Smart DC: An AI and Digital Twin-based Energy-Saving Solution for Data Centers

Ziting Zhang*, Yu Zeng, Haoran Liu, Chaoyue Zhao, Feng Wang, Yunqing Chen
AI Research Centre, China Telecom Research Institute (CTRI)
Beijing, China
Email: {zhangzt9, zengyu, liuhr2, zhaocy5, wangfeng6, chenyq}@chinatelecom.cn

***Abstract*—With the rapid growth of mobile internet, Internet of Things (IoT), and cloud computing, the demand for data services has arisen sharply. As the core data service infrastructure, the number of data centers (DCs) has surged and led to higher energy consumption, which is not conducive to energy conservation, emission reduction, and sustainable development. In this paper, we proposed an energy-saving solution based on Artificial Intelligence (AI) and digital twin in DC scenarios, called Smart DC. The proposed solution can reduce DCs' energy consumption by optimizing air distribution and reducing cooling redundancy. Specifically, the digital twin model in this solution is used to verify and optimize AI strategies, and solve the problem of insufficient data in physical data center. Data for AI training and information mining is limited because the environment in the DCs change little. Moreover, in order to ensure that the DCs operate at a safe temperature, the adjustment of parameters should be conservative, so there is still room for cooling redundancy. We combined digital twin and AI, exploring the temperature rise boundary in the digital DCs and mine more data pairs, which has proven to increase the robustness of the AI model and achieve better energy-saving effect. The simulation and experiment results show that the proposed solution can ensure safe and efficient operation and keep the energy-saving rate of the cooling system to reach 41.07%.**

Keywords*—*data center (DC), energy conservation, digital twin, AI

I. Introduction

Currently, as the demand for mobile Internet services increases, the amount of data that needs to be processed has increased dramatically. To carry such a large volume of data and provide quality service, data centers (DCs) form the backbone of various services offered via the Internet [1]. The continued expansion of DCs results in an explosive increase in energy consumption. According to prediction, the energy consumption of DCs accounts for 3% of total electricity consumption in 2017 and will reach 4.5% in 2025 [2]. The power consumption is expected to grow from 200 TWh in 2016 to 974 TWh in 2030 [3]. High energy consumption and OPEX (Operating Expense) have brought great challenges to operators and negatively impacted the environment. Government and operators worldwide have set several goals for energy saving and emission reduction [4]. Safe and efficient energy-saving solutions are indispensable for ensuring future greener DCs.

Cooling system consumes about 40% of the total energy used in the DCs [5]. To utilize the natural cold sources in the high latitude areas, some organizations and companies are building new DCs in the Pan-Arctic region [2]. For the DCs that still need artificial cooling, it's necessary to increase cooling efficiency and reduce cooling redundancy. To reduce energy consumption caused by overdesign and inefficient air-conditioning operation, researchers are developing cooling systems for open architecture rooms with in-row containment [6]. However, the practical application of these designs is limited by the high complexity and long periodicity of rebuilding and repairing DCs. Developing efficient strategic control plans based on energy consumption modeling and prediction is considered a cost-effective and energy-efficient method to deduce cooling power consumption in a software way [7]-[9].

The aforementioned traditional optimization methods are hard to deal with complex systems with nonlinear linkages effectively. To tackle the difficulty in modeling, solution discovery, and dynamic adjusting, artificial-intelligence (AI) based controlling approaches characterized by immediacy, automation, adaptability, and scalability, are introduced into DCs' energy-saving [10]. With AI technology and combinatorial optimization, the system can learn and judge in complex environments autonomously and further make decisions to save energy [11]. However, learning AI-based models requires a large number of samples. Coincidentally, in order to ensure security, it is impossible to provide many samples outside the safe range in the actual data center scenario.

Digital twin is a promising method to provide extra data sets for training. Specifically, digital twin can not only provide physical characteristics of the DC system, but also dynamically adjust scene parameters through programming [12]. In this way, many samples are obtained to assist model training and improve fault tolerance. In Gartner's opinion, digital twin will proliferate industries, and when combined with AI technology, digital twin will enable open, connected, and coordinated intelligent spaces [13]. The seamless connection and real-time data exchange between the physical and digital twin allow us to conduct real-time energy consumption simulation and energy-saving control. Therefore, the combination of AI technology and digital twin is conducive to researching adaptive, intelligent, and fault-tolerant DCs energy saving schemes in a more flexible and dynamic way.

