online resource allocation in container-based clouds (RAC) model, considering VM overhead, VM type, and similarity constraints. Then, the author designed a collaborative co-evolutionary genetic programming super-heuristic method to solve the RAC problem. This method automatically generates allocation rules for Container-VM and VM-PM to minimize overall energy consumption. Additionally, Menouer et al. [76] introduced a novel container scheduling policy for Kubernetes, KCSS, intending to reduce makespan and global power consumption. KCSS adopts a multi-criteria-based scheduler to sort the containers submitted by users first. Subsequently, an optimal computing node is selected for each incoming container, considering user requirements and the state of the cloud system.

Meta-heuristics approach: Imdoukh et al. [77] proposed a multi-objective genetic algorithm container scheduler considering availability, task allocation, power consumption, resource balancing, and the number of tasks allocated. Adhikari et al. [66] designed a novel energy-efficient scheduling strategy for a container-based cloud that can handle various types of IoT and batch tasks. The proposed method adopts an accelerated particle swarm optimization technique to find a suitable container for each task with minimal delay. The EECS strategy minimizes the overall energy consumption and task calculation time through effective resource utilization and further reduces the computing server's total carbon emissions and temperature. In addition, it is noteworthy that Moalmi et al. [67] formulated the two-stage placement problem (container-VM and VM-PM) framework as a single optimization problem and, for the first time, proposed a whale optimization algorithm to deal with this optimization problem. The proposed method solves the problem of placing containers and VMs in CaaS while optimizing power consumption and resource utilization.

Container Consolidation and Migration. Compared with VMs, containers occupy fewer resources and have lower deployment costs, which provide more flexible ways to integrate and migrate resources [34,78]. Kumar et al. [68] designed a CaaS-based green energy-aware multi-index work classification and a scheduling method to save energy. The suggested solution distributes the incoming workload to DCs with enough green energy for execution. The proposed scheme is divided into three key steps: (1) Multi-indexed Classification and Scheduling Scheme, (2) Renewable Energy-Aware Host Selection Scheme, and (3) Container Consolidation and Migration Scheme. The proposed multi-controller architecture includes a global controller and multiple local controllers. The global controller is responsible for selecting the DC for the workload to raise the proportion of green energy in the power supply system. The local controller plays the role of deploying the container to the server. The container consolidation is usually modeled as a multi-objective optimization problem. The heuristic algorithm is ideal for solving this problem because it can explore multi-Pareto optimal solutions in one round of exploration. Shi et al. [79] developed a two-stage multi-particle swarm optimization algorithm to optimize the additional energy cost of container resource integration operations. The seamless combination of greed and heuristic algorithm effectively balances system service performance and operating cost. Similarly, Hussein et al. [80] designed an ant colony optimization algorithm based on the best fit to solve container placement on VMs. Although placing as many containers as possible on a VM or PM can reduce the number of instantiated VMs or activated PMs, it is difficult to guarantee the service performance of an overloaded VM or PM, and it will even shorten the hardware life cycle.

3.2.3. Joint VM and container resource

Most previous works have focused on either VM consolidation or container consolidation to achieve energy saving in DCs. In addition, work [81] confirmed that container consolidation is more energy efficient than VM consolidation. Therefore, the joint consolidation of VMs and containers is a promising solution, which aligns more with the actual resource management requirements in the new generation of DCs. Gholipour et al. [69] proposed a novel framework and flow chart for the joint management of VM and containers. The framework classifies the virtual resource management into seven sub-problems, including (1) overloaded host detection, (2) underloaded host detection, (3) identifying the VMs/containers, (4) selecting the VM to be migrated from candidate VM lists, (5) VM placement, (6) select the containers to be migrated from candidate container lists, and (7) container placement. Additionally, to address the third subproblem above, the author proposed a new strategy of joint VM and container multi-standard migration decision technology, focusing on power consumption, SLA violations, and the cost of VM/container migrations. An extensive evaluation of the proposed solution using the ContainerCloudSim simulator concluded that this combined solution performs better than a single VM or container consolidation in energy-efficient. Similarly, Khan et al. [70] studied how to consolidate and migrate VM, container, and containerized applications to reduce data center power consumption while ensuring no negative impact on workload performance. Subsequently, the author proposed a resource consolidation method to manage resources in heterogeneous containerized DCs. This work uses an energy prediction module to estimate the energy consumption of each migratable entity to find the target platform with the best performance for each entity. Numerical simulation shows migration VM has higher performance efficiency, but migration container is more energy-saving than VM. In addition, migrating containerized applications inside a VM can reduce power consumption and improve system performance.

3.3. Thermal management

Fig. 5 illustrates the thermal management framework of a data center with infrastructures including a typical chilled water system and a raised floor rack room. The key components of the chilled water system are CRACs, pumps, chillers, plate heat exchangers, and cooling towers. The chillers and cooling towers provide chilled water and condensed water, respectively. The pumps offer pressure and water flow to drive the chilled and condensed water cycles. Note that the waterside economizer is generally used as a plate heat exchanger to reduce the cooling load. Rack rooms with raised floor cooling usually have enclosed cold/hot aisles to avoid mixing hot and cold air. The cold air

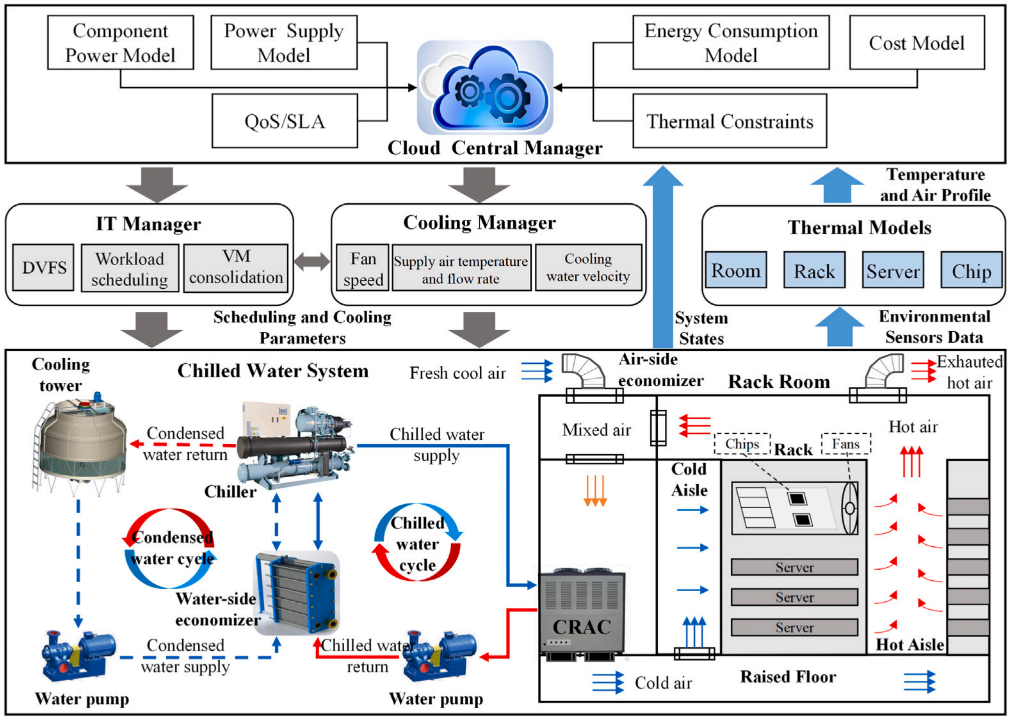

Fig. 5. Thermal management frame of a typical chilled-water air-cooled data center.

blown by the CRACs enters the cold aisle from the raised floor through the ventilated floor. Subsequently, the fans inside the server pull the cold air into the server removing the internal heat. Finally, most hot air is exhausted to the outside and partially reused. Importantly, to take full advantage of free air cooling, an air-side economizer is adopted to pump fresh cool air from outside into the room, mix it with hot air and return it to the CRAC.

