# Thermal Modeling and Thermal-Aware Energy Saving Methods for Cloud Data Centers: A Review

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***Abstract*—Constructing energy-efficient cloud data centers (CDCs) is an essential path for the further expansion of cloud computing. As one of the core subsystems of a data center, the cooling system provides a reliable thermal environment for the safe operation of IT equipment while posing a huge energy consumption and carbon emission problem. Thus, it is evident that optimizing energy management of cooling systems with considerable energy-saving potential will be essential to realize the green and low-carbon development of CDCs. Therefore, to track the research progress of data center thermal management technologies, this review focuses on two research efforts: thermal modeling and thermal-aware energy saving methods. First, various thermal modeling approaches are reviewed for air-cooled and liquid-cooled data centers. Secondly, a comprehensive review of existing advanced thermal management approaches is conducted from three perspectives: thermal-aware IT load scheduling, cooling system control optimization, and joint optimization of the IT and cooling systems. Finally, we put forward some open issues and future research directions for thermal management that have not been completely solved. This review aims to provide reasonable suggestions to enhance cooling energy efficiency and further promote the transformation of CDCs to lower energy consumption and sustainable direction.**

***Index Terms*—Cloud data center, thermal modeling, thermal management, energy saving, air cooling, liquid cooling.**

## 1 Introduction

CLOUD data centers provide computing, storage, and network resource services for information systems in various industries. They have become one of the powerful engines driving the advancement of the world's digital economy. Simultaneously, the explosive growth of CDCs (including hyper-scale, regional large-scale, and edge data centers) not only poses a tremendous challenge to the global energy supply but also leads to severe environmental problems [1]. As reported by Science in 2020 [2], the power consumption of CDCs worldwide was about 205 terawatts in 2018, accounting for 1% of global power generation, and will keep growing steadily in the future years. Therefore, promoting the decarbonization of green data centers is significant for achieving the goals of Carbon Peak and Carbon Neutrality.

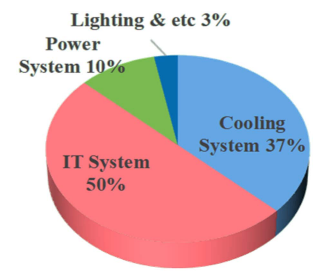


Fig. 1. Data center energy breakdown [4].

CDCs are energy-intensive infrastructures, primarily consisting of IT, cooling, power supply, and lighting systems, whose energy breakdown is shown in Fig. 1. The IT system provides on-demand, subscription-based cloud hosting services to end users via the network. The physical carrier of the IT system is the numerous computing and communication servers in the rack room, which account for over 50% of the energy consumption [3]. Beyond that, the cooling system, which maintains the temperature and humidity of the rack room, is the second major energy consumer of the CDC, accounting for about 37% or more [4]. The efficiency and energy consumption of the cooling system not only affects the reliability and computing performance of IT facilities but is also a critical factor in determining the power usage effectiveness (PUE) of the CDC. Therefore, to achieve green sustainability at the data center level, some effective measures must be taken to optimize the cooling system's energy efficiency.

In recent years, the industry's focus on advanced energy-saving technologies has gradually expanded from IT to cooling systems. Various optimization techniques for cooling architecture, equipment, and controls have been adopted to promote the energy efficiency of cooling systems [5]. Following extensive research, existing trends focus on the technical areas of using natural cooling sources, employing high-efficiency cooling equipment, optimizing airflow organization, improving temperature set-points, fine-grained cooling control, and optimizing

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TABLE I
COMPARISON WITH RELATED REVIEWS

| Ref. | Year | Thermal modeling: Air-cooled System | Thermal modeling: Liquid-cooled system | Energy-saving methods: Thermal-aware IT load scheduling | Energy-saving methods: Cooling system control optimization | Energy-saving methods: Joint optimization of IT and cooling systems | Focus on |
|---|---|---|---|---|---|---|---|
| [7] | 2018 | √ | | | √ | | Thermal modeling and cooling energy optimization |
| [12] | 2018 | | | | √ | | Active cooling and passive cooling technologies |
| [1] | 2019 | | | √ | √ | √ | Energy efficiency and sustainability of cloud computing |
| [4] | 2021 | | | | √ | | Cooling technology and power consumption modeling |
| [13] | 2021 | | | √ | | √ | Energy-saving technologies |
| [14] | 2021 | √ | | √ | √ | | Thermal management approaches and thermal models |
| Our Work | - | √ | √ | √ | √ | √ | Thermal modeling and energy-saving methods |

cooling parameters. As we observed, an essential prerequisite for achieving efficient thermal management is quickly and accurately evaluating the thermal distribution in a data center. However, the complex equipment layout and airflow pattern in the server room pose a great challenge for developing thermal models for data centers [6]. With the advancement of modeling theory and IoT technology, thermal modeling approaches have gradually evolved from traditional computational fluid dynamics (CFD) simulation modeling and simplified physical models to gray-box thermal modeling approaches incorporating thermodynamics and data-driven [7]. These emerging thermal modeling approaches have effectively reduced modeling overhead and improved model generalization.

Meanwhile, the proposal of various novel thermal models has significantly contributed to the update and application of thermal-aware energy-saving methods. For these widely adopted energy-saving technologies and methods, this work focuses on the following three categories [8], (1) Thermal-aware IT load scheduling. This method utilizes the spatio-temporal characteristics of workloads for flexible scheduling and migration, thereby balancing the thermal distribution of the computer room and avoiding thermal risks [9]. (2) Cooling system control optimization. This method first adopts sensors or thermal models to evaluate the dynamic thermal variation of IT equipment, following which the cooling parameters are operated in real-time to match the supply and demand of cooling capacity [10]. (3) Joint optimization of IT and cooling systems [11]. This approach uses the thermal environment as a link connecting IT and cooling systems and then adopts intelligent algorithms to optimize global energy efficiency. In general, these modeling and energy-saving methods mentioned perform well in different application scenarios, while some limitations need further optimization. Therefore, it is essential to conduct a comprehensive survey and summary of existing thermal modeling and energy-saving techniques for CDCs, and to point out the key remaining scientific issues and practical solutions.

To our best knowledge, some existing reviews [1], [4], [7], [12], [13], [14] have surveyed research advances in data center thermal modeling and energy conservation methods. However, as theories and technologies continue to innovate, various novel cooling techniques and solutions are proposed and applied to data centers. Therefore, a new comprehensive review and evaluation of the work related to thermal management need to be presented. Furthermore, we compared the focus of this work with related reviews in Table I. Most related reviews focus on the overview of various energy-saving methods and techniques, while few discuss thermal modeling approaches, especially emerging liquid cooling systems. Generally, this review covers existing energy-saving methods and supplements the thermal modeling methods for air-cooled and liquid-cooled systems.

The three significant contributions are highlighted as follows. (1) The various thermal modeling approaches for data centers are updated and reorganized, with exceptional tracking of liquid-cooled systems. (2) Our work systematically tracks and investigates existing thermal-aware energy-saving techniques into three aspects: thermal-aware IT load scheduling, cooling system control optimization, and joint optimization of IT and cooling systems. (3) Based on the observation of research advances, some open issues and corresponding solutions for data center thermal management are pointed out. In conclusion, this work guides researchers or data center managers in selecting thermal models and management techniques.

This review collected papers from several authoritative electronic libraries (IEEE Xplore,[1] ScienceDirect,[2] SpringerLink,[3] ACM Digital Library,[4] and arXiv).[5] A multi-keyword combination search was used to search related papers. The search terms include data center, thermal management, cooling technology,

1.[Online]. Available: https://ieeexplore.ieee.org/Xplore/home.jsp
2.[Online]. Available: http://www.sciencedirect.com
3.[Online]. Available: http://link.springer.com
4.[Online]. Available: http://dl.acm.org
5.[Online]. Available: https://arxiv.org

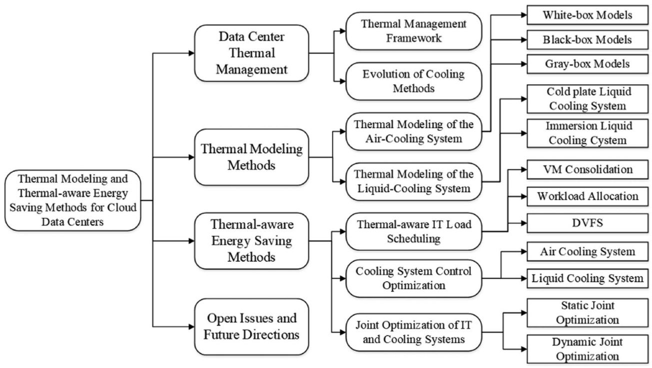


Fig. 2. Organization of the review.

energy saving, energy efficiency, green, thermal modeling, and liquid cooling. Besides, to cover the research progress in thermal modeling and energy-saving technologies for CDCs, we not only focus on the latest published work but also track some long-standing and seminal work. A total of 132 relevant papers were collected in this work, including 107 journal papers and 25 conference papers.

The organization of this review is shown in Fig. 2. Section II introduces the thermal management framework for CDCs. Section III surveys and categorizes the existing thermal modeling approaches, following the characteristics of air-cooled and liquid-cooled systems. Section IV provides a comprehensive analysis and taxonomy of existing energy-saving methods from three perspectives: thermal-aware IT load scheduling, cooling system control optimization, and joint optimization of IT and cooling systems. In Section V, some existing open issues and directions for further research are pointed out. Finally, the work is concluded in Section VI.

## II Data Center Thermal Management

### A. Thermal Management Framework

The thermal management framework [7] is shown in Fig. 3, and its key components include an IT room, cooling system, IoT-based data platform, thermal model, and cloud manager. The IoT-based data platform links numerous distributed sensors, which are mainly responsible for monitoring the operational status information of IT and cooling equipment in real-time. Subsequently, the pre-processed sensor data is fed into the thermal model to predict the thermal profile of the IT room in the current operating state. Finally, the cloud manager formulates IT load management policies and cooling system control parameters based on the thermal profile and constraints to ensure that all IT equipment operates in its acceptable thermal environment. Additionally, the energy consumption models of IT and cooling equipment need to be considered when energy optimization is considered.