To realize green and safe DCs, a novel energy saving solution is proposed in this paper. The main contributions are summarized as follows:

(1) An AI and digital twin-based Smart DC solution is proposed to reduce the cooling system's energy consumption in DCs.

(2) The proposed solution can build the digital space of DCs by using building information modeling (BIM) and Computational Fluid Dynamics (CFD). The digital space can provide extra data sets under different parameters configurations through software programming, which is helpful to train the eXtreme Gradient Boosting (XGBoost) model with higher accuracy, thus reducing the energy consumption of DCs.

(3) The simulation and experiments are conducted under the 6SigmaDC program and a real data center environment. The results show that the proposed Smart DC solution reduced the Power Usage Effectiveness (PUE) from 1.1503 to 1.0838 and realized a refrigeration energy-saving rate (RESR) (41.07%) , which verifies the outstanding energy-saving performance of Smart DC .

II. Related Works

Traditional Energy-Saving. The conventional energy-saving measures focus on optimizing air distribution (such as closing cold and hot passages, installing blind plates, and so on) and the local transformation of refrigeration systems (such as frequency conversion transformation of the compressor, water pump, and fan)[14]-[16]. However, the above traditional energy saving schemes can not cope with complex data center systems with nonlinear functions, and the cost is relatively high.

AI-Based Energy-Saving. AI is an effective way to fit and approximate nonlinear functions [17] [18]. The authors of [19] point out that by monitoring the cooling system of DCs and collecting temperature information, the AI-based strategies can realize the management, prediction, and control of the temperature. Considering the dynamic and complexity of DCs, the authors of [11] introduced AI technology into the refrigeration engine and construct a green cloud data center. The authors of [20] proposed a task scheduling algorithm supported by wolpertinger architecture, which is based on the model-free deep reinforcement learning framework and can optimize resource use and decrease energy consumption. However, the generalization ability of the above AI-based algorithms relies on sufficient training samples.

Digital Twin Assisted DCs Management. Digital Twin can provide the digital representation of DCs. The authors of [21] use EnergyPlus software to model and simulate DCs to obtain the digital twin of the real DC. The thermal model is constructed through energy measurement, and PUE is measured to evaluate the performance. The authors of [22] introduced a digital twin platform for DC network automation and intelligent management: NetGraph. NetGraph has been deployed in Huawei's DC network, serving more than 50000 devices and providing millions of network connection information (such as links and terminal points). The statistics in real network scenarios show that NetGraph has a wide range of network model coverage and supports various functions. The authors of [23] verify that the combination of AI and digital twin simulation tools is one of the main technology trends affecting DC management automation.

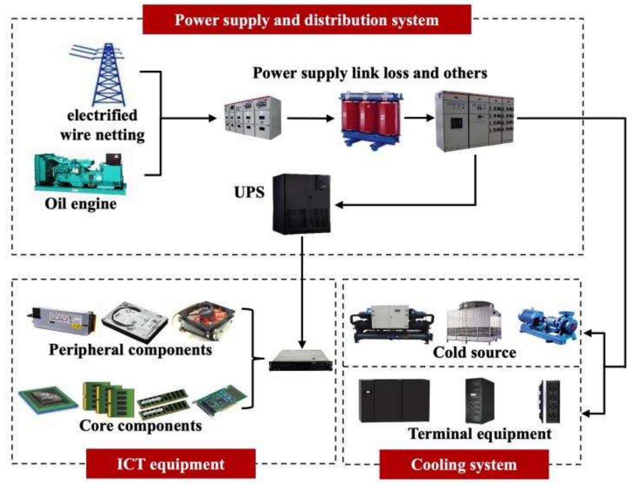

Fig. 1. The energy consumption composition in DCs

To address the overfitting problem caused by insufficient samples, we designed Smart DC to generate extra data sets for training AI models.

III. System Model

As illustrated in Fig. 1, DCs mainly include the following energy-consuming elements:

- Power supply and distribution system: electrified wire netting, oil engine, UPS, power supply link loss and others.
- ICT equipment: peripheral components and core components, such as servers, storage, switches, routers and so on.
- Cooling system: cold source and terminal equipment.

The inappropriate design of air distribution in DCs will lead to local hot spot in the operation stage of IT equipment. Lowering the send/return temperature of air conditioners can eliminate local hot spots, but excessive power will cause local cold spots and energy waste. Therefore, we mainly focus on the energy saving for cooling system and propose a Smart DC to realized automatic, green, safe and efficient operation.