Managers often adopt over-cooling strategies for data center cooling management to avoid thermal risks, leading to inefficient cooling and energy wastage. Conversely, if the cooling set-point is too high, the temperature of IT devices exceeds the red-line temperature forming local hot spots in case of unexpectedly high power loads. Therefore, accurately evaluating the temperature distribution and evolution of the data center is essential for controlling the cooling knobs. Moreover, the cloud central manager makes real-time IT scheduling and cooling management decisions based on system resource status, workload service demands, energy costs, and thermal constraints. This section will discuss and analyze the existing data center thermal modeling and management techniques.

3.3.1. Thermal modeling

Robust thermal modeling solutions allow data center managers to recognize potentially local hotspots and rapidly estimate cooling alternatives. However, owing to various factors such as building layout, thermal characteristics, and airflow recirculation, the thermal field of the server room presents a non-equilibrium and dynamically changing state. Following an investigation, existing thermal models for DCs are broadly classified into the following three types based on modeling principles and techniques, (1) computational fluid dynamics/heat transfer-based (CFD/HT) models, (2) simplified models, and (3) reduced-order/data-driven models. A comparison of the information density, accuracy, and execution time of these three thermal models is shown in Fig. 6.

CFD/HT models. The CFD/HT-based numerical modeling method uses a computer to solve non-linear partial differential fluid flow equations to describe the fluid state. CFD/HT-based thermal models provide

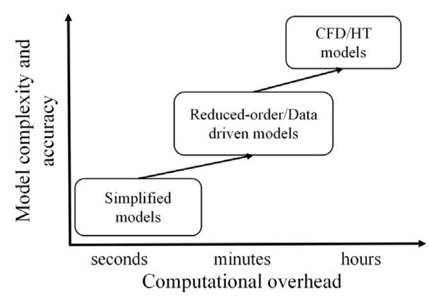

Fig. 6. Comparison of thermal models.

complete and accurate predictions of the thermal field but require massive numerical calculations and specific geometrical parameters [82]. Therefore, the model is only suitable for evaluating solutions in the design phase but not for the fast simulation of thermal distributions in the operational phase.

Simplified Models. Compared with CFD/HT-based thermal modeling methods, simplified models based on thermodynamics perform poorly in accuracy. Nevertheless, due to its short execution time, it can be used for parameter research and rapid temperature and airflow distribution prediction. For example, Zhang et al. [83] proposed an RC Thermal model to represent the thermal profile of a semiconductor chip. The model predicts the chip temperature after time t based on the initial state, real-time power, and ambient temperature, which can be expressed as,

$$T = PR + T_{amb} + \left(T_{\text{initial}} - PR - T_{amb}\right) \times e^{-\frac{t}{RC}} \tag{1}$$

where $T_{initial}$ (unit °C) is the initial temperature of the chip, P (unit W) is the chip power and T_{amb} (unit °C) represents the ambient temperature. In addition, R (unit °C/W), C (unit J/°C) represent the thermal resistance and specific heat capacity of the chip, respectively. Some follow-up works [84,85] modified the RC model to represent the thermal evolution of the chip, taking into account fan speed, and convective resistance.

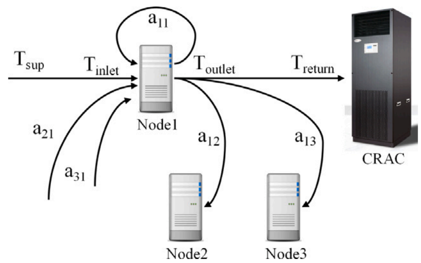

Fig. 7. Heat recirculation.

Reduced-Order/Data-Driven models offer an acceptable trade-off between modeling accuracy and computational overhead. To be precise, the model maintains prediction accuracy close to CFD/HT models while achieving a computational overhead comparable to simplified models. For example, physics-based models evaluate airflow and thermal fields based on fundamental physical laws, such as mass, energy and momentum diffusion, and convective transfer. The zonal method is a commonly used thermal modeling method, which divides the target region into several coarse grids and applies the relevant conservation laws [86]. The method assumes that physical quantities such as pressure and temperature are homogeneous within each coarse grid, significantly reducing computation time, but requires a full-scale CFD model or experimental data to determine the boundaries. Moreover, Heuristic models focus on sensor data, including chip temperature, server power, server inlet and outlet temperature, supply cooling temperature, and wind speed. In 2006, Tang et al. [87] presented an abstract thermal model that used distributed temperature sensor data to characterize the thermal recirculation patterns of airflow in the computer room. This model's most significant feature is considering the thermal cross-effects between nodes, as shown in Fig. 7.

where the inlet temperature, T_{inlet}, of node $Node_1$ is a mixture of the supplied cold air, T_{sup}, and the re-circulated hot air from the other nodes. Part of the hot air exhausted from node $Node_1$ will return to the CRAC, and the remainder will constantly flow to other nodes or to itself. The coefficient a_{ij} represents the percentage of heat flow from node i to j called the cross-interference coefficient. Nevertheless, this method lacks consideration of the time dimension and therefore can only predict the steady-state thermal distribution. Subsequently, the work [88] proposed a dynamic thermal model to represent the impact of CRACs operating conditions and recirculating hot airflow on the inlet temperature of the rack. The model evaluates the inlet temperature after a time interval Δt through a discretized representation of the temperature. Furthermore, work [18] proposed a spatio-temporal thermal model considering the coupling of temperature profiles in the temporal and spatial dimensions. The RC model was adopted to characterize the thermal evolution of nodes in the time dimension.

Data-driven models evaluate output values based on one or more input variables and are regression prediction models. Pioneering work [89] uses sensor network-based measurement and management technologies to develop novel strategies to improve energy efficiency in DC facilities. Subsequently, many follow-on studies have been conducted to develop data-driven thermal models using machine learning models such as SVR, GPR, XGBoost, and ANN [90]. Compared to CFD simulations, ANN-based thermal distribution evaluation can stay within an acceptable error tolerance and has less computational overhead [91]. Recent work [92] conducted extensive experiments to compare the predictive performance of multiple data-driven thermal models under different sample sizes, room layout reconfigurations, and cooling failure scenarios. The findings indicate that ensemble learning models (XGBoost,[7] LightGBM[8]) require only limited training samples to achieve acceptable prediction accuracy and are less susceptible to uncertainties such as external disturbance or internal parameter perturbation. In general, data-driven modeling is low in complexity but dependent on the quality and quantity of training samples.

Consequently, a grey-box thermal modeling approach incorporating data-driven and physical laws is proposed. Specifically, a data-driven approach is adopted to evaluate the key variables of the model. Subsequently, the predicted key variables are substituted into a simplified physical model to output the target temperature distribution. For example, Fang et al. [93] used an artificial neural network to characterize the thermodynamics of the server room, that is, the matrix of cross-interference coefficients of the nodes. Subsequently, a thermal recirculation model was employed to calculate each node's inlet and outlet temperatures. Additionally, for enclosed cooling layouts, the zonal method is often used to divide the thermal region into several coarse grids and assume that the physical properties within the grid are homogeneous. The work [94] used an ANN model to predict the pressure distribution and input it into a homogeneous grid model to solve for the target temperature. In short, the grey-box model has better extrapolation prediction capability than the data-driven model and higher prediction accuracy than the reduced-order model.