Thermal management removes the heat released by the operating IT device into the atmospheric environment [8]. More specifically, for room-level thermal management, the cooling control knob is regulated according to the ambient temperature

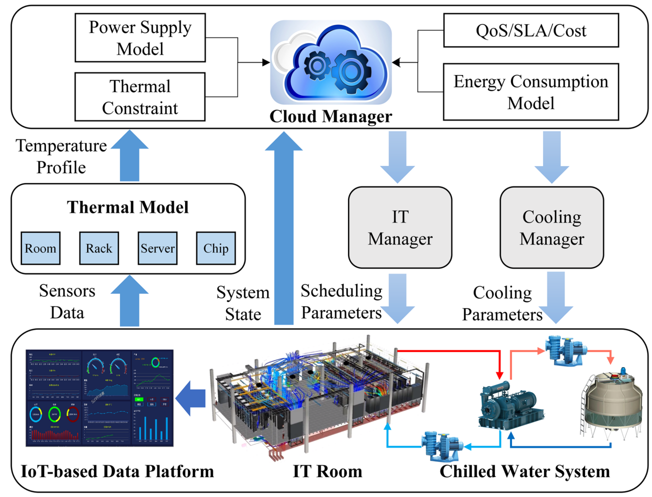


Fig. 3. Thermal management framework.

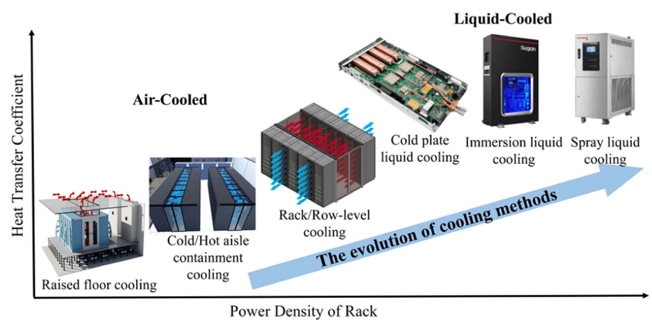


Fig. 4. Evolution of cooling methods.

of the computing node. The ambient temperature usually refers to the inlet temperature of the server or rack. According to the ASHRAE standard [15], to ensure the reliability of the internal electronics, the maximum inlet temperature of the computing node must be below the red line temperature (typically 32 °C), expressed as $T_{Inlet} \leq T_{redline}$. Once the inlet temperature exceeds the red line temperature, the probability of thermal risk increases significantly, which will likely shorten the IT equipment's lifetime and degrade service performance. Besides, OS-level thermal management is more concerned with the temperature of the internal components (especially the chips). Since the chip is the primary source of heat generation inside the host, most existing work roughly equates the chip temperature to the host temperature. In summary, data center thermal modeling aims to evaluate computing nodes' inlet and outlet temperatures and the internal chip temperatures.

### B. Evolution of Cooling Methods

As shown in Fig. 4, as the data center's power density continues to rise, the cooling method is constantly evolving and updating. Most traditional CDCs use raised floors to deliver pressurized cold air to IT rooms. The computer room air conditioner (CRAC) outputs cold air passes through perforated tiles into the cold aisle. The cold air is absorbed by the front of

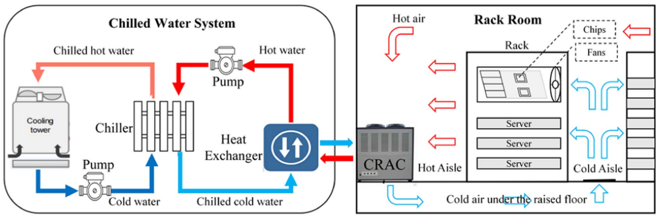


Fig. 5. Air-cooled system architecture.

the rack, taking heat away from the server components and exiting through the back of the rack. Subsequently, hot air is absorbed by the CRAC unit and exhausted to the outside [16]. The hot/cold aisle configuration has the advantage of reduced fan speed and hot/cold air mixing. But in fact, this cooling layout still has the possibility of hot and cold air mixing, which tends to form thermal recirculation and low cooling energy efficiency. Therefore, the physical method of cold and hot aisle containment can be adopted to minimize this undesirable thermal mixing and cold air bypass [17].

Furthermore, cold air is prone to loss and leakage during transmission. The longer the cooling supply distance, the more the loss. Therefore, the rack/inter-row cooling configuration [18] is widely adopted to shorten the supply cooling distance. Compared to traditional no-airflow containment room-level cooling, its cooling path is shorter and more dedicated. Furthermore, this cooling approach with higher airflow predictability enables higher power density by leveraging the rated cooling capacity of the CRAH.

With the rapid increase in racks and power density in CDCs, traditional forced convection air-cooled systems have proven insufficient to meet computer room high-density cooling requirements [19]. The innovation of liquid cooling technology has brought more options for thermal management in CDCs. The current liquid cooling solutions most widely accepted by CDCs are cold plate liquid cooling, immersion liquid cooling, and spray liquid cooling [8]. Cold plate liquid cooling uses water or water-based fluids to cool high heat density components, while built-in fans for secondary cooling cool the remaining devices. Immersion liquid cooling is a cooling technology that directly immerses the heat-generating device entirely in the dielectric coolant and performs heat exchange through direct contact. Spray liquid cooling drips coolant onto the heat-dissipating components of the server by spraying them to remove heat. More details are described in Section III.B.

Compared with air cooling, liquid cooling can bring several benefits to CDC owners [5]. (1) Liquid cooling systems provide precise heat dissipation for devices with high heat generation density, reducing air conditioning and fan energy consumption, and can optimize PUE to 1.1 or less. (2) Liquid cooling technology helps to increase the number of servers deployed in limited space and significantly improves the computing power of DCs. (3) Liquid-cooled servers can ignore environmental influences such as altitude and geography. (4) Liquid has high heat transfer efficiency, more conducive to waste heat recovery. Nevertheless, rapidly promoting data centers to embrace liquid cooling technology will still face many obstacles, such as scenario limitations, equipment supplier support, and deployment costs.

In a nutshell, with the innovation of cooling and IoT technologies, the cooling management of DCs has evolved from coarse-grained centralized to fine-grained distributed. The emergence of novel cooling methods, such as liquid and free cooling, has significantly reduced the PUE and promoted sustainable CDC construction.

## III Thermal Modeling Methods

The heat generated by IT devices directly determines the cooling load. Conversely, variations in the cooling operating parameters affect IT energy consumption. The energy consumption of the two is coupled with each other due to the thermal environment. More specifically, most of the energy consumed by IT equipment is emitted in the form of heat, which consequently causes changes in the ambient temperature, expressed as,

$$\Delta T = \frac{\Delta Q}{cm}, \tag{1}$$

where $\Delta T$ is the temperature variation value and $c$, $m$ are the component's specific heat capacity and mass, respectively. The temperature variation of the whole IT room over a period of time depends on the total heat generated by the equipment and the heat exhausted by the cooling system, which is expressed as,

$$\Delta T^{room} = \frac{H_{room} - Q_{room}}{M_{room} C_p} = \frac{\Delta I_{room}}{M_{room} C_p}, \tag{2}$$

where $M_{room}$ and $C_p$ denote the data center's total internal mass and specific heat capacity, respectively; $H_{room}$ denotes the heat generated by the entire data center. $Q_{room}$ indicates the heat removed by the cooling system. In fact, thermal management of CDCs relies on rapid and accurate evaluation of temperature profiles. Reliable and precise thermal models allow managers to identify and predict potential or impending thermal risks and make timely cooling regulation actions. However, due to the influence of building layout, thermal heterogeneity of equipment, fluid patterns, etc., the temperature and airflow distribution in the server room are non-equilibrium and dynamic. Therefore, the thermal modeling of CDCs needs to consider complex thermodynamic laws and mathematical expressions, which is a severe challenge. In this section, existing thermal modeling methods are classified and discussed in air-cooled and liquid-cooled systems.

### A. Thermal Modeling of Air-Cooled System

Traditional DCs typically employ chilled water systems and raised floors for cooling, as shown in Fig. 5 below. The critical cooling devices of the air-cooled system are the built-in fans of the server, the CRACs inside the server room, and the chilled water system. Each server is usually equipped with multiple fans to maintain the temperature of electronic components. The CRAC and chilled water system are more concerned with the thermal profile of the entire server room, adjusting the supply temperature and air speed to ensure a temperature and humidity environment for the safe operation of IT equipment.

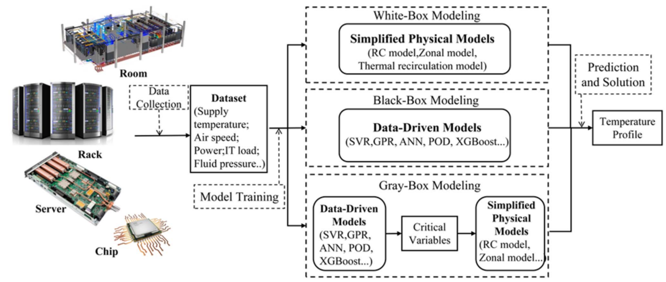


Fig. 6. Flow chart of thermal modeling.

The temperature distribution of the rack room has dynamic characteristics such as non-linearity, strong coupling, time variation, and time delay. What is more, for different application scenarios, the objectives of the thermal model concern differ [20]. Specifically, IT scheduling scenarios usually focus on the chip or host temperature. Cooling control scenarios pay more attention to the temperature profile of the racks and rooms. According to ASHRAE [15], the server inlet temperature is often adopted as a measure of the thermal environment of the rack room. The server inlet temperature is determined by a combination of CRAC supply temperature, wind speed, and power distribution of the cabinet. After extensive research, the target objects of most existing thermal modeling efforts are CPU temperature and server entrance temperature. The related modeling approaches are broadly divided into three categories, white box-model, black-box model, and gray-box model. The corresponding modeling principles and flow are shown in Fig. 6.

White-box models, which are based on physical laws (laws of thermodynamics, three conservation laws, etc.), establish mathematical expressions of the target object. The premise of establishing this model is to understand the described object's operation clearly. Moreover, the factors that affect objects' input-output relationship also need a scientific basis. In short, this modeling method gives a clear physical explanation of the thermal variation, but the model is solved with high order and complexity.

Black-box models are also called data-driven models [6]. It adopts an appropriate machine learning (ML) model to fit the input-output non-linear mapping relationship without pursuing the intrinsic mechanism too much. The modeling approach can better balance complexity, precision, and computational cost. The black box model has a simple structure, low order, and low modeling overhead, but the performance depends on the quality and quantity of the training data.