As illustrated in Fig. 2, the proposed Smart DC architecture consists of physical space, AI engine, and digital space.

A. Physical Space

The physical space mainly includes the device layer and control layer.

The device layer includes IT equipment, terminal air conditioners, electricity meters, and multiple sensors. The device layer is used for data acquisition. The collected data involves:

- air supply temperature value.
- air conditioning switch state.
- real-time fan speed.
- upper limit of fan speed.

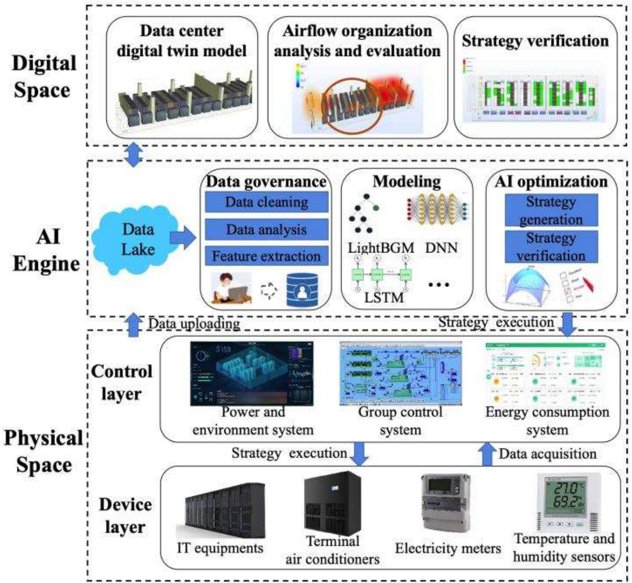

Fig. 2. The proposed Smart DC architecture

- lower limit of fan speed.
- outside temperature.
- outdoor humidity.
- rack temperature.
- rack power.

The control layer includes the power and environment system, group control system, and energy consumption system. The control layer is responsible for collecting data from device layer and distributing energy saving strategies generated from the AI engine. Specifically, the control layer can adjust the parameters of the equipment through the control interfaces of the power and environment system, group control system or other controllers.

B. AI Engine

AI engine is used to train AI models based on the data sets collected from the physical space and the digital space, such as rack temperature prediction model, heat balance model, and power consumption predication model.

Many factors affect the Precision Air Conditioning (PAC) control logic in DCs, including the airflow channel, the PAC brand, the PAC power, the data center server self-cooling capacity, and the racking and unloading of servers. Besides, the structure and layout of DCs will affect the accuracy of the model results. The number of PACs is also a factor. Therefore, it is necessary to consider the relative position and competition between different PACs in the modeling process.

In the AI engine, we choose a common machine learning model in the industry, eXtreme Gradient Boosting (XGBoost). XGBoost is an end-to-end air conditioning control model, which can output the control parameters of the air conditioner through the input ambient temperature and humidity, the calorific value of the server, and the operating load rate of the server [24]. The loss function can be minimized to optimize model parameters, which can be formulated as

$$Loss = \sum_{j=1}^{T}[G_j w_j + \frac{1}{2}(H_j + \lambda)w_j^2] + \gamma T \qquad (1)$$

where T denotes the number of leaves, w_j denotes the value the jth leaf node. G_j and H_j denote the sum of the first and the second partial derivatives of the samples contained by the jth leaf node. λ and γ represent weight parameters.

The XGBoost model is optimized according to the real-time feedback in the training process. However, the original samples collected from the physical space are insufficient for training because the high temperature will pose a great threat to the safety of DCs. Fortunately, the digital twin model in the digital space can simulate different temperature scenes in DCs and provide additional data sets for training models.

C. Digital Space

The digital space is implemented using BIM and CFD according to the building information, device operating parameters, load rate, and temperature collected from the physical space. BIM is a multi-dimensional model information integration technique to realize the application of the whole life cycle of the building. CFD is a novel interdisciplinary subject integrating fluid mechanics and computer science, which can effectively simulate and analyze nonlinear problems in fluid mechanics with various mature discrete numerical approximation algorithms as tools [25].

BIM first creates space partitions for each data center in the digital space. Then the building information such as the geometric and physical architecture of DCs is aggregated and fed into BIM to obtain the associated energy consumption mode. Subsequently, CFD is adopted to predict the airflow organization, the temperature distribution of DCs, and figure out the short-circuit of airflow and the return of hot air, which may cause energy waste or local hot spots. Finally, a complete mirroring of DCs' environment is established through the collaborative analysis of the BIM and CFD modules.