3.3.2. Thermal optimization techniques

Efficient thermal management is fundamental to the safe operation of data center infrastructure. The heat generated by IT systems determines the cooling load, while the cooling set point, in turn, influences the operating environment of the IT facility. The thermal environment creates a complex coupling of IT and cooling systems [2]. This section gives a comprehensive overview of energy-efficient thermal management from three technical perspectives: thermal-aware IT system optimization, cooling control optimization, and joint IT and cooling system optimization.

IT system optimization. The double superposition of unbalanced IT load distribution and temperature fields exacerbates thermal imbalances and additional cooling supply. Commonly accepted thermal management strategies are reducing the server room's temperature gradient by scheduling or regulating IT loads between compute nodes to minimize the cooling supply and thermal risk. Upon investigation, existing thermal-aware IT management techniques focus on dynamic voltage frequency scaling (DVFS), workload scheduling, and VM consolidation.

DVFS technology regulates system power by dynamically tuning the chip's voltage and clock frequency setpoints [95]. The dynamic power of the CPU, $P_{dynamic}$, is proportional to f^3 as the CPU runs at frequency f. Therefore, lowering the frequency can significantly reduce power consumption but also means sacrificing computational performance. In addition, the node power will affect the inlet and outlet temperatures of itself and other nodes. Therefore, Zhao et al. [96] dynamically tuned the CPU frequency of compute nodes in the cluster to suppress the thermal gradient due to unbalanced node load, thus reducing the thermal interference between nodes.

Thermal-aware workload scheduling typically adopts server inlet temperatures as a security metric for thermal environments. Therefore, Tang et al. [97] simplified the overall energy minimization problem to a peak inlet temperature minimization problem through workload allocation. Then, two solutions based on genetic algorithms and a heuristic algorithm were given. Subsequently, various heuristic algorithms [98], meta-heuristics [99–102], and DRL-based online optimization algorithms [103,104] were designed to address this optimization problem. Moreover, Khalaj et al. [99] developed a reduced-order thermal model to evaluate the thermal profile and use a particle swarm algorithm to find the best energy-efficient workload distribution scheme. Also, work [100] developed a holistic power consumption model covering

[7] https://github.com/dmlc/xgboost

[8] https://github.com/Microsoft/LightGBM

cooling and IT systems. Subsequently, a genetic simulated annealing (GSA) algorithm is designed to allocate workloads to reduce peak node inlet temperatures. Moreover, Gupta et al. [101] suggested a multi-objective optimization framework combining a thermal model and a genetic algorithm (GA) to achieve a trade-off between PUE and exergy efficiency. Notably, considering the impact of node failure on workload allocation and thermal balancing, work [102] developed a hybrid meta-heuristic algorithm-based allocation strategy to redistribute workload from failed nodes to other operational nodes. Unlike heuristic and meta-heuristic scheduling solutions, DRL-based scheduling agents explore the optimal scheduling policy through multiple iterations of learning. For example, Li et al. [103] trained a DRL scheduler for allocating compute-intensive jobs in a simulated cloud environment, taking into account the throughput and thermal behavior of the system. Also, to address the long training time and instability of the DRL scheduler in large-scale computing systems, work [104] adopted expert experience to guide the agent to learn the scheduling policy faster.

Apart from workload scheduling, VM consolidation is also a practical approach to handling thermal emergencies or reducing cooling loads [35]. Considering that temperature gradients increase the cooling load, work [105] evaluated temperature evolution based on the current state and proactively performed VM allocation and migration to achieve multi-objective optimization of energy consumption, migration latency, and overhead. Moreover, Ilager et al. [106] attempted to construct a data-driven thermal model to guide VM allocation or migration to the "coldest" active host. Considering the impact of the thermal behavior of neighboring servers on each other's performance, work [107] uses the relative location of servers as a constraint on the VM allocation solution, thus avoiding local hotspots. Feng et al. [108] proposed a two-step algorithm for reducing data center overhead in cooling, computing, and networking. Firstly, a simulated annealing algorithm minimizes the computation and cooling overheads. Secondly, VMs with high traffic costs are placed on servers close to that location to reduce network overhead. Following this, work [109] designed a novel VM placement strategy based on a simulated annealing algorithm considering thermal recirculation and multiple physical resources. The strategy shows two significant features that enable the data center to achieve an approximate optimal thermal balance and considerable energy savings by reducing the number of active servers.

Cooling control optimization. The goal of cooling control optimization is to precisely assess the cooling needs of IT facilities and adjust cooling set points in real-time to achieve supply–demand matching. As seen in Fig. 5, the essential cooling components of an air-cooled data center are the servers' built-in fans and a chilled water system consisting of CRACs, chillers, cooling towers, and pumps. The fan control strategy determines the performance and power of the server. The higher the fan speed, the lower the temperature-dependent chip leakage power. Meanwhile, high fan speed means high fan power. This, therefore, means that there is a trade-off between fan and CPU power. The work [110] demonstrated that both CPU leakage power $P_{leakage}$ and fan power P_{fan} are convex functions with respect to the fan speed fs for a CPU running continuously at a fixed frequency. Therefore, $P_{leakage} + P_{fan}$ is convex so that the unique optimal fan speed can be determined. Based on this optimal theory, the work [111] constructed an empirical model by monitoring and collecting leakage and fan power from enterprise servers. Later, a model-based fan controller is designed to determine the optimal fan setpoint for a given CPU utilization. Nevertheless, due to the cooling latency, this reactive control method may lead to CPU overheating. Therefore, work [112] proposed an active fan control strategy with a CPU temperature prediction mechanism to compensate for the cooling latency. Furthermore, some dynamic thermal management (DTM) work combines fan and system parameters to improve cooling energy efficiency. Work [113] models DVFS, thread migration, and active cooling as a complex multi-dimensional constrained optimization problem, proving a unique optimal solution. Work [114] uses RL to dynamically tune the frequency, fan speed, and active cores to achieve a performance-power trade-off while satisfying thermal constraints.

CRACs and chillers account for about 75% of the total power consumption of chilled water systems [115]. As a result, existing dynamic cooling management techniques are biased towards improving cooling energy efficiency by controlling the blower speed, chilled water temperature, and flow rate of CRACs. For example, work [116] proposed a multi-setpoint cooling control solution capable of regulating multiple fan speeds to meet the cooling needs of different zones. This fine-grained thermal management approach suits DCs with unstable airflow patterns. In addition, the operator regulates the supply temperature by regulating the chilled water temperature, and flow rate set points to ensure that the temperature in the server room is always kept below the red line [117]. Since the power of a CRAC is negatively related to the supply temperature, an appropriate increase in the supply temperature can significantly reduce the cooling power. Similarly, work [118] controlled the airspeed and chilled water flow rate of CRACs to regulate the temperature and pressure inside the raised floor. Additionally regulating the knobs of the fan and chilled water system, free air cooling is also a potential direction for energy savings. Cool air from outside is pumped into the server room to cool IT equipment or used to lower the return air temperature of CRACs to reduce the load on the chilled water system [119]. However, free air cooling is limited by the temperature and humidity conditions of the surrounding environment.

