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Abstract. With the rapid development of large-scale artificial intelligence models, the construction of data centers has been gradually accelerating. Data centers are equipped with numerous servers and network devices, and energy consumption is expected to keep increasing in the future. To improve thermal management, data center energy modeling has become a new challenge. Traditional numerical simulations are time-consuming and poor transferable, while data-driven machine learning models provide a feasible solution for data center modeling. Physics-informed neural networks embed prior physical knowledge into the loss function as soft constraints, guiding the modeling process to follow both data patterns and physical laws. To decouple multi-physics field modeling in data centers, we propose a dual-branch physics-informed neural network (Dual-PINN). Meanwhile, we design an adaptive loss re-weighting mechanism on the loss function based on the logistic function (Sigmoid) nonlinear transformation to balance the convergence speed among different loss terms. In the experiments, to comprehensively evaluate the proposed Dual-PINN, we choose the standard PINN, standard neural network, and random forest for comparison. Finally, we used MAE, RMSE, and the number of trainable parameters to measure model performance in terms of accuracy and complexity. The results demonstrate that Dual-PINN achieves the highest prediction accuracy with the fewest trainable parameters, compared with standard PINN, Dual-PINN reduces the MAE and RMSE by 19.95% and 15.79% for temperature prediction, 34.01% and 31.86% for velocity prediction, respectively. The Dual-PINN provides a novelty solution to physical fildes modeling to optimize the operation of data center.

Keywords: Physics-informed neural networks, data center, thermal management; prediction

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ДЕРЕКТЕР ОРТАЛЫҒЫНЫҢ АУА АҒЫНЫНЫҢ ЖЫЛДАМДЫҒЫНА ЖӘНЕ ТЕРМИЯЛЫҚ МОДЕЛЬДЕУГЕ АРНАЛҒАН ЕКІ ТАРМАҚТЫ ФИЗИКАЛЫҚ АҚПАРАТТЫҚ НЕЙРОНДЫҚ ЖЕЛІЛЕР

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Аннотация. Ірі ауқымды жасанды интеллект модельдерінің қарқынды дамуына байланысты деректер орталықтарының құрылысы біртіндеп жеделдеуде. Деректер орталықтары көптеген серверлермен және желілік құрылғылармен жабдықталған, сондықтан олардың энергия тұтынуы болашақта одан әрі артады деп күтіледі. Жылулық басқаруды жақсарту мақсатында деректер орталықтарының энергетикалық моделін құру жаңа өзекті мәселе ретінде қарастырылуда. Дәстүрлі сандық модельдеу әдістері көп уақытты талап етеді және олардың тасымалдану қабілеті шектеулі, ал деректерге негізделген машиналық оқыту модельдері деректер орталықтарын модельдеу үшін тиімді шешім ұсынады. Физикалық ақпаратпен толықтырылған нейрондық желілер априорлық физикалық білімді шығын функциясына жұмсақ шектеулер түрінде енгізіп, модельдеу процесін деректер заңдылықтарына да, физикалық заңдарға да сәйкес бағыттайды. Деректер орталықтарындағы көпфизикалық өрістерді модельдеуді декомпозициялау үшін бұл жұмыста екі тармақты физикалық ақпаратпен толықтырылған нейрондық желі (Dual-PINN) ұсынылады. Сонымен қатар, әртүрлі шығын мүшелерінің жинақталу жылдамдығын теңестіру мақсатында логистикалық функцияның (Sigmoid) бейсызық түрлендіруіне негізделген шығындарды бейімделмелі қайта салмақтау механизмі әзірленді. Эксперименттерде ұсынылған Dual-PINN моделін жан-жақты бағалау үшін салыстыру әдістері ретінде стандартты PINN, стандартты нейрондық желі және кездейсоқ орман таңдалды. Соңында, модельдің дәлдігі мен күрделілігін бағалау үшін MAE, RMSE және оқытылатын параметрлер саны қолданылды. Нәтижелер Dual-PINN моделінің ең аз оқытылатын параметрлер санымен ең жоғары болжау дәлдігіне қол жеткізетінін көрсетеді. Стандартты PINN моделімен салыстырғанда, Dual-PINN температураны болжауда MAE және RMSE көрсеткіштерін тиісінше 19,95% және 15,79%-ға, ал жылдамдықты болжауда тиісінше 34,01% және 31,86%-ға төмендетеді. Dual-PINN деректер орталықтарының жұмысын оңтайландыру үшін физикалық өрістерді модельдеудің жаңа шешімін ұсынады.