Gray-box models incorporate physical laws with data-driven methods to explore approximate model parameter values [21]. Hence, gray-box models are more prevalent than data-driven models and have higher accuracy predictions than white-box models. The specific steps for modeling the gray-box model are as follows. (1) collect training data by CFD simulation and IoT-based data platform; (2) construct data-driven models to predict key variables; (3) put predicted key variables into the simplified model to solve the temperature distribution.

*1) White-box Models:* **A. Node-level thermal modeling**

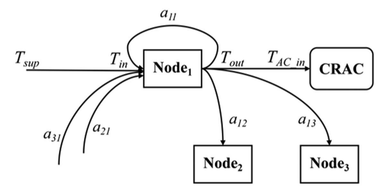


Fig. 7. Thermal recirculation model.

In 2006, Tang et al. [22] introduced an abstract thermal recirculation model for an air-cooled CDC, which considered the thermal disturbance influences between the computing nodes in the rack room (Fig. 7).

In this thermal model, the node inlet temperature is jointly determined by the air conditioning supply temperature $T_{sup}$, the node power distribution $P$ and the thermal cross-interference relationship between the nodes. Therefore, the node inlet temperature $T_{in}$ can be mathematically expressed as,

$$T_{in} = T_{sup} + DP, \tag{3}$$

where the thermal cross-interference matrix $D$ can be specifically expressed as,

$$D = \begin{vmatrix} d_{11} & d_{12} & d_{31} \\ d_{21} & d_{22} & d_{ij} \\ d_{31} & d_{ij} & d_{nn} \end{vmatrix}, \tag{4}$$

where $d_{ij}$ denotes the degree of thermal disturbance to the inlet temperature of the $Node_i$ from $Node_j$. The matrix $D$ records the thermodynamic characteristics of the machine room, which can be solved by measuring the airflow parameters and the power distribution of the nodes at different locations. Nevertheless, the thermal model lacks consideration of time, predicting the temperature distribution in a steady state. Moreover, the method assumes that the cold air can completely and timely remove all the heat generated by the nodes, while the heat transfer coefficient will limit it. Subsequently, to address the above limitations of the thermal recirculation model, Zhou et al. [23], [24] derived a simplified dynamic model from the basic mass and energy balance principles to describe the complex mass and energy flows within an air-cooled data center. The model determines the effect of CRAC operating states (including supply air temperature, *SAT,* and variable frequency drive, *VFD*) and recirculating hot air on the node inlet temperature, giving a discretized quantitative representation of the inlet temperature of node i as follows.

$$\begin{cases} T_i(t+1)_i = T_i\left(t\right) + F_i + C_i \\ F_i = \sum_{j=1}^{N_{crac}} g_{i,j}\left[T_{sup,j}\left(t\right) - T_i\left(t\right)\right] \times VFD_j\left(t\right) \end{cases}, \tag{5}$$

where $T_i(k+1)$ and $T_i(k)$ are the inlet temperatures at time $t+1$ and $t$, respectively. $F_i$ represents the weightedness of all CRAC operating parameters on temperature. $C_i$ denotes the effect of thermal recirculation on temperature. Besides, $g_{i,j}$ quantifies the joint effect of the VFD and SAT of the $j$-th CRAC unit on $Node_i$. Notably, considering the node temperature correlation in space and time, the work [9] designed a spatio-temporal thermal model to characterize the thermal behavior within a data center, which

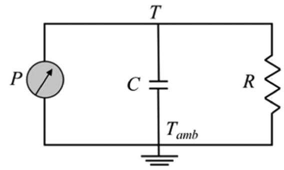


Fig. 8. RC model.

combines the RC model and the thermal recirculation model. To be specific, a thermal distribution matrix is used to establish the spatially correlated behavior of the inlet temperatures of each node. In addition, the RC model is adopted to describe the evolution of the temperature of each computing node in time. Thus, the transient temperature of node $Node_i$ at time $t$ is denoted as,

$$T_i(t) = (1-f)\left(P_i(t)R + T_{sup} + \sum_{k=1}^{m} d_{i,k}P_k(t)\right) + fT_i(t-1). \tag{6}$$

For simplicity, define $f = e^{-\frac{\Delta t}{RC}}$ and assume $\Delta t = 1$. *P, R, C* denote the power consumption, thermal resistance and specific heat capacity of the server, respectively. After a long enough time, the node temperature will eventually converge to the steady-state temperature, which can be expressed as,

$$T_i^{SS} = P_i(t)R + T_{sup} + \sum_{k=1}^{m} d_{i,k}P_k(t). \tag{7}$$

Therefore, (6) can also be expressed as,

$$T_i(t) = (1-f)T_i^{SS} + fT_i(t-1). \tag{8}$$

**B. Chip-level thermal modeling**

Considering the obvious duality between the heat transfer of semiconductor chips and the thermal phenomenon of RC circuits, thermal RC circuits are often adopted to model the temperature profile of the chip [25]. As shown in Fig. 8, the chip thermal model based on the lumped RC model can be expressed as,

$$T = PR + T_{amb} - RC\frac{dT}{dt}, \tag{9}$$

where *T* (unit °C) represents chip temperature, $T_{amb}$ (unit°*C*) represents the ambient temperature (generally refers to the server inlet temperature). *P* (unit *W*), *R* (unit°*C/W*), and C (unit *J/°C*) denote the power, thermal resistance, and specific heat capacity of the chip, respectively. Assuming that the power *P* is fixed in the time period [0, *t*]. According to Kirchhoff's law and Ohm's law, the temperature of the chip at time t can be derived as,

$$T_{cpu} = PR + T_{amb} + (T_{initial} - PR - T_{amb}) \times e^{-\frac{t}{RC}}, \tag{10}$$

where $T_{initial}$ is the initial temperature of the chip. Eq. (10) indicates that $T_{cpu} = T_{initial}$ when time t tends to 0, while as time *t* keeps increasing, $T_{cpu} = PR + T_{amb}$, the chip temperature eventually converges to a specific value, called steady-state temperature. Based on this thermal model, work [26] constructed a transient RC thermal model that considers the effects of convection resistance and fan speed on the thermal behavior of the chip, denoted as,

$$T_{cpu}(t+\Delta t) = T_{cpu}^{\infty}(t+\Delta t) + (T_{cpu}(t) - T_{cpu}^{\infty}(t+\Delta t))\, e^{-\frac{\Delta t}{R(t+\Delta t)C}}, \tag{11}$$

$$T_{cpu}^{\infty}(t) = P_{cpu}(t)R(t) + T_{amb}(t), \tag{12}$$

$$R(t) = R_{cond} + R_{conv}(t), \tag{13}$$

$$R_{conv}(t) = \frac{1}{k_n V(t)^n}, \tag{14}$$

$$V(t) = \sqrt[3]{k_p P_{fan}(t)}, \tag{15}$$

where $\Delta t$ is a time step and $T_{cpu}^{\infty}(t)$ denotes the steady-state temperature. Besides, *R*, $R_{cond}$, and $R_{conv}$ denote thermal resistance, conductive resistance, and convective resistance, respectively. The relationship between $R_{conv}$, airflow volume *V*(*t*), and fan power $P_{fan}$ is shown in (14)–(15). Model parameters *n*, $k_n$, $k_p$ can be determined by experiments. Similarly, work [27] designed a novel physics-based CPU thermal model that more explicitly characterizes the effect of the number and speed of fans on CPU temperature variation. The steady-state temperature of the CPU is expressed as,

$$T_{cpu} = Q\left(\frac{C_1}{(n_f \cdot FS)^{n_R}} + C_2\right) + T_{amb}, \tag{16}$$

where $T_{amb}$ indicates the ambient temperature. *Q* indicates the heat released by the CPU. Besides, *n* and *FS* denote the number of fans and speed, respectively. For simplicity, all fans are assumed to have the same speed, and *R* represents the holistic thermal resistance. Moreover, when the time granularity of CPU power variation is smaller than the thermal time constant, a transient-state thermal model needs to be considered to predict the CPU temperature. Here, assuming that the prediction time interval $\Delta t$ is 1 second, then (16) can be extended as,

$$C_3\frac{dT_{cpu}}{dt} = \frac{C_4}{R}(T_{amb} - T_{cpu}) + Q, \tag{17}$$

$$\Delta T_{cpu}(k+1) = \left(1 - \frac{\Delta t C_4}{C_3 R}\right)\Delta T_{cpu}(k) - \frac{\Delta t}{C_1}Q, \tag{18}$$

$$R = \frac{C_1}{(n_f \cdot FS)^{n_R}} + C_2, \tag{19}$$

where $C_1\frac{dT_{cpu}}{dt}$ denotes the CPU temperature variation rate, $\frac{C_2}{R}(T_{amb} - T_{cpu})$ denotes the heat transfer rate. The model parameters $C_1$, $C_2$, $C_3$, $C_4$ need to be obtained by experimental measurements.

*2) Black-box Models:* **A. Node-level thermal modeling**

Ghosh et al. [28] adopted a mathematical approach, proper orthogonal decomposition (POD), to evaluate the temperature distribution in IT rooms. This approach enables capturing the time-series characteristics of node thermal loads from multi-dimensional sensor data to evaluate the temperature profile quickly, but the extrapolation prediction is poor. Note that artificial neural network (ANN), with their powerful nonlinear fitting capability, is also gradually and widely adopted for the thermal modeling of data centers [29], [30], [31]. Song et al. [29] collected server inlet temperature and perforated tile flow data from a CFD simulation model to train an ANN-based thermal model. Furthermore, this thermal model was taken to guide a multi-objective genetic algorithm to explore the cooling management strategy of the data center. In work [30], the thermal distribution evaluated by the ANN-based thermal model remains within an acceptable prediction error compared to that obtained by CFD simulation. Distinct from the above CFD simulation-based work, Lloyd et al. [31] collected sensor data from 52 public clouds to serve as a dataset. Besides, this work adopted a clustering technique to group objects with similar temperature and physical characteristics, which were subsequently stored in a knowledge base. The ANN-based thermal model trained from this knowledge base can be generalized for deployment to various data centers for temperature prediction. In addition, the work [32] developed and compared various ML-based thermal models, including ANN, Gaussian process regression (GPR) models, and linear regression (LR) models. Subsequently, the authors applied the proposed thermal model to a multi-node thermal-aware task scheduling scenario, saving the overall energy consumption by 17% while maintaining performance.