Joint IT and Cooling System Optimization. The lack of collaboration between IT and cooling systems in a DC tends to result in inefficient cooling [120]. Therefore, joint optimization of IT and cooling systems to enhance the energy efficiency of DCs is desirable.

The joint optimization problem in steady-state scenarios is often formulated as a multi-constraint optimization problem. Specifically, mathematical, heuristic, and meta-heuristic algorithms are used to solve a global optimal parameter combination for a given IT load, available computational resources, and adjustable cooling parameters. For example, Fang et al. [121] designed a two-time scale control approach to solve the two-system control mismatch problem. Specifically, a steady-state thermal model was designed to determine the DVFS set point and job allocation solution. A transient thermal model was proposed to characterize the rack room's thermal evolution and guide the cooling knobs. In addition, Li et al. [122] modeled VM consolidation and CRAC cooling supply as a multi-constraint optimization problem. The objective is to find the optimal VM consolidation solution and cold air supply temperature to minimize the total energy costs while satisfying the thermal constraints and SLA. Furthermore, Mirhoseininejad et al. [47] proposed a joint cooling and workload management framework that considers the thermal interaction between IT systems and cooling devices. The framework achieves significant power savings by realizing the collaboration of cooling control and workload management. Other work has used meta-heuristics such as simulated annealing [123] and genetic algorithms [124] to determine optimal or sub-optimal IT load allocation schemes and cooling set points. In summary, the key to solving this joint optimization problem is twofold: the solver's performance determines whether a globally optimal solution can be explored; the fidelity of the system modeling is related to the ability to represent the controlled object and the thermal environment accurately.

The joint IT load scheduling and cooling control optimization problem in transient scenarios is modeled as a continuous Markov decision model. Subsequently, the DRL model was used to learn the optimization policy by interacting directly with the environment without modeling the system [118]. For example, Ran et al. [125] proposed DeepEE, a model-free framework based on DRL, to solve the joint control of IT job scheduling and cold air flow in a dynamic environment. Moreover, to address the inconsistency in the action space representation of the two systems, the authors used a parameterized action space

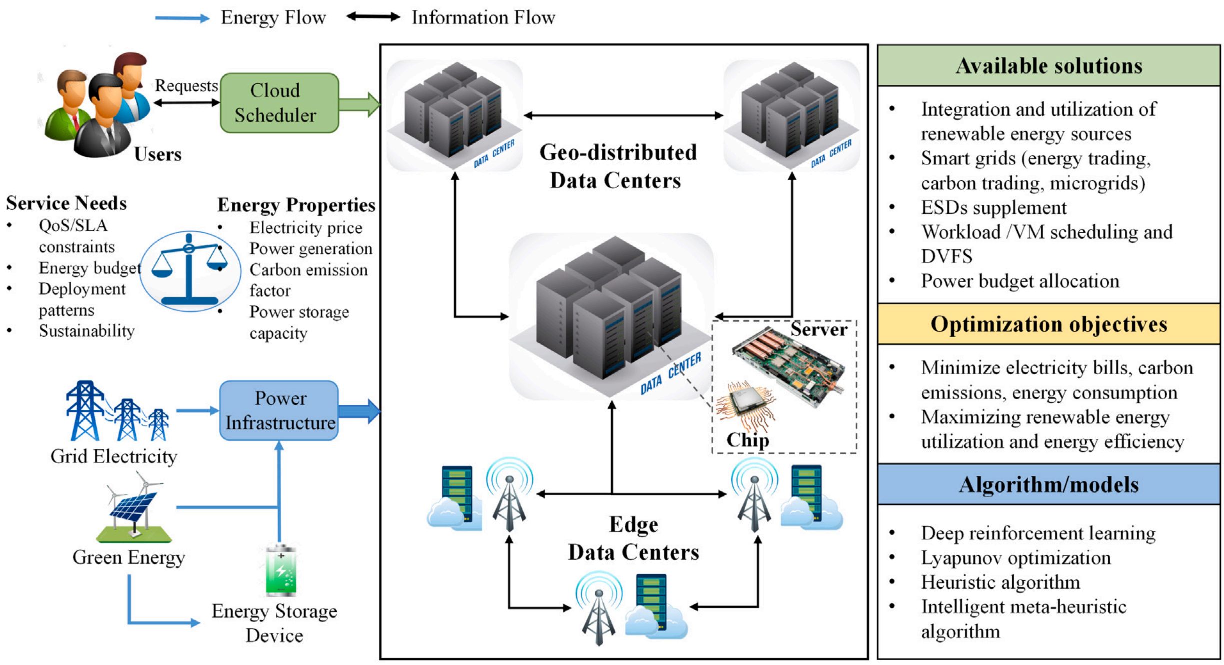

Fig. 8. Energy management optimization framework.

technique [126] to generate continuous cooling control actions and discrete job scheduling actions, respectively. Furthermore, the work [127] adopted a multi-agent RL joint control approach using two DRL-based controllers to generate discrete actions for IT load scheduling and continuous control parameters for CRAC, respectively. Note that the two control agents jointly optimize the energy-saving goals by sharing state and action decisions. In addition, Zhou et al. [128] extended previous work [125] by proposing a unified framework for joint IT and cooling optimization based on DRL to solve the scalability problem and obtain an optimal control strategy over a long period. The proposed multi-agent control approach is well suited to solve the control time granularity mismatch between IT and the cooling system. Specifically, DQN and Deep Deterministic Policy Gradient (DDPG) models are adopted to learn decision policies for IT task scheduling and cooling control, respectively. This proposed multi-agent control approach is well suited to solve the control time granularity mismatch between IT and the cooling system. As observed, considering the operational security of physical DCs, most DRL-based solutions use a virtual environment consisting of multiple high-fidelity theoretical models to train the control models. The trained controllers are then deployed to the real data center to ensure operational reliability and security. Overall, DRL-based model-free controllers offer good prospects for energy efficiency improvements in DCs over traditional model-based optimization methods.

3.4. Energy management

Data centers are energy-intensive infrastructures whose energy management efficiency determines operational costs, carbon footprint, and cloud services' sustainability. With the evolution of cloud paradigms and technologies, various novel energy management solutions such as integrated renewable energy, smart grids, energy storage supply, and power budget allocation are emerging. Therefore, we formulated a unified energy management optimization framework (Fig. 8) to cover energy management scenarios and solutions for single, geographically distributed, and edge DCs.

3.4.1. Within a data center

Current research on energy management in DCs is focused on the integration and utilization of RESs, IT energy efficiency optimization, and energy storage supply. Specifically, the complete adoption of brown energy is no longer in line with the green development perspective. Therefore, integrating RESs will significantly reduce the carbon footprint and power costs on the energy supply side [127]. Secondly, IT technologies like load scheduling, virtual resource consolidation, and DVFS create more opportunities for green energy utilization and system energy efficiency advancement. Finally, energy storage devices as energy buffers are often adopted to weaken the intermittency of renewables and power shaving. All in all, the in-depth integration of energy and IT technologies will become an inevitable tendency for data center energy systems.