Түйін сөздер: Физикаға негізделген нейрондық желілер, деректер орталығы, жылулық басқару; болжау

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ДВУХВЕТВЕВЫЕ ФИЗИЧЕСКИЕ ИНФОРМАЦИОННЫЕ НЕЙРОННЫЕ СЕТИ ДЛЯ МОДЕЛИРОВАНИЯ ВОЗДУШНЫХ ПОТОКОВ И ТЕПЛОВЫХ УСЛОВИЙ В ЦЕНТРАХ ОБРАБОТКИ ДАННЫХ

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Аннотация: *Актуальность.* Быстрое развитие крупномасштабных моделей искусственного интеллекта сопровождается ускоренным строительством и расширением центров обработки данных. Такие центры оснащены большим количеством серверов и сетевого оборудования, что приводит к росту энергопотребления и повышает требования к эффективности теплового управления. В этих условиях энергетическое и тепловое моделирование центров обработки данных становится актуальной научно-прикладной задачей. Традиционные численные методы моделирования требуют значительных вычислительных ресурсов и обладают ограниченной переносимостью, тогда как модели машинного обучения могут обеспечить более гибкое и эффективное решение. *Цель.* Разработать и оценить двухветвевую физически информированную нейронную сеть Dual-PINN для моделирования воздушных потоков и тепловых условий в центрах обработки данных. *Методы.* В исследовании предложена двухветвевая физически информированная нейронная сеть Dual-PINN, предназначенная для декомпозиции моделирования мультифизических полей в центрах обработки данных. Физически информированные нейронные сети включают априорные физические знания в функцию потерь в виде мягких ограничений, что позволяет модели одновременно учитывать закономерности данных и физические законы. Дополнительно разработан адаптивный механизм перевзвешивания потерь, основанный на нелинейном преобразовании логистической функции Sigmoid, для балансировки скорости сходимости различных компонентов функции потерь. В экспериментальной части модель Dual-PINN сравнивалась со стандартной PINN, стандартной нейронной сетью и моделью случайного леса. Для оценки точности и сложности модели использовались метрики MAE, RMSE и количество обучаемых параметров. *Результаты и выводы.* Полученные результаты показывают, что Dual-PINN достигает наиболее высокой точности прогнозирования при наименьшем количестве обучаемых параметров. По сравнению со стандартной PINN предложенная модель снижает MAE и RMSE при прогнозировании температуры на 19,95% и 15,79% соответственно, а при прогнозировании скорости воздушного потока - на 34,01% и 31,86% соответственно. Результаты подтверждают эффективность двухветвевой архитектуры и адаптивного перевзвешивания потерь при моделировании связанных физических процессов в центрах обработки данных. Практическая значимость исследования заключается в возможности применения Dual-PINN для оптимизации теплового управления, повышения энергоэффективности и поддержки принятия инженерных решений при эксплуатации центров обработки данных.

Ключевые слова: физически информированные нейронные сети, Dual-PINN, PINN, центр обработки данных, воздушные потоки, тепловое управление, прогнозирование, MAE, RMSE, Sigmoid

Introduction. With the development of artificial intelligence (AI) and big data technologies, the requirements for data storage and computation have been continuously increasing. To ensure the efficient and reliable utilization of data resources, centralized data centers have become critical infrastructure in the digital revolution. Data centers are equipped with a large number of servers and network devices, which generate considerable heat during operation, imposing strict requirements on the control of the building environment (Lu et al., 2026)the energy consumption of AI tasks has experienced exponential growth, and how to schedule arriving AI tasks in a low-carbon manner is worth investigating for data centers. However, due to the computationally intensive and resource-demanding properties of AI tasks, current deferral-based scheduling methods cannot efficiently fit a large AI task (e.g., training a large language model. Therefore, to guarantee the reliable operation of data centers, a significant amount of electricity is consumed by cooling systems to maintain the data center temperature within an optimal range. Currently, data centers worldwide consume approximately 460 TWh of electricity annually, accounting for about 2% of global electricity consumption (Liu et al., 2026). Given that emerging large AI models with billions of parameters require massive data resources during training, the power consumption of data centers will continue to rise in the future.