To compare the robustness of multiple data-driven thermal models subjected to external or internal parameter perturbation, the work [6] constructed multiple application scenarios to test four models (ANN, SVR, GPR, and POD). Besides, the work [20] focuses more on workload distribution, model hyperparameters, and server location on thermal models. Our previous work [33] comprehensively compared the performance of the six most popular thermal models (SVR, GPR, XGBoost, LightGBM, ANN, LSTM) in CFD models under steady-state and cooling failure scenarios. A surprising conclusion of our work is that the boosting models XGBoost, and LightGBM outperform previous thermal models in various engineering metrics and have good prospects for industrial applications.

**B. Chip-level thermal modeling**

To overcome the limitations of physical modeling methods, collecting server built-in sensor data and operating system state to construct CPU thermal models is also gradually being adopted. For example, the work [34] first proposed a meta-heuristic thermal modeling approach based on Grammatical Evolution, which considers the time dependence to evaluate the CPU and ambient temperature of a server. The work shows that the dominant factors determining CPU temperature are power, fan speed, and server inlet temperature. Most uniquely, this thermal model generated using an unsupervised approach is more suitable for optimizing the prediction model at runtime. Moreover, the work [35] chose a nonlinear auto-regressive network with exogenous input to capture the features of multivariate time-series data to predict CPU temperature. The specific model is represented as,

$$\hat{y}\left(t+1\right) = f\left(y\left(t\right),\ldots,y\left(t-n_y\right),u\left(t\right),\ldots,u\left(t-n_u\right)\right), \quad (20)$$

where $y(t)$ and $u(t)$ denote the CPU temperature and utilization at time $t$, and $\hat{y}(t+1)$ is the predicted temperature at time $t+1$.

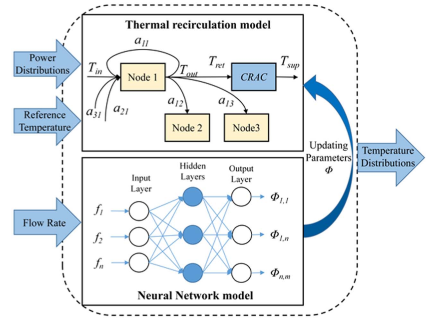


Fig. 9. Room-level gray-box thermal model.

Besides, the delay order $n_y,\ n_u \geq 1$. Moreover, Ilager et al. [36] collected sensor data from a private cloud to construct an XGBoost-based CPU temperature prediction model. Subsequently, the authors used the feature importance analysis method of the XGBoost model to filter out the three most important features: host power, fan speed, and the number of running VMs. Notably, the proposed method is generic and can be applied to chip-level temperature evaluation for different physical environments and parameters.

*3) Gray-Box Models:* This Section describes the principles and characteristics of the gray box thermal model with three different cooling methods and layouts (Room, Row and Rack-level).

**A. Room-level thermal modeling**

Each rack and CRAC in the IT room can be considered a node on the thermal network. These thermal nodes not only exchange heat with each other but also receive thermal interference from other nodes [37]. Given $N$ rack nodes, the outlet and inlet temperatures are denoted as $T_{ro,i}$ and $T_{ri,i}$, respectively. In addition, there are $M$ CRAC nodes with inlet and outlet temperatures and reference temperatures represented as $T_{ci,j}$, $T_{co,j}$, and $T_{ref,j}$, respectively, so that the mathematical form of the thermal recirculation model is formulated as,

$$\begin{cases} T_{ro,i} = T_{ri,i} + \frac{P_{r,i}}{\beta f_i C_p},\ i\ =\ 1,\ldots,N \\ T_{co,j} = T_{ref,j}, j\ =\ N+1,\ldots,N+M \\ T_{in} = \Phi T_{out}. \end{cases}, \quad (21)$$

where $P_{r,\ i}$, $\rho$, $f_i$ and $C_p$ represent the power, air density, airflow rate, and specific heat capacity of the nodes, respectively. Note that the thermal cross interference matrix $\Phi$ is assumed to change with the airflow rate and supply temperature of the CRAC. Therefore, the work [21] constructs a gray-box thermal model that combines a neural network and a thermal recirculation model to replace the time-consuming CFD simulation. The specific modeling process is shown in Fig. 9. First, the model feeds the airflow rate distribution $F = [f_1, f_2,\ \ldots, f_N]^T$ of the rack to the neural network and outputs the cross-interference matrix $\Phi$. Subsequently, the updated matrix $\Phi$ is substituted into the thermal recirculation model to evaluate the inlet and outlet temperatures, $T_{in}$, $T_{out}$ of each node.

**B. Row-level thermal modeling**

Unlike room-level cooling, row-level cooling deploys CRAH units embedded between racks and encloses the hot and cold

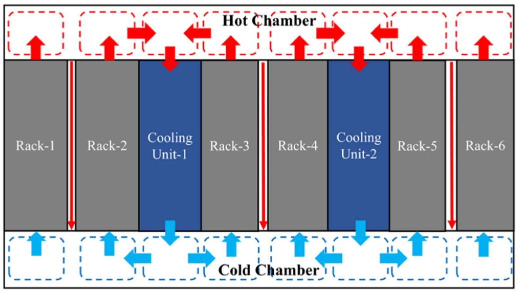


Fig. 10. Row-level cooling layout.

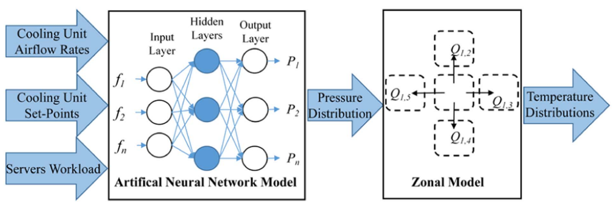


Fig. 11. Modeling flow chart.

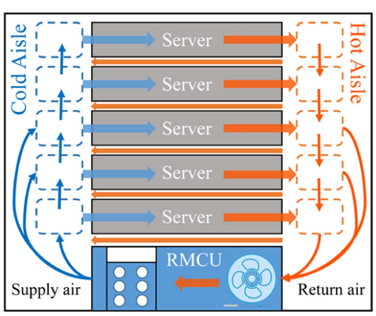


Fig. 12. Rack-level cooling layout.

aisles (Fig. 10). The Zonal model [38] is often employed to divide the thermal environment into a series of coarse grids for this enclosed cooling layout. Each grid is assumed to be homogeneous in physical properties and can be characterized by a nonlinear coupling equation comprising mass, momentum, and energy conservation laws. Compared to CFD simulations, the Zonal model significantly reduces the solution overhead while maintaining performance. Inspired by this model, the work [18] developed a gray box thermal model for row-level cooling layouts to evaluate the CPU and inlet temperatures of the server. The modeling process is shown in Fig. 11. This gray box model takes the grid pressure distribution as the predicted key variable, determined by the cooling unit's airflow rate, supply temperature, and server workload. Similarly, work [39] constructs a similar gray-box thermal model to guide fault detection and diagnosis in data centers. However, the authors also consider chilled water temperature's effect on the thermal profile.

**C. Rack-level thermal modeling**

Fig. 12 shows a typical rack-level cooling layout with N servers and a rack-mountable cooling unit (RMCU). The bottom RMCU outputs cool air into the cold aisle, which is drawn in by the servers. Hot air leaves the server into the hot aisle and returns to the RMCU. Moreover, due to the gap between devices, there is leakage airflow from the hot aisle to the cold aisle. The cooling layout with RMCU embedded in the rack has several advantages, as follows, (1) Significantly shorten the cold air transfer path and effectively reduce the energy consumption of fans [40]. (2) Enclosed hot and cold aisles significantly avoid hot air recirculation and cold air bypass. (3) Faster cooling regulation response, suitable for real-time control.

For this rack-level cooling layout, the work [41] designed a novel thermal model, ThermoCast. This model models the server inlet temperature by collecting workload and airflow sensor measurement information in real-time. To be specific, ThermoCast is based on Zonal models to construct thermal networks between adjacent nodes and takes a data-driven approach to explore the fitted values of crucial network parameters. Besides, this federated modeling framework, which constructs a corresponding prediction model for each server, is computationally and physically scalable. The latest work [42] proposed a novel state-space gray box model to evaluate the thermal profile of a rack. The model uses a zonal modeling approach to model the rack thermal environment as a state-space structure. Specifically, mass, energy, and momentum conservation laws are adopted to simplify the characterization of the physical properties of each grid. Then, the prediction-error method is used to estimate the free estimable parameters in the state-space model. Compared with the data-driven model, the proposed gray-box model has good extrapolation prediction capability and fast response time.

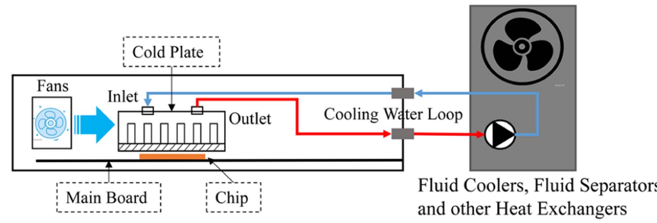


Fig. 13. Cold plate liquid cooling system.

### B. Thermal Modeling of Liquid-Cooled System

The liquid cooling system's coolant with a high heat storage capacity is used to remove heat by direct or indirect contact with the server components. As a result, liquid cooling can achieve higher heat transfer rates than air cooling. The liquid-cooled approach is the most promising technology to solve the various problems cooling systems face in high-performance computing. This section describes the thermal modeling approach for cold plate and immersion liquid cooling systems commonly employed in the industry.

*1) Cold Plate Liquid Cooling System:* A typical cold plate liquid cooling system is shown in Fig. 13. The coolant does not directly touch the electronics but flows through coolant channels inside the cold plate (a metal plate with high thermal conductivity) on top of the electronics and absorbs heat through the metal tube walls. The coolant is usually delivered to the

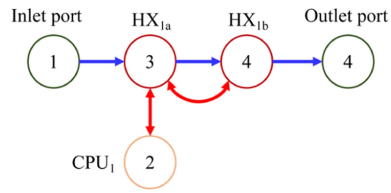


Fig. 14. Thermal network model of a single CPU liquid-cooled unit.