Goiri et al. [129] designed the first green data center prototype capable of dynamically managing workloads and hybrid energy sources (renewable, battery, and grid). This work validates that intelligent workload scheduling and energy management can significantly reduce overhead and carbon emissions. Subsequently, Li et al. [128] proposed an energy management framework, GreenWorks, for green High-Performance Computing data centers. The framework consists of elemental load power, intermittent power, and standby power. GreenWorks fully uses hybrid renewable energy systems to achieve coordinated management across power sources, significantly facilitating power-to-load matching. Subsequently, Li et al. [130] proposed a cross-layer power management and coordination framework for the HPC server cluster with a multi-source power supply, further boosting the depth of renewable energy penetration. Furthermore, Liu et al. [131] proposed a novel internal power switching network (DiPSN) for DCs, which manages multiple heterogeneous power supplies in a fine-grained manner. The proposed DiPSN can increase solar utilization by 39.6%, save energy costs by 11.1%, enhance service performance by 33.8%, and extend battery life by 9.3%. To solve the matching problem between the power requirement and provision of the green DC, Mtt et al. [132] first modeled the joint management of IT and energy in a green DC. Subsequently, the author introduces a semi-black box method based on game theory, which models the IT and energy supply subsystems as buyers and sellers in the negotiation game, respectively. Finally, a negotiation algorithm is suggested to find a trade-off between power demand and supply.

Moreover, considering ESDs with limited capacity can only cope with power peaks over short periods, work [133] adopted ESDs and workload scheduling to deal with low and high-frequency power fluctuations, respectively. Likewise, works [134] predict green energy generation and actively use ESDs to smooth the power curve. Then, the spatiotemporal characteristics of delay-tolerant workloads are used to formulate lower carbon and electricity price scheduling solutions while satisfying QoS. Observably, ESDs achieve a controlled transfer of power resources in the time dimension, giving more opportunities and benefits to increase the proportion of green energy use, while the lifetime and capacity of ESDs need to be thoroughly considered.

Considering the single-point failure and power loss of centralized UPS architectures, distributed UPS architectures are designed to guarantee system reliability and improve energy efficiency. For example, Google implements distributed UPS at the service level to reduce the power loss incurred by two cascaded converters [135]. Similarly, Facebook designs rack-level UPSs to shorten the distance between backup power and IT equipment, reducing the likelihood of failure and power loss [136]. Moreover, some works use the integrated power supply with lithium-ion batteries to realize distributed UPS functionality, e.g., local energy storage (LES) developed by Microsoft [137]. Also, work [138] proposed a novel distributed UPS architecture utilizing lithium-ion ultracapacitors (LIC) to improve system efficiency and reduce reactive power.

3.4.2. For geo-distributed data centers

For the energy management of distributed geographic data centers, it is essential to fully consider the renewable energy generation at different locations, grid electricity prices, and available natural resources to achieve the matching of green energy supply and workload distribution. Furthermore, based on the characteristics of geo-distributed DCs and the flexibility of smart grids, energy networks are constructed to allow energy flow and trading to mitigate regional energy production and cost gaps.

Chen et al. [139] considered the optimal workload and energy management of a multi-cloud network. Subsequently, a systematic framework was proposed to integrate RES, ESDs, cooling devices, and dynamic energy prices into workload and energy management. In response to the uncertainty of RES, the resource allocation problem is mathematically expressed as a robust optimization problem to minimize the net cost in the worst-case scenario. Additionally, to reduce the computational complexity and additional network overhead of multi-DC energy management decisions, work [140] designed a distributed alternating direction multiplier approach, which allows each DC to have autonomous control decisions. The solution trades off system costs (electricity, water consumption, and carbon emissions) and the performance of batch workloads based on current system information without prior knowledge. Similarly, work [141] suggested a spatio-temporal task migration mechanism to achieve multi-regional green energy complementarity and thus offset carbon emissions. To be specific, latency-insensitive workloads are scheduled to DCs with sufficient RES, and execution times are determined based on the dynamic production of RES. Note the work [142] simplified the model by assuming that RESs generation and regional electricity prices are accurately predictable. The total profit maximization problem with multi-task response time constraints is modeled as a nonlinear optimization problem with constraints. Following that work, the authors in work [143] further proposed a multi-objective optimization approach for determining task allocation in distributed DCs to minimize average task loss and maximize vendor profit. Nevertheless, these works ignore the impact of green energy and task uncertainty on scheduling decisions. Moreover, leveraging regional power price gaps to migrate VMs for cost savings is feasible, but large-volume VM migration leads to additional network energy. Therefore, the work [144] formulates the problem of minimizing energy costs (both DC and network energy) as a mixed integer linear programming problem and solves it in a reasonable time using the CPLEX solver.

Smart grids (SGs) integrate multiple energy sources, including RES, ESDs, and brown energy. SGs are a promising energy management solution that supports bidirectional information flow and microgrids. To address microgrids' temporal and spatial coupling issues, work [145] presented a stochastic planning problem considering electricity prices, RES production, and workload uncertainty. Subsequently, a real-time distributed algorithm based on Lyapunov optimization techniques and a multiplier-based alternating direction approach is designed to minimize the long-term operating costs of microgrids. To make these energy-intensive distributed clouds greener, Camus et al. [146] suggested that, based on the flexibility of the smart grid, the exchange of green energy between distributed nodes can help further improve the holistic improvement of the cloud's self-consumption of on-site green energy. Specifically, the proposed solution adopts VM migration and energy exchange to balance the energy production and demand of each node in the interconnection network while taking into account the network communication delay and brown energy demand. Additionally, Gu et al. [147] formulated energy management as a complex mixed integer linear programming problem with millions of decision variables and proposed a green task scheduling and energy management architecture. The authors pay attention to two optimization issues: (1) Minimizing total energy costs by workload scheduling. (2) Minimize total carbon emissions within the energy cost budget. This work verifies that integrating energy storage devices into the DC power system is an effective way to reduce carbon emissions. In addition, grid-based energy trading mechanisms have a significant impact on improving energy utilization and saving costs. In addition, considering the variation of electricity prices in different regions due to supply and demand, time and production costs, work [148] proposed an evolutionary-based heuristic algorithm to solve the Pareto-optimal solution for request scheduling and resource allocation for multiple DCs.

3.4.3. For edge data centers

The edge computing paradigm advocates extending computing and storage resources to network terminals, effectively alleviating the impact of time-constrained IoT applications in data transmission delays [149]. Nevertheless, with the extensive deployment of edge clouds, the vast energy consumption has become a limit for expanding edge cloud DCs [147]. Since the computing power and deployment density of edge DCs are primarily different from traditional data centers, traditional data center-level methods are challenging to replicate directly to edge systems. Some cutting-edge research work began to explore the possibility of edge computing, renewable energy, and smart microgrids. The device of edge nodes is relatively small, which allows them to be deployed flexibly to locations where renewable energy can be used more efficiently. Additionally, the microgrid [150] can significantly shorten the distance between energy production and use and effectively integrate distributed renewable energy in adjacent areas. In this way, the microgrid will supply power to nearby edge devices with higher transmission efficiency and lower operating costs. In the green cloudlet network architecture, each edge cloud is powered by green energy and traditional power grids. Due to the dynamic changes in energy demand and green energy production, the energy supply and demand relationship between different edge clouds is unbalanced, which leads to the increased grid-connected power consumption of edge clouds. Therefore, Aujla et al. [151] developed a green energy-aware edge cloud placement approach, considering minimizing the edge cloud's total cost and delay requirements. This strategy migrates avAtars (private VMs used to perform offloading tasks) according to the green energy gap of edge clouds in the cloudlet network to achieve computing nodes' energy supply and demand balance. Further, the work [152] considers both scheduling workloads across multiple edge clouds and tuning node frequency to achieve a balance of QoS and renewable energy utilization for edge computing.