To optimize the design and operation of data centers, effective measures are necessary to be taken to reduce energy consumption while ensuring the reliable performance of IT equipment. Accurate and efficient airflow and thermal modeling techniques provide a fundamental basis for decision. Although experimental proofs can provide accurate and detailed data for modeling, they are limited by high material and labor costs Importantly, data centers host numerous cloud service systems involving critical fields, making experimental investigations highly impractical. Traditionally, data center modeling relies highly on physical simulations, such as the simplified lumped-capacitance models (Rasku et al., 2024) and computational fluid dynamics (CFD) simulations (Lin et al., 2023)”id”:”ITEM-1”,”issue”:”3”,”issued”:{“date-parts”:[[“2023”]]},”page”:”571-590”,”publisher”:”IEEE”,”title”:”Thermal modeling and thermal-aware energy saving methods for cloud data centers: A review”,”type”:”article-journal”,”volume”:”9”},”uris”:[“http://www.mendeley.com/documents/?uuid=164bd5c1-e06a-47fc-9147-6438a140b541”]}],”mendeley”:{“formattedCitation”:”(Lin et al., 2023. The simplified lumped-capacitance models are computationally fast and low-cost. However, with the increasing requirements of automatic control and the spatial layout, the thermal coupling has become more complex. Simplified lumped-capacitance models cannot accurately describe the spatiotemporal variations of temperature and airflow. While CFD simulations have long been the dominant method for thermal behavior modeling in data centers. By setting the geometry and boundary conditions, CFD discretizes the target domain into grids and computes the airflow and temperature distribution. Nevertheless, the detailed parameter input and condition setup result in a high knowledgeable barrier. Meanwhile, with the construction of large-scale data centers and multi-timescale control strategies, CFD faces challenges in terms of computational cost and generalization ability.

With the development of machine learning (ML) techniques, data-driven models have emerged as an efficient alternative. By extracting the relationship between input and output variables from massive observation data, parameterized ML models are constructed to characterize the spatiotemporal variations of environmental parameters in data centers. However, the performance of data-driven models relies on the reliability and size of the training dataset, which limits their application scenarios and compatibility. Physics-informed machine learning (PIML) embeds prior knowledge or physical theorems into the ML model as soft constraints, alleviating the heavy dependence of data-driven models on training data. As a representative method of PIML, physics-informed neural networks (PINNs) (Lawal et al., 2022) take the residuals of physical constraints as a regularization loss term, guiding neural networks to learn data patterns while complying with physical laws.

Data center modeling has been mainly focused on customized physical field prediction for specific applications (LOI et al., 2026)Heating, Ventilation, and Air Conditioning (HVAC, and accelerated computation using PINNs in physical simulations (Deng et al., 2026)machine learning (ML. However, the inconsistency in magnitude and significance between the data residual loss and the physical constraint loss leads to convergence difficulties in ML models. Several studies have proposed methods to address convergence issues, such as optimizing the loss function (Wang et al., 2025)providing a powerful approach for solving forward and inverse PDE problems. During training, physical loss calculation relies on predefined spatiotemporal collocation points. However, when solving equations with steep gradients or singularities, conventional fixed or randomly distributed training points often fail to capture critical solution structures, reducing PINN's prediction accuracy. Inspired by firefly phototaxis, this paper proposes a bio-inspired dynamic training point movement strategy named firefly adaptive collocation point movement (FAM and adjusting the neural network architecture (Zheng et al., 2026)we develop interface-gated physics-informed neural networks (IG-PINNs. Nevertheless, PINNs for multi-physics field prediction in data centers still lack sufficient attention.

In this paper, we propose a dual-branch PINN (Dual-PINN) for predicting the temperature and velocity distribution in data centers. To decouple the physical fields, we employ a dual-branch architecture. Meanwhile, to align the convergence pace of losses between the two branches, we apply the logistic function for normalization mapping. Finally, we conduct experiments to evaluation the performance of the model. Our contributions are as follows:

- Architecture design. We design a novel Dual-PINN to decouple temperature and velocity into branches for prediction and alleviate convergence conflicts.
- Loss function optimization. We reconstructed the loss function and adjusted the weights of loss terms using the logistic function.
- Application Expansion. We successfully use a novel Dual-PINN for the data centers airflow velocity and thermal modeling.

Literary review.

Physics-informed neural networks.

The application of PINNs in data centers focuses on the prediction and analysis of physical fields. As a variant of PINNs, Physics-Consistent Neural Networks (PCNNs) are applied to building thermal modeling for the first time, regarding physical information and data labels as distinct modules (Di Natale et al., 2022). To improving the generalization of PCNNs, the adaptive physical consistency neural network (APCNNs) framework replaces the traditional preset system with the Softplus activation function, reducing the parameter trial-and-error cost for temperature prediction (D. Chen et al., 2025). Furthermore, knowledge graphs are combined with PINNs, raising the interpretability and response of PINNs, to achieve accurate prediction of the airflow field in data centers (LOI et al., 2026). In terms of optimization control, the combination of PINNs and model predictive control (MPC) effectively improves the robustness and generalization ability of thermal control (D. Chen et al., 2026). With the digital transformation of data centers, the cost of data acquisition has decreased. A parameterized PINN framework is developed, and the hybrid modeling combining physical constraints and labeled data effectively improves the prediction accuracy (Hashemi et al., 2025).