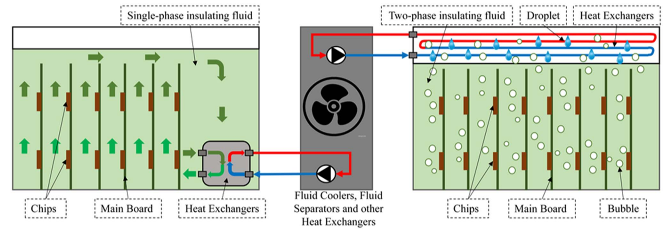


Fig. 15. Single-phase/ two-phase immersion liquid cooling system.

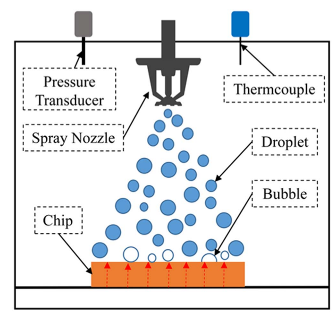


Fig. 16. Spray liquid cooling system.

processor that generates the most heat, while the remaining components (Memory, RAID) are cooled with the aid of fans.

Recent work [43] modeled a cold-plate liquid-cooled server as a component network with aggregated thermal properties and local temperature dynamics interactions. As an example, a thermal network model of a single CPU liquid-cooled unit is shown in Fig. 14. Specifically, coolant enters the manifold microchannel (MMC) from the inlet and is directed through the jet plane into the MMC. Then, the heated coolant recirculates within the MMC, exchanging heat with the shell of the exchanger until it reaches the outlet. The thermal network uses two series-connected heat exchanger nodes $HX_{1a}$, $HX_{1b}$ to describe the temperature dynamics of a single MMC device.

As a supplementary note, reusable nodes in thermal networks can be divided into two categories, hot nodes and transport nodes. Hot nodes (e.g., storage heater, CPU, etc.) participate in thermodynamics by acting as local heat sources. In contrast, transport nodes have an infrastructure characteristic used only to describe the cooling loop topology and are not directly involved in thermodynamics. Each type of node is dedicated to specific modeling demands when capturing the temperature dynamics of a liquid-cooled server. Moreover, the work [44] used numerical statistical analysis to explore the relationship between the core temperature $T_{core}$ and three dynamic parameters of the liquid cooling system (flow rate $F$, inlet temperature $T_{inlet}$ and IT load $L_{IT}$), which can be expressed as,

$$T_{core} = f\left(F, T_{inlet}, L_{IT}\right), \tag{22}$$

Then, a regression model was used to fit the input-output relationship. Finally, it was concluded that the chip temperature is proportional to the inlet coolant temperature and IT load. Conversely, it is inversely proportional to the flow rate.

*2) Immersion Liquid Cooling System:* Immersion liquid cooling (ILC) systems rely on direct contact between the coolant and the components to remove heat. The coolant is mostly a non-corrosive, insulating fluorocarbon. ILC can be broadly divided into single-phase immersion (Fig. 15, left), two-phase immersion liquid cooling (Fig. 15, right), and spray liquid cooling (Fig. 16). The essential difference between single-phase and two-phase immersion liquid cooling is whether the coolant undergoes a phase change during the heat exchange cycle. Besides, spray liquid cooling involves atomizing the coolant into tiny droplets through a spray nozzle and then directly onto the components or indirectly onto the cold plate to cool the electronic components. Generally, this cooling method has a high convective heat transfer coefficient and is suitable for high heat-generating components. However, complex maintenance and high cost also limit its large-scale application.

Existing modeling approaches on ILC systems have CFD-based modeling methods. For example, the work [45] constructed a CFD model of a natural convection immersion cooling system to evaluate the cooling performance of high-power servers. Moreover, the work [46] used the simulation tool to construct a two-phase immersion cooling simulation model to perform a 3D numerical analysis of various heat source deployment structures. Similarly, the work [47] was based on CFD models to verify the effect of different coolant flow rates and heat sink materials on the overall cooling effect. It was concluded that the coolant flow rate significantly affects the cooling effect, while the heat sink material does not. Nevertheless, these CFD simulation-based works focus more on the physical modeling and property analysis of the ILC system and do not apply to real-time cooling control.

Therefore, to construct a control-oriented thermal model of the ILC system, the work [48] used a graph-based modeling approach to model the single-phase immersion liquid cooling system as a directed graph to describe the coolant and heat source states. The ILC system is modeled as a heat transfer graph $G = (V, E)$, where the vertices $V = \{v_i: i \in \{1, 2, \ldots, N_v\}\}$ represent the capacitive elements of the system that can store energy and the edges $E = \{e_i: i \in \{1, 2, \ldots, N_e\}\}$ represent the direction of heat transfer between two adjacent vertices. The graph model allows taking an energy conservation equation to derive the states of each key component and employing experimental data to evaluate the model parameters.

## IV Thermal-aware Energy Saving Methods

As mentioned above, thermal modeling is one of the critical keystones to achieving efficient thermal management in data centers. After an extensive survey, existing energy-saving technologies and methods based on thermal models focus on three significant aspects, thermal-aware IT load scheduling optimization, cooling system control optimization, and joint optimization of IT and cooling systems.

### A. Thermal-aware IT Load Scheduling

Thermal-aware scheduling technology is a promising method to boost cooling energy efficiency in CDCs while meeting thermal constraints. The approach reduces CPU and server temperature profile gradients by scheduling and migrating workloads to avoid thermal risks and additional cooling overhead. This section will investigate three aspects of VM consolidation, workload allocation, and DVFS.

*1) VM Consolidation:* Thermal-aware VM consolidation is an energy efficiency approach that has been widely proven by a wide range of cases. Assume that the power column vector of $N$ computing nodes in the server room is $\vec{P}_{comp} = [P^1_{comp}, \ldots, P^N_{comp}]$, and the total computational power consumption is $E_{comp}$; the cooling energy consumption is $E_{CRAC}$, and the performance coefficient of CRAC is $CoP$; the thermal distribution matrix between the nodes is $D$. The objective is to find a supply temperature $T_{sup}$ and a power consumption vector $\vec{P}_{comp}$ to minimize the total energy consumption, defined as follows.

$$Min\ E_{total} = E_{comp} + E_{CRAC} = \left(1 + \frac{1}{CoP\left(T_{sup}\right)}\right) \cdot \sum_{i=1}^{N} P^i_{comp}, \tag{23}$$

$$st.\ T_{sup} \leq T_{red} - max_{1\leq i<N}\left\{D\vec{P}\right\}, \tag{23.1}$$

where the node power is related to the on/off state, CPU utilization, and frequency, etc.; the other constraint (23.1) indicates that the inlet temperature is guaranteed to be below the red line temperature $T_{red}$. The approach considers the thermal consequences of VM placement and migration between servers, reducing essential cooling while keeping hosts below a safe temperature threshold [49]. Meanwhile, VM consolidation also inevitably brings adverse effects such as service performance degradation and local hotspots. For these issues, many works have developed various solutions to cope with them. For example, the work [50] proposed an active thermal-aware VM consolidation scheme to address the imbalance of thermal distribution in the server room. The scheme is based on predicting temperature profiles and active VM consolidation to optimize overall energy consumption, migration latency, and network overhead but ignores thermal airflow recirculation. Besides, Li et al. [51] used a thermal model to guide the scheduling of VMs and the setting of CRAC capacity to improve cooling efficiency while satisfying SLA and thermal constraints.

Considering that thermal gradients exacerbate the thermal recirculation effect in the server room, the work [52] uses dynamic VM migration of overloaded hosts and shutdown of underloaded hosts to maintain thermal balance. This solution reduced considerable total energy consumption while increasing the number of acceptable hotspots. Nevertheless, the work assumes that the flow field is stable and ignores the effect of the cooling system on the thermal field. Apart from this, to minimize the peak temperature of host nodes, Ilager et al. [36] take CPU utilization and temperature to identify overloaded and overheated hosts and assign VMs to the "coolest" active hosts. Moreover, Xiao et al. [53] designed a VM management framework with two layers of control logic. The first layer is the host control layer, which uses a Q-learning algorithm to find the optimal host configuration considering the host load and the thermal state. The second layer is the VM control layer, which performs a load-balancing policy for VM consolidation and migration based on the optimal host configuration. This control decoupling design enables effective resource management, but its host configuration model considers only three power states, which is insufficient for fine-grained thermal management. Similarly, work [54] constructed a lightweight thermal-aware resource management framework, ThermoSim. The framework integrates a recurrent neural network based thermal model to guide energy and thermal-aware VM scheduling. Furthermore, the work [55] further considers the impact of heat transfer from neighboring servers on each other's performance. Therefore, the relative locations of physical machines are considered when assigning VMs to avoid local hotspots.

Furthermore, meta-heuristic algorithms are effective methods for solving this optimization problem. Work [56] develops a genetic algorithm-based heuristic to solve a nonlinear integer optimization problem considering computational and cooling energy consumption. Similarly, Feng et al. [57] proposed a two-step algorithm to reduce the data center overhead in three aspects: cooling system, computing system, and network. Specifically, a simulated annealing algorithm is first employed to minimize the computational and cooling overheads. Then, virtual machines with high traffic costs are placed on servers close to that location to reduce the network overhead. However, the algorithm does not sufficiently consider how to define a threshold for server utilization and a VM selection policy. Then, work [58] fills this gap by designing a novel VMP policy based on a simulated annealing algorithm that considers thermal recirculation and multiple physical resource allocation to reduce the cooling cost of CRACs. The proposed strategy significantly reduces the average temperature gradient and the number of active hosts in the IT room. Moreover, considering the heterogeneity of VM demand resources, Aghasi A et al. [59] proposed an improved gravity search algorithm to solve the optimal VM consolidation scheme. An adaptive mechanism based on fuzzy logic is used to enhance the exploitation and exploration performance of the control algorithm. In general, existing thermal-aware IT load scheduling methods rely on a fixed flow field. They rarely consider that the thermal flow field varies with the node power distribution and cooling parameters.