As a flexible energy carrier, the microgrid can conveniently match dynamic local demand with on-site supply [153]. Based on Fog computing and microgrid, Jalali et al. [154] introduced a method to alleviate the growth of IoT energy costs. This method uses microgrids to reduce energy transmission distances and losses, while fog computing provides computing and storage services for local IoT workloads. Numerical simulation results show that this seamless combination of fog computing and micro-grid method simultaneously performs localized management of computing services and energy supply, significantly reducing IoT applications' energy consumption. Note that the edge node is the energy consumer, and the microgrid is the energy provider, with significant uncertainty and stochasticity. Therefore, real-time information exchange is the foundation for the collaborative optimization of both systems. For this purpose, Li et al. [147] proposed a unified energy management framework to enable a sustainable edge computing paradigm with distributed RES. The framework aims to bridge the lack of collaboration between microgrids and edge computing systems. The cooperation and supplementation of edge computing and microgrid systems contribute to leveraging RESs, reducing the system's brown energy while providing superior QoS for time-constrained IoT applications. Moreover, Munir et al. [155] decomposed the problem of using microgrids to power edge servers into two sub-problems. Subsequently, the clustering method DBSCAN was adopted to solve the task allocation of edge clouds and DRL to derive the power supply solution for microgrids. The proposed approach mitigates the uncertainty in task load and microgrid energy generation. Overall, integrating microgrid and renewable energy technologies is a potential direction for energy management in edge data centers and deserves further exploration.

3.5. Waste heat recovery

Waste heat recovery (WHR) means taking measures to capture the thermal energy emitted by IT equipment to produce useful energy products. The main barriers to implementing WHR systems into DCs are the low-quality waste heat (below 85 °C) and the high investment costs. Considering the thermodynamic conditions, deployment, and applicability of data center operations, the waste heat recovery technologies that have attracted the most attention from operators are district heating, on-site power generation, and absorption cooling system.

3.5.1. District heating

The basic idea of district heating (DH) is to leverage local thermal resources to cover local heating demands [156]. Waste heat from DCs is a prospective thermal resource [157]. Firstly, DCs are energy-intensive infrastructures, consuming enormous amounts of electricity and converting it into bulk heat. Secondly, the data center's uniformly distributed load curve and waste heat production are stable and available heat sources. Second, the uniformly distributed load profile and waste heat generation make DCs a reliable heat source [158]. Finally, Most CSPs build data centers close to the DH system to efficiently transport waste heat to the DH network in exchange for economic benefits. To sum up, recovering waste heat from DCs for DH systems has been proven both technically and economically feasible [158]. For example, Severin et al. [159] reported using coolant from a hot water-cooled supercomputer for space heating. Heat recovery efficiencies as high as 80% and energetic efficiencies of 34% were achieved at coolant temperatures up to 60 °C. Moreover, He et al. [160] designed a distributed cooling solution to use DC waste heat to provide district heating in Hohhot, China. The authors claim to save 18,000 tons of standard coal and 10% of electricity per year compared to a conventional coal boiler heating system.

However, the supply–demand mismatch for thermal energy is also a severe challenge for the DH system [13]. The heat demand in the DH system is greatly affected by many factors. For example, the generating capacity of power plants is affected by time and season, and the heating demand of buildings is affected by climate and human activities, which are full of significant volatility and uncertainty [161]. Some researchers have introduced thermal energy storage (TES) technology to address the issue of eliminating supply–demand mismatch and peak-setting in DH systems. The work [162] investigated energy systems with heat pumps and long-term TES to meet building complexes' heating and cooling needs, achieving sustainable operation. Additionally, work [163] integrated industrial waste heat into existing urban DH systems to increase the system's income. Specifically, a high proportion of industrial waste heat is transferred from summer to winter using seasonal heat storage. This solution addresses the energy gap in different seasons and obtains more economic profit. Furthermore, work [164] configured water tanks (WT) in DH systems to reduce peak loads using load-shifting effects, thereby reducing system operation and maintenance costs.

3.5.2. On-site power production

Waste heat-based power generation technology is a sustainable way to save energy and reduce emissions in DCs. To better reuse the low-quality waste heat generated by data centers for power generation, commonly used technologies include Power Plant Co-location (PPC) and Organic Rankine Cycle (ORC) [12].

Specifically, PPC uses waste heat generated by the DC to preheat boiler water from a nearby power plant. This technology effectively shortens the distance of thermal energy transmission and reduces the loss of thermal energy, which reduces fossil fuel and the cost of electricity generation. Furthermore, thanks to the compatibility between the waste heat temperature and thermodynamic properties of the organic fluid, the ORC system is considered a promising power generation technology. Its operating principle is similar to the steam rankine cycle, but uses a low boiling organic fluid rather than water/steam as the working fluid. Fig. 9 describes an ORC system, including an expansion turbine, a condenser, a pump, an evaporator, and a superheater. The critical factor of this technology is that ORC is not limited by the temperature of the heat source and can operate normally with various high- and low-quality waste heat. The thermal and chemical properties of the organic working fluid determine the operating temperature range and efficiency of the ORC [165]. In addition, ORC has good waste heat compatibility and can use various heat sources, such as solar [166], renewable geothermal, fuel energy, and waste heat. Moreover, ORC has more flexible deployment methods and fine-grained power generation control than the traditional power cycle. Importantly, ORC has a good match with the waste heat generated by liquid cooling and two-phase cooling systems. Therefore, compared to the water/steam Rankine cycle, these characteristics make ORC more suitable for on-site power generation using waste heat. Recently, Ebrahimi et al. [167] evaluated the effectiveness of ORC systems in reusing waste heat in DCs from a thermodynamic and economic perspective. The work also analyzed the best server refrigerant and working fluid choice under operating conditions. Araya et al. [168] are committed to applying ORC systems to data center operations and designed a 20 kW ORC system prototype to prove its feasibility and economy. Araya et al. [169] developed a laboratory-scale ORC system based on the ultra-low (40 °C to 85 °C) waste heat conditions of typical server racks in data centers. The author describes how to implement the ORC system in actual data centers from experimental and theoretical aspects.

3.5.3. Absorption cooling system

Conventional air conditioning is cooled by vapor compression, which requires significant energy consumption. An absorption cooling system (ACS) can be adopted to reduce the cooling load and power to replace the vapor compression system to provide the chilled water source [170]. ACS can operate at generator temperatures of 70 to 90 °C, which matches the available waste heat from liquid-cooled and two-phase cooled DCs. Nevertheless, there are some limitations to ACS, such

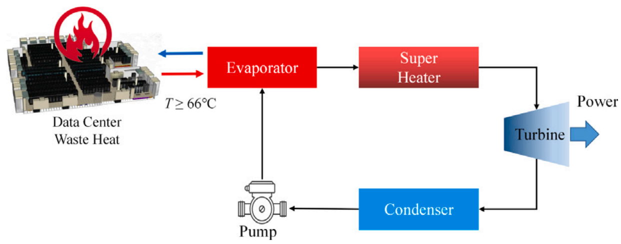

Fig. 9. Schematic diagram of organic rankine cycle by data center waste heat.

as the system not being suitable for air-cooled DCs without an extra heat booster and space constraints when retrofitting ACS to operating DCs. Fig. 10 illustrates a typical absorption cooling cycle where a circuit of absorbers, solution heat exchangers, liquid pumps, generators, and expansion valves, called chemical processors, replace a conventional vapor compressor [171].