The digital space is used to simulate temperature field and airflow according to the configuration parameters generated in the AI engine, exploring the temperature rise boundary and optimizing related configuration to meet the safety requirement in DCs. After multiple rounds of AI model optimization and simulation verification, a series of control operations are delivered to the physical space.

IV. Performance Evaluation and Simulation Results

A. Performance Evaluation

PUE and refrigeration energy saving rate (RESR) are adopted to measure the performance of the proposed energy-saving solution [21]. PUE denotes the ratio of all energy consumed by DCs to the energy consumed by the IT load, which can be formulated as

$$PUE = \frac{E_{total}}{E_{IT\ load}} \approx \frac{E_{IT\ load} + E_{AC}}{E_{IT\ load}} \qquad (2)$$

B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
B1	C10	D1	E1	F1	G1	H1	I1	J1	K1	L1	M1	N1	O1	Pavement Air exhaust
Pillar	Pillar	D2	E2	Pillar	G2	H2	I2	Pillar	K2	L2	Pillar	N2	O2	
		D3	E3		G3	H3	I3		K3	L3		N3	O3	
B2	C2	D4	E4	F2	G4	H4	I4	J2	K4	L4	M2	N4	O4	P1
B3	C3	D5	E5	F3	G5	H5	I5	J3	K5	L5	M3	N5	O5	P2
B4	C4	D6	E6	F4	G6	H6	I6	J4	K6	L6	M4	N6	O6	P3
B5	C5	D7	E7	F5	G7	H7	I7	J5	K7	L7	M5	N7	O7	P4
B6	C6	D8	E8	F6	G8	H8	I8	J6	K8	L8	M6	N8	O8	P5
B7	C7	D9	E9	F7	G9	H9	I9	J7	K9	L9	M7	N9	O9	P6
B8	C8	D10	E10	F8	G10	H10	I10	J8	K10	L10	M8	N10	O10	P7
B9	C9	D11	E11	F9	G11	H11	I11	J9	K11	L11	M9	N11	O11	P8
B10	C10	D12	E12	F10	G12	H12	I12	J10	K12	L12	M10	N12	O12	P9
AHU30	AHU31	AHU32	AHU33		AHU34	AHU35	AHU36	AHU37	AHU38	AHU39		AHU40	AHU41	
Closed channel		Closed channel		Closed channel		Closed channel		Closed channel		Closed channel		Closed channel		

Fig. 3. The layout of the server room

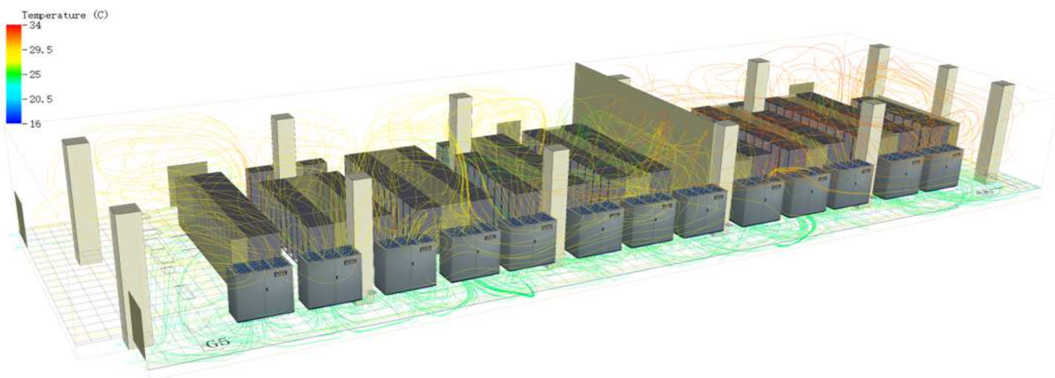

Fig. 4. The air supply flow of the server room

where E_{total}, $E_{IT\ load}$, and E_{AC} represent the energy consuming by DCs, the IT load, and air conditioning, respectively. The closer the PUE value is to 1, the better the energy-saving performance.