*2) Workload Allocation:* Thermal-aware workload allocation can be expressed as the rational allocation of workloads to minimize cooling overhead based on IT equipment power consumption and thermal behavior [60]. Two uncertainties in workload allocation: workload requests and thermal environment, intertwine and complicate the IT scheduling and cooling control. In the work [37], the cooling energy minimization problem is transformed into the problem of minimizing peak inlet temperature by task assignment (MPIT-TA). To be specific, given a data center with $n$ racks, each deploying $m$ servers containing two classes of power attributes $a$, $b$ respectively. A total of $q$ tasks, each task $k$ requiring $c(k)$ servers. The thermal distribution matrix between nodes is $D$. The objective is to solve a task allocation table $C$ to minimize the peak inlet temperature, which can be defined formally as,

$$Minimize\ max_i\left\{T_{in}^{i}\right\}, \tag{24}$$

$$st.\ c\left(k\right)-\sum_{j\,=\,1}^{n}c_{jk}=0, k\ =\ 1,\ldots,q, \tag{24.1}$$

$$t_{in}=t_{sup}+Db+D\odot Ca \tag{24.2}$$

$$\sum_{i=1}^{q}c_{ij}^{\prime}=c\left(j\right),\ j\ =\ 1\ldots n \tag{24.3}$$

$$m\geq\sum_{j=1}^{q}c_{ij}^{\prime}\geq 0,\ i\ =\ 1\ldots n \tag{24.4}$$

where $\odot$ is the row wise dot product of two matrices, yielding a vector. Subsequently, the authors designed a meta-heuristic algorithm and a nonlinear programming algorithm to solve this optimization problem. The proposed methods significantly reduce the cooling cost by 30%. Subsequently, work [60] extended this approach to batch workload distribution in geo-distributed DCs to optimize energy cost and fairness. Furthermore, some works [61], [62] design heuristic and model predictive control (MPC) algorithms to solve IT and cooling system management problems. The work [61] focused on allocating workloads with dependencies of subtasks to achieve energy-thermal efficiency trade-offs. In addition, to cope with sudden thermal anomalous behaviors of compute nodes (fan failure or excessive load), the work [63] designs an online scheduler called ThermoRing. This scheduler adjusts the task admittance of the nodes based on the real-time temperature to resist thermal anomalies. The work [64] noted that relying on server inlet temperatures to measure the host thermal state may not apply to heterogeneous DCs. The reason is that servers with different versions and hardware specifications can have varying thermal performance at the same ingress temperature and load level. Therefore, this work adopts the server outlet temperature as a metric to identify hotspots. Subsequently, a thermal-aware workload allocation and server relocation optimization solution are proposed to minimize the peak of the outlet temperature.

Meta-heuristic algorithms are also often adopted to solve the optimal workload allocation strategy with thermal constraints. The work [65] combines a reduced-order thermal model and a particle swarm algorithm to explore the optimal workload distribution for a given load. Moreover, the work [66] used chip temperature rather than inlet temperature to characterize the host thermal state and adopted a genetic algorithm (GA) to solve the optimization problem with constraints. The work [67] established a holistic power consumption model linking the cooling system to the IT system of the DC. A novel genetic simulated annealing algorithm (GSA) is designed to allocate the workload to reduce the node inlet peak temperature as much as possible. Also, works [68] design a multi-objective optimization framework combining a thermal model and genetic algorithm to trade off PUE and exergy efficiency. Besides, work [69] developed a thermal-aware task scheduling method for edge cloud scenarios to trade off the host thermal profile with the energy efficiency of IoT-based applications. The method predicts the host temperature based on task requests and host resource parameters to establish the optimal task-to-host mapping. For node failures that may occur during multi-node workload allocation, work [70] designed a hybrid algorithm to reallocate the workload of the failed node to other suitable nodes for operation.

However, due to the heterogeneity of IT devices and the complexity of thermal distribution, multidimensional constraints tend to increase the solution complexity of algorithms, making it difficult to scale to online large-scale application scenarios. To address the performance degradation of existing heuristic algorithms in the face of large-scale search and optimization, DRL was adopted to cope with such online optimization problems with large-scale solution spaces [71], [72], [73], [74]. The work [74] constructed an LSTM-based computational model to evaluate the system state (including the chip temperature and the server power). Subsequently, this computational model is adopted as a simulation environment for a DRL agent to explore scheduling strategies. Finally, this trained scheduling model is used to assign computationally intensive jobs online, significantly reducing the processor temperature while guaranteeing system throughput. Moreover, to reduce the training duration of the DRL scheduler, the work [75] uses an expert policy to provide scheduling experience to the agent. This method can limit its exploration space, thus helping the agent to learn the excellent scheduling policy quickly. Compared to heuristic and DRL scheduling algorithms, the proposed generative adversarial RL scheduling algorithm has better scheduling performance and stability for distributed High-Performance Computing (HPC) systems.

*3) Dynamic Voltage and Frequency Scaling (DVFS):* DVFS is also a widely recognized technique for server power saving, which dynamically regulates the frequency or power state of the CPU according to the system load [3], [76]. Most enterprise servers use performance state (P-state) to represent the ratio of power consumption to performance. The lower the P-state, the higher the power consumption, but for most servers, the lowest P-state (P0) is not the most energy-efficient state [77]. Therefore, finding the optimal server P-state set point is the key to enhancing server energy efficiency. The work [78] proposed a thermal-aware multi-step, scalable resource allocation method that considers the relationship between server P-state set-points and the power consumption of CRACs. The decision targets of this method are the P-states of multiple cores, the number of tasks assigned to the cores, and the CRACs outlet temperature. Nevertheless, the P-state of this method has only two optional states: the highest performance state (P0) or off, and thus is not applicable to fine-grained thermal-aware optimization. Moreover, Zhao et al. [79] proposed an energy-efficient scheduling method based on model predictive control (MPC). This method suppresses internal thermal perturbations due to load variations by dynamically adjusting the CPU frequencies of computing nodes, thus reducing thermal cycling among nodes. Similarly, the work [80] proposed a spatio-temporal thermal model to characterize the thermal behavior of data centers. Subsequently, DVFS is adopted to dynamically balance the load of each computing node and improve makespan.

### B. Cooling System Control Optimization

*1) Air Cooling System:* The chilled water system and server fans are the primary energy consumers of air-cooled systems. Therefore, optimizing the energy management of chilled water systems and fans is a highly profitable research area and has attracted extensive attention.

**A. Server fans**

The fan is the most direct cooling device for the server, and its role is to speed up the airflow to improve convective heat transfer. The performance of the fan plays a decisive role in the cooling effect of the server. Existing fan control strategies can be broadly summarized into the following three categories.

(1) Constant fan control strategy. This control strategy sets a fixed fan speed based on industry experience and server hardware configuration to guarantee that all components do not exceed the critical thermal threshold even at the worst ambient temperatures and highest loads. However, this control strategy can result in over-cooling in most cases [81].

(2) Reactive fan control strategy. This control strategy monitors key target values in real-time and performs real-time speed regulation based on a preset target value-speed mapping function. The commonly used control strategies are (a) PID regulation, which regulates the fan speed by the gap between the monitored value and the setpoint. (b) multi-stage regulation strategy, which sets the corresponding speed interval according to a specific temperature interval. (c) Real-time power control strategy sets the fan speed according to the heat generated by the host. Assuming the real-time power is *P,* and the rated power $P_{max}$, the fan speed percentage *r* is set as:

$$r = \frac{P}{P_{max}} \times 100\%. \tag{25}$$

(d) Minimum power control strategy [82], which seeks the fan speed corresponding to the minimum power consumption $P_{total}$. *P* is the total of the CPU leakage power $P_{leakage}$ and fan power $P_{fan}$ of the server, which can be expressed as.

$$P_{total} = P_{leakage} + P_{fan}, \tag{26}$$

where $P_{leakage}$ is related to the CPU core temperature *T*, defined as,

$$P_{leakage} = k_2 * e^{k_3 * T} + C. \tag{27}$$

Besides, the fan power $P_{fan}$ has a cubic polynomial exponential growth relationship with the fan speed *x*, defined as,

$$P_{fan} = k_1 * x^3 + k_2 * x^2 + k_3 * x + C, \tag{28}$$

where *k* and *C* represent a series of coefficients and constants. While these reactive fan control strategies are simple and effective, there are obvious limitations, such as that fan speed reacts to variations in target values (power and temperature) in behavior that can lead to significant oscillations in fan speed. This oscillation phenomenon can generate power spikes and cause hardware wear. Moreover, reactive control takes action only after the component temperature exceeds the boundary, which can lead to impaired component performance due to cooling hysteresis.

(3) Active fan control strategy. The active fan control strategy regulates the fan speed in advance to a specific interval based on the predicted target temperature. This dynamic thermal management (DTM) approach requires a predictive model of the controlled object and advanced system regulation based on the predicted values. The work [83] adds the prediction of future CPU temperature to the minimum power control strategy [82] to cover the thermal delay of the chip. More specifically, the authors proposed a leakage-aware fan control strategy that estimates the expected CPU temperature for a given workload and actively sets the speed to the optimal state in advance to reduce the total power of the fan plus leakage. Similarly, the work [81] constructs a neural network-based CPU thermal model that considers CPU utilization, frequency, and fan speed. Guided by this thermal model, the proposed fan control method can eliminate fan power oscillations and achieve thermal-aware multi-core load balancing. Moreover, to overcome the thermal disturbance of the server by workload fluctuations, the work [84] proposes a decoupling control algorithm based on active disturbance suppression. The authors reformulate the thermal disturbance suppression problem and optimize the control parameters using a genetic algorithm, considering both performance and energy. Apart from this, the work [85] observed that the mechanical vibrations generated by the fans degrade the operating performance of SATA disks. Therefore, the authors design a convex optimization-based active fan control strategy that takes into account the mechanical interference of fans, system resource utilization, and cooling requirements for efficient server thermal management.

There is also some DTM work on joint fan and CPU operation parameters (CPU utilization, frequency, and core count) control to minimize the holistic energy of the server. The work [86] modeled DVFS, thread migration, and active cooling as a performance-per-watt (PPW) optimization problem with multi-dimensional constraints. Subsequently, PPW is shown to be a quasi-concave (single-peaked) function of the chip and fan speed with a unique optimal solution. The work [27] also introduces a core capping strategy to limit CPU utilization and thus reduce the leaked power generated by overheating CPUs. Besides, the work [87] adopts a reinforcement learning algorithm to select the DVFS setpoint, fan speed, and number of active cores to control the processor temperature.