Single-effect absorption cooling systems are widely used in DC cooling systems to reuse low-quality waste heat [171]. Chen et al. [172] proposed a two-stage LiBr/H2O absorption system that reduced the PUE from above 1.67 to 1.4. Heywood et al. [173] took low-quality waste heat to drive the 10-ton single-effect LiBr/H2O absorption cooling device, specifically the system for transferring the heat generated by the server to the absorption cooling unit. Additionally, combining green energy and waste heat in the DC power system to achieve refrigeration and heating has become a novel method to reduce DC energy consumption [174]. For example, mixing solar energy with ACS is a suitable choice. Izquierdo et al. [175] proposed an ACS prototype system with single-effect and double-effect ACS and 48 square meters of flat solar collectors. The test results show that the heat provided by the solar collector can reach the working temperature of the prototype single-effect mode, but the ACS based on the double-effect mode may require additional energy. Similarly, to raise the energy efficiency of the single-effect LiBr/H2O absorption system, Sharifi et al. [176] proposed a solar-assisted LiBr/H2O absorption system, which takes generator and evaporator temperatures as variables. Subsequently, a multi-objective multi-variable genetic algorithm was adopted to optimize the system to maximize exergy and energy efficiency under different operating conditions. Furthermore, as a continuous, high-quality heat source, geothermal energy also meets the requirements of the ACS. Han et al. [177] proposed and studied a novel LiBr/H2O absorption refrigeration system using abandoned wells based on the enhanced geothermal system. Numerical experiments show that the refrigerating capacity is maintained above nine MW, and the chilled water temperature provided has reached the temperature of the LiBr/H2O double-effect refrigeration system. Therefore, CSPs can prioritize building large-scale data centers in areas rich in solar and geothermal resources. In addition, the close integration of ACS and renewable energy will be a promising direction for building a sustainable DC.

4. Real-world datasets

Section 3 has investigated and classified green-aware management technologies and solutions. Validating and evaluating these solutions in a realistic environment is time-consuming and expensive, especially for large-scale solutions. Simulation has therefore become the preferred method to address this problem, which allows reproducible experiments to be conducted in a controlled environment, thus speeding up theoretical research. After investigation, we found that some reviews [178,179] have systematically investigated cloud simulation tools, but there are few works to collect real-world datasets. Therefore, some real-world datasets related to the topic of this review (including workload traces, renewable energy source, meteorological data, and electricity price trace) were classified and summarized to facilitate better research.

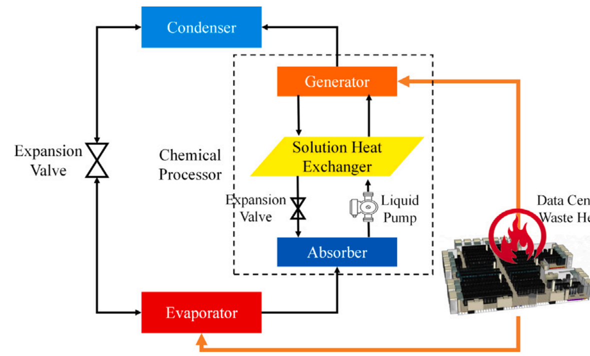

Fig. 10. A schematic of a simple absorption cooling system.

4.1. Workloads trace

4.1.1. Google cluster trace

The workload repository is provided by Google and includes the workload traces of the server clusters in the Google data centers. To date, two versions of workload traces have been publicly released, clusterdata-2011 trace and clusterdata-2019 trace. The available access link is: https://github.com/google/cluster-data.

4.1.2. Alibaba open cluster trace

The workload repository is provided by Alibaba Group and includes traces and machine attributes of multiple types of workloads in real production clusters. So far, Alibaba has released two versions of workload traces, cluster-trace-v2017 and cluster-trace-v2018. These traces include not only interactive online service requests and batch workloads, but also hardware information of the machines in the cluster. The available access link is: https://github.com/alibaba/clusterdata.

4.1.3. Parallel workloads archive

The Parallel Workloads Archive provides raw logs and models of workloads running on Parallel systems. These workloads can be used to validate and simulate workload management for large parallel high-performance computers. The available access link is: https://www.cs.huji.ac.il/labs/parallel/workload/.

4.1.4. Statistical Workload Injector for MapReduce (SWIM)

The SWIM repository is provided by Facebook and includes the workload traces of the server clusters in the Facebook data centers. SWIM is often adopted to test and assess the performance of MapReduce systems. To date, two versions of workload traces have been publicly released, FB-2009 trace and FB-2010 trace. Moreover, the available access link for this SWIM is: https://github.com/SWIMProjectUCB/SWIM/wiki.

4.1.5. Wikipedia access traces and WikiBench

Wikipedia access traces contains a trace of 10% of all user requests issued to Wikipedia during the period between September 19th 2007 and January 2nd 2008. In addition, WikiBench, as a web-hosting benchmark, can be used to stress test servers or systems where Web applications are deployed. The available access link for this WikiBench and Wikipedia access traces is: http://www.wikibench.eu/.

4.2. Renewable energy sources and meteorological data

4.2.1. The National Renewable Energy Laboratory (NREL)

NREL provides some developed data sets, maps, models, and tools used to analyze renewable energy and energy efficiency technologies. In addition, large amounts of real-time meteorological data for the United States, including solar radiation, cloud cover, and wind speed, are available from the National Solar Radiation Database (NSRDB). The available access link for the NREL homepage and NSRDB are: https://www.nrel.gov/ and https://nsrdb.nrel.gov/, respectively.

4.2.2. Photovoltaic Geographical Information System (PVGIS)

PVGIS provides three tools, including PV performance tool(grid connected, tracking PV, off grid), solar radiation tool (monthly, daily, hourly) and typical meteorological year tool(temperature, wind, humidity, air pressure). The available access link for PVGIS is: https://ec.europa.eu/jrc/en/pvgis.

4.2.3. National Climatic Data Center (NDCD)

NDCD provides researchers with hourly, daily and monthly solar radiation tracking data for some cities in the United States from 2000 to 2021. The available access link is: http://www1.ncdc.noaa.gov/pub/data/uscrn/products.

4.2.4. Solar Radiation Data (SoDa)

SoDa provides global solar radiation and meteorological database called HelioClim-3, which provides many additional services for research activities, such as AI-based solar forecast, long-term irradiation time-series, weather forecast data, and so on. The available access link for SoDa is:http://www.soda-is.com.

4.2.5. Windfinder

Windfinder provides a large amount of wind and meteorological observation data collected by 21,000 weather stations around the world since 1999. The available access link for Windfinder is: https://www.windfinder.com/historical-weather-data/.

4.3. Electricity price trace

4.3.1. The Independent Electricity System Operator (IESO)

IESO is the core of Ontario's electricity system, providing Ontario's hourly electricity demand for the next 34 days. In addition, the IESO not only provides forecasts of available solar and wind power generation in the next 48 h, but also provides easy access to market price data, including real-time and historical reports. The available access link for IESO is: https://ieso.ca/en/.

4.3.2. Comed's HOURLY PRICING program (ComEd)

ComEd provides the price and the trend of dynamic hourly electricity prices of U.S. regions based on wholesale market prices. The available access link for ComEd is: https://hourlypricing.comed.com/.

4.3.3. U.S. Energy Information Administration (EIA)

EIA provides independent statistics and analysis of the U.S. power system, including hourly electricity demand, renewable energy generation forecasts, and average retail electricity prices. The available access link for EIA-Electricity is: https://www.eia.gov/electricity/.

4.3.4. Southwest Power Pool (SPP)

SPP conducts statistics and analysis on the power systems of 17 states in the central United States, including price contour map, generation mix and comparison analysis of energy production forecast and actual demand, etc. The available access link for SPP is: https://www.spp.org/.