With ΔE_{AC}^{+} and E_{AC}^{-} respectively denoting the average daily power saving of air conditioners after implementing the energy-saving strategy and the average daily power consumption of air conditioners before the implementation, RESR can be formulated as

$$ESR = \frac{\Delta E_{AC}^{+}}{E_{AC}^{-}} \tag{3}$$

B. Simulation Results

The digital twin model of the DC is constructed by 6SigmaDC, which is a software for simulation of data center air distribution developed by Future Facilities, UK. 6SigmaDC contains many model databases of equipment manufacturers:

- air conditioning model database.
- rack model database.
- IT equipment model database.
- UPS model database.
- chips, fans, and materials model database.

The server room of the DC can be set up visually through the parameters of the software programming model. In this way, the thermal environment in DCs can be simulated and predicted, and the temperature field, airflow field, pressure field, and humidity can be displayed by animation and video.

A sample data center from China Telecom is adopted to verify the performance of the proposed solution in this section. The layout of the server room is illustrated in Fig. 3. The server room is 40 m long, 9.5 m wide, 4.8 m high and covers an area of about 380 m^2. The number of racks is 179 (A1 ~ P9), and the rated power consumption of the rack is 4 kW. The server room is equipped with 13 chilled water air conditioners with rated cooling power of 70.7 kW. Two standby air conditioners have been closed for a long time (AHU32 and AHU38). Under-floor air supply is adopted, and the cold passage is closed.

As shown in Fig. 4, the 3D air supply flow is visualized by 6SigmaDC. There are local cold spots in the server room, which indicates it results in waste of energy.

Fig. 5 provides the temperature nephogram after the first optimization by AI. There are local cold spots in the hot channel in the blue frame, which indicates that there is still room for energy-saving.

TABLE I. THE STRATEGY BASED ON THE FIRST OPTIMIZATION BY CFD

	The supply air temperature	The fan speed
AHU33	from 24 °C to 25 °C	from 70% to 50%
AHU34	from 24 °C to 25 °C	from 70% to 50%
AHU37	from 24 °C to 23 °C	remains at 70%
AHU39	from 24 °C to 23 °C	remains at 70%