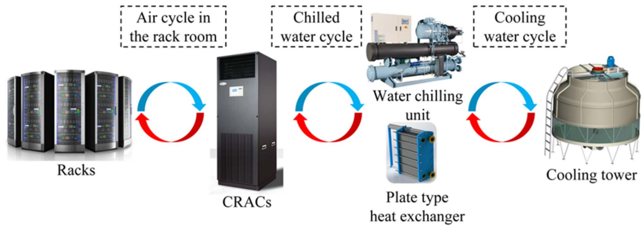


Fig. 17. Heat transfer process.

Surprisingly, some works have adopted the novel thin-film material, thermoelectric cooler (TEC), to handle the local hot spots of the chip from the perspective of combining hardware and software [88], [89]. The work [89] proposes a hierarchical optimization framework to coordinate TEC, fan, and DVFS to optimize the energy efficiency of servers with multi-core processors. Extensive research shows that this collaborative hardware and software cross-stack design approach improves new perspectives for improving server cooling efficiency [90].

**B. Chilled water system**

The operation mechanism of the cooling system in the server room is that the heat released from IT equipment is discharged to the outdoors through the circulation of heat transfer media (air, water, refrigerant, etc.) driven by a certain temperature difference [4]. The architecture of the chilled water air conditioning system is shown in Fig. 17, which includes the terminal air conditioner, water pump, chiller, plate heat exchanger, and cooling tower. The entire cooling system is driven by fans and pumps, and other equipment to carry out three thermal cycles, which are air circulation in the server room, chilled water circulation, and cooling water circulation.

The operating parameters of most existing cooling control methods focus on the supply and return air temperature of CRACs, fan speed, chilled water temperature, and flow rate. The work [91] constructs an MPC-based facility fans control method for modular data centers, which considers the effects of fan flow rate, fresh air temperature, and server load on CPU temperature. Guided by the CPU thermal model, the proposed method can find an optimal fan speed set-point under different air temperatures and IT loads while satisfying the thermal constraints. Yao et al. [92] proposed a novel multi-objective optimization method that considers the energy consumption and the rack intake temperature of CRACs. Subsequently, the authors adopted the non-dominated sorting genetic algorithm II (NSGA-II) to solve for the optimal fan speed and cooling unit outlet temperature. The proposed scheme shows significant energy savings in both winter and summer scenarios. Moreover, the work [93] uses a regression model to learn the fan speed control strategy for air handling units (AHUs) from the historical operating data of the CDC. Unlike the single-setpoint control method, this work [94] proposed a multi-setpoint cooling control scheme, which can regulate multiple fan speeds according to the cooling demand of each zone in the server room. While this scheme performs well in modular DCs, it may not be applicable to open-cooling DCs with complex airflow patterns.

RL and DRL models have recently been widely adopted to manage cooling systems. Lazic et al. [95] used a model-based RL to regulate the temperature and airflow inside the floor by controlling the fan speed and chilled water flow rate inside the AHUs. Considering the requirements for supply air temperature and relative humidity in free-cooled CDCs, Van et al. [96], [97] developed a DRL scheme with constraints to control the set points of supply and exhaust fan flows in the server room. Compared to the MPC method, the DRL-based solution effectively reduces cooling energy consumption by 3%-7% by regulating the amount of return air mixed with fresh cold air. Apart from this, Li et al. [98] developed an energy-aware cooling control algorithm (CCA) based on the Actor-Critic framework. To be specific, CCA can regulate the supply air temperature and cooling water temperature set points based on the current IT load and weather information to improve the cooling efficiency.

***2) Liquid Cooling System:*** **A. Cold-plate liquid cooling system**

As mentioned in Section II.B, liquid cooling systems with high heat transfer efficiency have a vast potential for waste heat recovery. Therefore, optimizing servers' thermal management is a promising direction while considering improving waste heat recovery efficiency [99], [43]. The work [99] used CFD models to simulate the coolant flow and heat transfer mechanisms of a hybrid cooled server. The authors improve the efficiency of the cooling and air-side thermal waste heat recovery by optimizing the baffle geometry design and active flow control. Distinct from CFD simulations, the work [43] constructed a network-based thermal model to characterize the thermal behavior of an enterprise cold-plate liquid-cooled server. Subsequently, a receding horizon control method is proposed to solve the coolant flow dynamic control problem. This strategy improves the output coolant temperature by reducing the coolant flow rate under thermal constraints, which is more conducive to waste heat recovery. Beyond that, for the problem of hot spots and large temperature gradients due to uneven heat distribution at the chip level, work [100] proposed a feasible cooling solution combining a dynamic cold plate and a thermosensitive flow control device. To be specific, the coolant would be targeted to particular modules to substantially reduce the temperature gradient while significantly increasing the control complexity and hardware cost. Besides, the work [101] is concerned with the impact of the operating conditions parameters of the rack-side and cooling source-side fluids on the system power consumption. The authors designed a novel method to find the optimal cooling water set-points under various chip thermal constraints and thermal loads. Note that the solution applies to other liquid-cooled systems and can guide the design of water-cooled systems equipped with cooling towers at optimal operating conditions. Still further, the work [102] quantifies the extent to which ambient temperature affects system power consumption and efficiency. More specifically, a thermal management model combining a thermal model and a power model is developed to find the relationship between chip power consumption and cooling power consumption under different water operating conditions and ambient temperatures. Finally, the work gives a fitting expression to represent the optimal inlet temperature and flow rate for various ambient temperatures.

Furthermore, some advanced works have started to optimize liquid cooling systems from the perspective of cooling solutions and hardware structure design [103], [104]. The work [103] designed a multi-output convolutional neural network model to select the chip's optimal cooling solution and parameters. Moreover, the work [104] developed a thermal model for finned water-cooled heat sinks to explore the impacts of cooling water outlet location, fin height, thickness, and spacing on thermal and flow resistance performance. Then, a theoretical optimization method for radiator structures is proposed to guide other emerging cooling system designs.

**B. Immersion liquid cooling system**

For the cooling efficiency of single-phase immersion liquid cooling systems, related work focuses on controlling coolant flow and temperature [19], [105], server placement optimization [106], and dielectric fluid selection [107], [108]. The work [105] constructs a simplified model to characterize the relationship between pressure, flow, and temperature of the processor liquid cooling system. Subsequently, a deep neural network-based explicit MPC control method (Deep Explicit MPC, DEMPC) is proposed to control the coolant temperature and flow rate, which effectively reduces the overheating time of the processor and pumping power. Except for controlling the cooling parameters, the employed dielectric fluid's thermal properties also significantly impact the system's cooling performance [107]. Furthermore, work [106] investigates the effect of server placement interval on the surface temperature in a two-phase liquid cooling system. The authors adopt six representative cases to analyze the partial power usage efficiency (pPUE) and COP of liquid-cooled systems with different power loads. Finally, the arrangement of the immersed servers is optimized based on the simulation results. Considering the cooling needs of high-power electronics in extreme environments, the work [108] designs a prototype of a high-performance two-phase closed passive immersion cooling system. The authors compared the cooling performance of three dielectric fluids (ethanol, FC-72, and R113) on the prototype system, with ethanol performing the best. Beyond that, the work constructs a thermal resistance network to characterize the thermal profile of the heat source, which greatly improves the precision of the theoretical model. In conclusion, the cooling technique can cope with high-power devices cooling in extreme operating conditions.

Though immersion cooling technology has numerous potential advantages, it requires large amounts of dielectric fluid, which undoubtedly brings high costs to large-scale deployments [109]. Sprayed liquid cooling is a strongly targeted cooling technology that requires less dielectric coolant and is more economical to deploy than immersion liquid cooling. Some related works have investigated various operational parameters of drench-jet systems to optimize cooling energy efficiency, such as coolant flow rate and characteristics [110], [111], heat source surface roughness [112], and nozzle physical structure and orientation [113, [114], [115]. Moreover, the latest work [116] developed a spray-cooled rack system that can be used to cool high-performance servers in tropical climates.

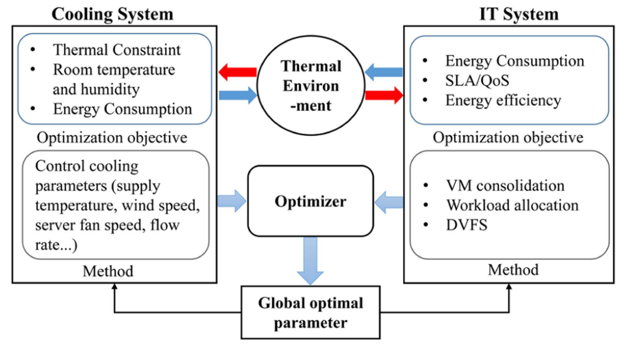


Fig. 18. Static joint optimization framework.

Extensive validation experiments to evaluate the extent to which the operable parameters of the spray cooling system (nozzle flow rate, condenser fan power, condenser flow rate, heat load, etc.) affect the cooling efficiency. The results show that the nozzle flow primarily influences thermal performance. Besides, the condenser's fan power and flow rate are the essential knobs to regulate the pressure in the spray chamber.

### *C. Joint Optimization of IT and Cooling Systems*

The joint optimization problem is a multi-objective optimization problem with multi-constraints. The key to solving this problem is to develop a predictive model of the controlled object and to manage the system in advance. After extensive research, the existing joint optimization methods can be roughly divided into static joint optimization (SJO) and dynamic joint optimization (DJO). To be specific, SJO refers to finding the optimal combination of parameters to satisfy the global optimization objective based on a theoretical model and multidimensional constraints under a specific steady state. DJO emphasizes exploring optimal dynamic scheduling and control strategies to achieve global objective optimization under time-varying system states.

*1) Static Joint Optimization:* Fig. 18 illustrates the SJO framework, where the cooling and IT systems have biased optimization objectives and methods. The SJO approach models the joint optimization problem as a multi-objective optimization problem with multiple constraints. Subsequently, heuristic algorithms or solvers are used to explore globally optimal parameter combinations for workload scheduling and cooling operations [92].

Considering the control mismatch problem caused by the difference in control time constants of IT scheduling and cooling control, work [117] used a two-timescale control method to coordinate DVFS, server resource allocation, and cooling management in an HPC data center. The approach adopted a steady-state thermal model to guide CPU frequency regulation and task allocation and a transient thermal model to dynamically adjust the cooling supply. Similarly, Wan et al. [118] modeled the minimizing holistic energy problem as a mixed integer nonlinear programming problem and developed an efficient joint algorithm to address it. The method collaborates system components from different control layers to minimize overall energy consumption. Specifically, the technique applies DVFS at the chip level, workload scheduling, and dynamic server shutdown at the server level, and fan control at the room level.