4.3.5. Balancing Mechanism Reporting Service (BMRS)

BMPS provides operational data of the U.S. power system, focusing on power prices in various regions, the actual power demand of the system, and forecasts of wind energy production. The available access link for BMRS is: http://www.bmreports.com.

5. Open issues and future directions

Numerous efficient green-aware management techniques and solutions have been proposed and widely adopted. However, there are still many challenges to constructing sustainable DCs that still need to be thoroughly addressed. Based on the observations of existing works, we put forward some open issues and promising directions for sustainable DCs.

5.1. Distributed workload management framework

For multi-cloud workload management, most existing work adopts a centralized management scheme; that is, a single global controller makes scheduling decisions according to the current state of each cloud. Nevertheless, this centralized method has two limitations. On the one hand, it will increase the complexity and delay of system decisions. On the other hand, since many heterogeneous data centers are distributed in different geographical locations, it is not possible to obtain all the global state information at any time to make optimal decisions. Therefore, developing a distributed method for multi-cloud workload management is an open issue.

As an emerging technology, multi-agent Deep Reinforcement Learning (MADRL) [180] has achieved good results in many application scenarios. Therefore, it is feasible to configure a DRL agent as a personal scheduler for each cloud node while jointly managing multiple nodes based on multi-agent interaction and cooperation mechanisms. Compared with the single-agent system, the multi-agent system has high learning efficiency, robustness, and scalability. Therefore, developing a MADRL-based distributed workload management framework will be a feasible and promising direction.

5.2. Heterogeneous virtual resource management

Most CSPs provide containers and VMs as service resource units for users. Nevertheless, as described in Section 3.2.2, there are many differences in features and structures between containers and VMs, which not only increase the complexity of resource integration and migration but also easily form resource fragmentation and reduce resource utilization. Moreover, previous efforts focused on the consolidation and migration of either the VM or the container. Therefore, efficiently managing heterogeneous virtual resources with different granularities in the cloud platform is a problem worthy of further study.

In addition, although resource consolidation and migration among cloud nodes can effectively improve resource utilization of each node and reduce energy consumption, it also brings problems such as network overhead, service delay, and additional energy costs. Previous work has proposed resource compression techniques to reduce data transfer volume and service latency, but VM sizes typically exceed 10 GB, resulting in SLA violations and additional power costs. Therefore, how to trade off the possible benefits and costs of resource migration is an open issue.

5.3. Energy-efficient cooling management

Promoting cooling energy efficiency mainly starts from two directions: liquid cooling and natural cooling sources. As racks' power and heat density increase, air cooling can no longer satisfy their cooling requirements. Therefore, liquid cooling with higher cooling efficiency is undoubtedly the superior choice. Instead of using chillers and air conditioners, liquid cooling systems use liquid to come into direct or indirect contact with chips and other devices to remove the heat generated so that the PUE value can be below 1.09. In addition, compared to air-cooled systems, the waste heat temperature of liquid-cooled systems reaches 40–60 °C, which provides better heat recovery performance. Meanwhile, building a data center in an area with low year-round temperatures or extensive natural cooling sources can significantly reduce the PUE of the data center. Therefore, the cooling solution with liquid cooling as the primary cooling load and non-liquid cooling as auxiliary cooling is undoubtedly the tendency of the new generation data center cooling system.

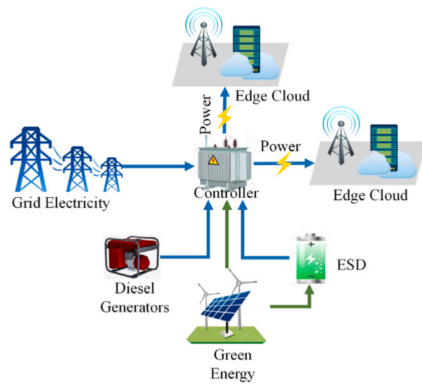

Fig. 11. Microgrid.

5.4. Integration and utilization of renewable energy

Integration and utilization of RESs is a potential measure for building sustainable DCs, but many challenges exist. Firstly, the generation of RES is particularly intermittent and dynamic. In particular, onsite green energy production is influenced by location, weather, and facilities, making it difficult to predict accurately. Secondly, the mixed supply pattern of multiple heterogeneous energy sources also increases the supply system's insecurity of switching operations and power instability. Finally, the dual volatility of power demand and energy production in DCs makes it extremely difficult to match energy supply and demand.

Therefore, AI technology can be adopted to predict the generation of green energy based on historical records and weather traces. In addition, ESDs act as an energy buffer, allowing for peak and valley shaving of power. Specifically, ESDs charge when green energy generation exceeds power consumption and discharge when power peaks, thus making full use of carbon-free energy.

5.5. Microgrid for edge clouds

The edge cloud is generally powered by the grid and equipped with green energy production equipment and ESDs (Fig. 11). Edge clouds act as both consumers and producers of energy. Meanwhile, the energy demand and output of edge cloud are easily affected by workload and weather, which leads to an imbalance between energy supply and demand. Therefore, achieving the energy supply and demand balance of distributed edge clouds is an open issue with the continuous evolution of DCs.

For this issue, the microgrid will be a good choice, which can effectively integrate various RESs located in the adjacent area, such as wind turbines, photovoltaics, diesel generators, ESDs, etc. This way can provide power for edge cloud with less transmission cost and more flexible supply. Therefore, the power supply scheme based on a microgrid also faces the challenge of dynamic switching and managing a multi-heterogeneous power supply.

5.6. Waste heat recovery

With the evolution and rapid adoption of liquid cooling technology, the waste heat from data centers will hold tremendous potential and benefits for recycling. In particular, compared with ordinary water-cooling technology, the cooling loop of warm/hot water-cooling technology operates at a water supply temperature above 40 °C for a long time. The return water temperature of more than 45 °C significantly improves the outdoor heat dissipation efficiency and even realizes free cooling. In addition, high-temperature wastewater can directly meet the water temperature requirements of urban floor heating and hot water supply, which is conducive to high-efficiency waste heat recovery in DCs. In addition to the three waste heat recovery technologies discussed in Section 3.5, waste heat can also be considered for drying biomass materials, maintaining the temperature of anaerobic digestion reactors, and desalinating seawater.

6. Conclusion

This review systematically surveys cutting-edge research work and routes in sustainable DCs. Firstly, a new conceptual model of sustainable DCs is constructed to cover the latest research advances in four significant systems and to indicate future evolutionary directions. Secondly, we analyze the characteristics and benefits of technologies such as workload scheduling, virtual resource consolidation, thermal modeling, cooling control optimization, power management, renewable energy integration and utilization, and waste heat recovery from a technical perspective. A systematic view of achieving efficient data center management is provided. Furthermore, to facilitate experimental work by researchers in the field, we have collected real-world datasets related to the topic, including workload traces, RESs, climate data, and regional electricity price traces. Finally, we identify and suggest some critical challenges and potential solutions for constructing sustainable DCs.

CRediT authorship contribution statement

Weiwei Lin: Writing – original draft, Supervision, Conceptualization. **Jianpeng Lin:** Writing – review & editing, Supervision, Investigation, Data curation. **Zhiping Peng:** Writing – review & editing, Data curation, Conceptualization. **Huikang Huang:** Writing – review & editing, Data curation. **Wenjun Lin:** Visualization, Investigation. **Keqin Li:** Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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