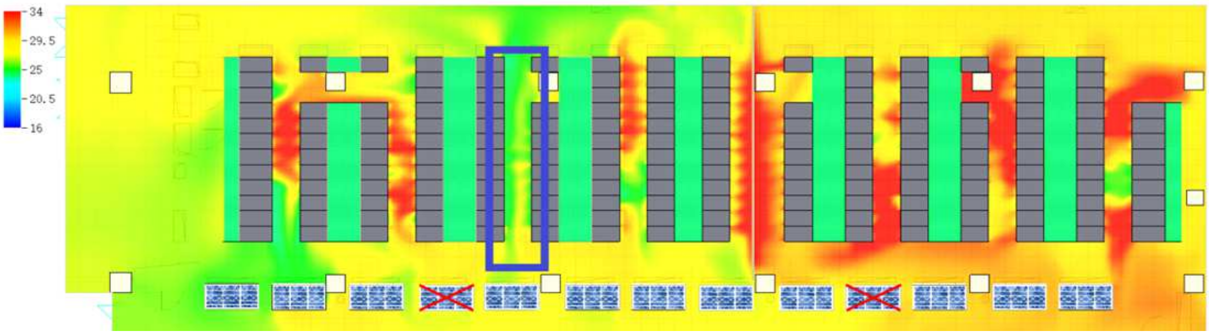

Fig. 5. The temperature nephogram after the first optimization by AI

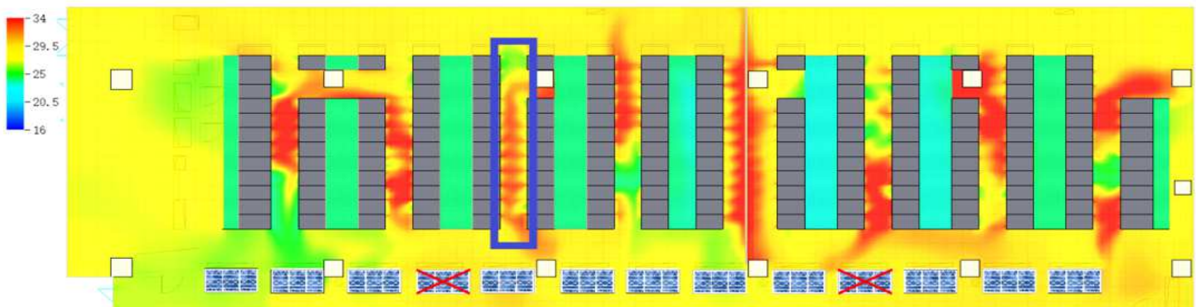

Fig. 6. The temperature nephogram after the first optimization by CFD

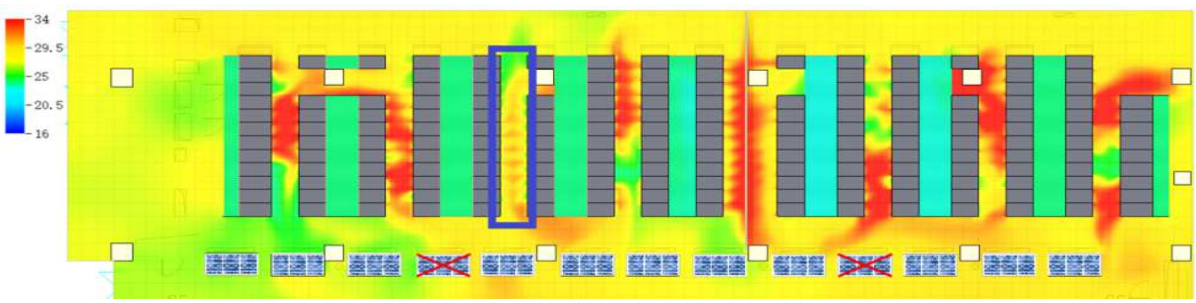

Fig. 7. The temperature nephogram after multiple iterations of the AI-CFD cycle

Table I shows the strategy based on the first optimization by CFD. Fig. 6 presents the temperature nephogram after the first optimization by CFD. The cold spots in the blue frame are eliminated, and the high temperature alarm is not triggered, which indicates that the energy-saving strategy can still be optimized.

TABLE II. THE STRATEGY BASED ON MULTIPLE OPTIMIZATIONS BY AI-CFD

	The supply air temperature	The fan speed
AHU33	closed	
AHU34	from 24 °C to 26 °C	from 70% to 50%
AHU37	from 24 °C to 23 °C	remains at 70%
AHU39	from 24 °C to 23 °C	remains at 70%

Table II illustrates the strategy based on multiple optimizations by the AI-CFD cycle. Fig. 7 illustrates the temperature nephogram after multiple iterations of the AI-CFD cycle. The temperature field distribution in the server room is more reasonable, which verifies the superiority of the proposed Smart DC solution.

Table III shows the energy-saving results when deploying our strategies in the real data center. The energy-saving strategies are optimized by AI models from Day 2, and AI-CFD optimizes the energy-saving strategy from Day 10. Before implementing of the energy-saving strategy, the average PUE from Day 0 to Day 1 is 1.1506.

After implementing the AI-based energy-saving strategy, the average PUE from Day 2 to Day 9 is 1.1288. After implementing the strategy based on AI-CFD, the average PUE from Day 10 to Day 13 is 1.0891. The solution based on AI-CFD has a lower PUE than the solution only based on AI. Compared with Day 0, the RESR on Day 9 is (1392.9-1200) ÷ 1392.9=13.8%. Compared with Day 0, the RESR on Day 13 is (1392.9-820.8)÷1392.9=41.07%. The solution based on AI-CFD has a much higher RESR than the solution based on AI. The PUE and RESR results verify the superiority of the proposed Smart DC solution in energy-saving performance compared with the AI-based solution.

TABLE III. THE ENERGY-SAVING RESULTS

	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13
$E_{IT\ load}$ (kWh)	9267	9222	9231	9225	9201	9234	9390	9588	9777	9834	9840	9795	9798	9789
E_{AC} (kWh)	1392.9	1392	1317.9	1116	1146	1149	1179.9	1194	1300.8	1322.7	1024.8	828	822	820.8
PUE	1.1503	1.1509	1.1428	1.1210	1.1246	1.1244	1.1257	1.1245	1.1330	1.1345	1.1042	1.0845	1.0839	1.0838

V. CONCLUSIONS

In this paper, we proposed Smart DC, an energy-saving solution which combined AI and digital twin for DCs. The proposed Smart DC includes physical space, AI engine, and digital space. The physical space is used for collecting samples of DCs. The digital space can provide extra data sets for training AI models, thus improving the energy-saving performance of the cooling system in DCs. The simulation results show that the PUE of the proposed Smart DC solution can reach 1.0891, and the RESR can reach 41.07%. Therefore, the proposed Smart DC solution can be used as a promising scheme for energy-saving in DCs.

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