Heuristic algorithms are also frequently designed to tackle this joint optimization problem. For example, Arroba et al. [119] proposed an optimization strategy that depends on a simulated annealing algorithm to achieve joint optimization of computational and cooling energy consumption. This strategy aims to explore the maximum cooling setpoint of CRACs to ensure that the inlet temperature of nodes is below the red-line temperature. Moreover, Zhou et al. [120] used a ML approach to model the cabinet temperature and cooling power for a given server power distribution and supply air temperature settings. Subsequently, a simple and effective heuristic algorithm is proposed to regulate the task distribution, server state, and air supply temperature settings. Fang et al. [121] designed a thermodynamic model to guide the establishment of the optimal control problem with constraints. Then, a two-step heuristic was adopted to solve the problem in the following steps. First, a thermal-aware resource allocation optimizer was designed to determine which resources to increase or decrease. Then, an economic model predictive controller was proposed to regulate the cooling setpoint with power variations.

To simplify the joint optimization problem modeling, the work [122] assumes that the servers are homogeneous. The complex minimization optimization problem can be transformed into a simple equivalence optimization problem for homogeneous DCs. Subsequently, this work demonstrates that optimal cooling set-points and workload distribution can be uniquely determined to obtain the minimum total energy consumption of the DC. Similarly, Mirhoseini et al. [123] proposed a framework for joint cooling and workload management that considers the thermal interrelationships between IT and cooling unit entities. This framework jointly optimizes workload allocation and cooling unit operating parameters guided by a thermal model to save by 11% compared to the closest baseline. Nevertheless, the assumption that the servers are homogeneous also limits the practical application of the approach. Therefore, the work [35] further considered real-world factors such as heterogeneity of cooling units (cooling cost, cooling capacity) and heterogeneity of servers (heat generation density and thermal power consumption) to propose a holistic data center infrastructure control framework. The framework constructed two complex thermal models to evaluate the servers' core and inlet temperature. Guided by the thermal models, jobs are assigned to efficiently cooled locations, and cooling parameters are tuned to save 16% power consumption.

Furthermore, for the multi-objective optimization trade-off problem, work [124] proposes a joint optimization framework that takes into account energy, exergy and computing efficiency, and thermal reliability constraints. The framework constructs rack-oriented physics-based spatio-temporal thermal models for optimizing workload distribution and cooling parameters. Moreover, Athavale et al. [125] developed a holistic energy efficiency optimization framework that includes an ANN-based steady-state thermal model, a thermodynamic model to evaluate the cooling energy, and a GA-based optimization model. Two case studies show that GA-based cooling control strategy reduces cooling power consumption by 52% and 20% compared to constant cooling setpoint and return air temperature control strategies respectively. Generally, the SJO method always finds the optimal parameter settings for IT and cooling systems in a given scenario. However, the technique relies on high-fidelity modeling and computational overhead, commonly applied to non-real-time operational scenarios.

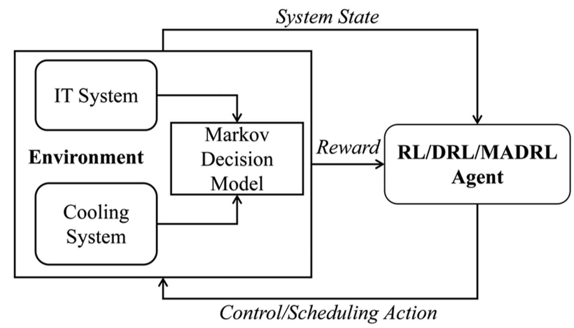


Fig. 19. Dynamic joint optimization framework.

*2) Dynamic Joint Optimization:* The DJO problem is usually modeled as a Markov decision model with continuous decisions (Fig. 19). Subsequently, model-free RL explores IT scheduling and cooling control strategies [95]. The RL-based agent interacts with the environment through a series of actions to obtain the corresponding rewards and learns global control optimization strategies based on a trial and error mechanism [126]. With the continuous advances in RL theory, DRL and multi-agent DRL are also gradually adopted to solve this joint optimization problem.

The work [95] focused on the air pressure difference between the front and rear ends of the rack and the temperature of the cooling aisles, which are affected by the power consumption distribution. A model-based RL algorithm is proposed to control the fan speed and chilled water flow rate within the air handling unit (AHU) to regulate the cooling air supply temperature and flow rate. Moreover, Ran et al. [127] suggested a DRL-based framework, DeepEE, to capture the dynamic nonlinear features of IT scheduling and thermal processes in data centers to achieve the co-optimization of job scheduling and cooling management. The proposed method saves up to 10% energy compared to the work [9] while maintaining QoS. Nevertheless, there is a sequential order for cooling control and IT scheduling decisions in DeepEE. This two-stage collaborative decision-making approach may be challenging to obtain the globally optimal decision. Therefore, to overcome this limitation, Chi et al. [128], [129] proposed a multi-agent-based joint optimization framework, MAD3C, to improve the synergy of the two systems. Unlike the work [127], MAD3C employed an asynchronous control algorithm based on a hybrid AC-DDPG architecture to enable the collaborative decision-making of IT and cooling systems to be performed in an asynchronous manner. Compared to DeepEE, the MAD3C reduces overload events around 21.98% and reduces total energy consumption by 42.82%. Beyond that, considering the actual scenario, the parameters of the end air conditioner have certain constraints, such as temperature and relative humidity. Additionally, considering the constraints of air conditioning parameters in real scenarios, Van et al. [97] designed an adaptive learning of optimal penalty weights to ensure that the DRL-agent can converge quickly while satisfying the condition of satisfying multiple constraints. Compared with the unconstrained DRL method, the proposed DRL method with constraints achieves less cooling energy consumption and fewer constraint violations. Notably, to solve the control mismatch problem of multiple systems, the work [130] introduced a two-time scale IT-facility optimization method based on an improved Deep Q-Network algorithm. The feature of this method is the control of IT and cooling systems by generating two actions on discrete and continuous space, respectively. Compared to the baseline based on expert domain knowledge, the trained control model saves up to 9% and 15% in cooling and IT energy in the actual CDC. Overall, RL performs well on online continuous decision optimization problems. Nevertheless, the trial-and-error mechanism of the RL-agent may lead to unexpected operational risks and failures.

## V. Open Issues and Future Research Directions

The existing advanced thermal modeling and energy-saving solutions have been summarized above. Nevertheless, there are still many open issues in thermal management that remain to be addressed. This section will discuss these issues and future research directions.

### A. Gray-Box-Based Thermal Models

Gray-box modeling, which combines physical laws and data-driven, is one of the potential directions for constructing the thermal model of the DC. The approach not only makes full use of massive sensor data to develop approximate model parameters but also provides a solid theoretical basis. In particular, there are significant differences in their physical properties and architectures for air-liquid and liquid cooling systems, which can increase the complexity and difficulty of modeling. Therefore, a feasible solution is to adopt a data-driven method to characterize the key variables that are susceptible to physical layout and hardware properties, while the rest is based on thermodynamics to construct simplified physical models.

### B. Multi-Agent-Based Cooling Control System

A server room usually deploys N+1 cooling units to ensure a 24x7 cooling supply. The impact of the cooling units on the cabinets depends on the relative position, blast speed, and floor ventilation rate. Besides, the heat power of cabinets is unpredictable and fluctuating, which can easily break the balance of local cooling supply and demand, and then lead to local temperature over-cooling or overheating phenomenon. Therefore, to reduce the thermal profile gradient, it is necessary to adjust the cooling capacity of nearby cooling units in real-time according to the cooling demand of different regions. To solve this problem, a multi-agent cooperative control framework [131] can be used to realize the joint control of multiple cooling units, which can maintain the global cooling supply-demand balance while considering the local thermal fluctuations.

### C. AL/ML-Based Joint Optimization of IT and Cooling Systems

Constructing a green CDC is a comprehensive system project requiring managing multiple subsystems collaboratively. Current IT and cooling systems show coupling and interdependence but lack linkage, prone to a mismatch of supply and demand, and low cooling energy efficiency. Therefore, it is challenging to integrate AI and ML to realize the collaborative management of multiple systems with different control granularity and time scales. AI/ML technologies can be applied to explore the workload patterns of IT systems to guide resource optimization and cooling control. Further, AI-based autonomic systems can be adopted to reduce the total cost of ownership in all phases of CDC management monitoring-analysis-planning and execution [132].

### D. Cooling Technology for High-Power IT Devices

With the rapid advances in high frequency, and integrated circuit technology for electronic components, solving the heat dissipation problem of high-power servers and chips is a fundamental challenge. A liquid cooling system is considered a potential and feasible technology. Liquid-cooled systems can achieve efficient thermal control by targeted cooling high-power heat sources. Besides, liquid-cooled systems are usually semi- and fully-enclosed structures, which are less affected by the deployment environment and remain stable even under extreme operating conditions. However, the large-scale implementation of liquid-cooling technology in CDCs still needs to overcome numerous challenges, such as the standardization of product design, the hardware and software strength of infrastructure manufacturers, and a well-established industrial chain.

### E. Waste Heat Utilization

Capturing and reusing a considerable amount of waste heat generated by CDCs, especially liquid cooling systems with high waste heat quality, to produce useful energy products or services (district heating, on-site power generation, and absorption cooling) would be a potential direction for sustainable data centers.

## VI. Conclusion

To better apply and develop effective cooling energy efficiency methods to construct sustainable CDCs, this review investigates two critical points for efficient thermal management in CDCs, thermal modeling and thermal-aware energy-saving methods. To summarize, data center thermal modeling is a complex engineering problem. No matter whether white-box, black-box, and gray-box modeling approaches have their own appropriate application scenarios and limitations. Especially for liquid cooling technology, which is in a rough and fast development period, the inconsistency of industry standards poses a severe challenge to thermal modeling. Therefore, the selection of modeling methods needs to take into account the specific application scenarios and characteristics of the objects. Moreover, various existing advanced thermal-aware scheduling and cooling control technologies all perform well in the thermal management of CDCs. Nevertheless, some problems have not been completely solved, such as the poor linkage between IT and cooling systems and delayed control response time. Therefore, this paper points out the challenges that data center thermal management may face in the future and the corresponding solutions. This review aims to help researchers in data center thermal management better understand cutting-edge research progress.

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