Dual-branch neural networks.

Dual-branch neural network architectures are commonly applied to solve strongly coupled problems in fields such as image recognition (Long et al., 2025) and industrial control (Zhao and Li, 2024). Information transmission in a single neural network suffers from mutual interference, whereas a dual-branch architecture enables the decoupling of coupled variables. In the building energy sector, dual-branch neural networks have been successfully applied to the energy consumption prediction of building chilled water systems (Chen et al., 2025) and the anomaly detection of building energy (Tian et al., 2026)equipment status, and human factors, posing significant challenges to the effective identification of anomaly patterns within these data. To address these challenges, a multi-task learning model based on a dual-channel graph attention network (GAT, demonstrating their applicability to complex building energy systems. Dual-branch neural networks for data center modeling have mainly focused on attention mechanisms, for resource allocation (Yu et al., 2026)scheduling, energy optimization, and sustainability. However, existing models face challenges in long-term cyclic predictions due to nonlinear and irregular fluctuations in resource data. To address this issue, we propose STL(C-TS or anomaly detection (Sun et al., 2025)this paper introduces a bidirectional cross-attention LSTM–Informer with uncertainty-aware multi-task learning framework (BiCA-LI via attention adjustment. However, research that combines dual-branch neural networks with physics-informed mechanisms remains blank.

Multiphysics modeling of data centers.

Building energy consumption is affected by multiple physical factors such as building layout and airflow distribution. Although the ultimate goal is to reduce energy consumption, multi-physics field analysis helps evaluate the reliability of results and analyze the spatiotemporal distribution of energy consumption. The research on multi-physics thermal management in data centers mainly focuses on liquid-cooled data centers. The Transformer-GRU model combines the self-attention mechanism with the gated recurrent unit (GRU) to achieve self-attention focus on the time series of data center liquid cooling (Ma et al., 2025). Although liquid cooling represents the future trend of data centers, the energy consumption of traditional air-cooled data centers cannot be ignored. The concept of an energy map is introduced to decouple the cooling process of data centers and analyze thermal energy changes (Li et al., 2025). Reinforcement learning has been used to comprehensively consider environmental parameters and operational data of data centers, thereby optimizing energy-efficient control (Suresh et al., 2026)the framework learns cooperative control strategies that eliminate redundant cooling. The agents’ learning is guided by a novel physics-informed reward function that divides the server’s thermal headroom into distinct operational zones, adding penalties to mitigate fan vibrations while dynamically balancing energy efficiency and thermal safety. To validate generalization, the MADDPG algorithm is trained in a simulation environment and subsequently deployed on experimental mock-up servers. A total of five configurations and power maps are used for validation. Each fan agent relies solely on local temperatures of its state space, while the centralized critic receives the global state of the server during training to penalize redundant cooling actions. The MADDPG controller reduced fan energy consumption by an average of 31.4 % compared to a conventional fan-table controller, while maintaining all component temperatures below their critical thresholds. The results also revealed that performance is highly dependent on server layout, with energy savings ranging from 43.8 % in centrally-located CPU configurations to 20.5 % when CPUs are at the chassis extremes, highlighting the importance of hardware-aware control policies.”,”author”:[{“dropping-particle”:””,”family”:”Suresh”,”given”:”Pratheek”,”non-dropping-particle”:””,”parse-names”:false,”suffix”:””},{“dropping-particle”:””,”family”:”Chang”,”given”:”Kai-Wei”,”non-dropping-particle”:””,”parse-names”:false,”suffix”:””},{“dropping-particle”:””,”family”:”Lua”,”given”:”Kim Boon”,”non-dropping-particle”:””,”parse-names”:false,”suffix”:””},{“dropping-particle”:””,”family”:”Wang”,”given”:”Chi-Chuan”,”non-dropping-particle”:””,”parse-names”:false,”suffix”:””}],”container-title”:”Applied Energy”,”id”:”ITEM-1”,”issued”:{“date-parts”:[[“2026”]]},”page”:”127168”,”title”:”Deep reinforcement learning for energy-efficient thermal management in 2U air-cooled server systems”,”type”:”article-journal”,”volume”:”404”},”uris”:[“http://www.mendeley.com/documents/?uuid=08e37a79-99db-4a6b-b4f1-a88a0b4c9174”]}],”mendeley”:{“formattedCitation”:”(Suresh et al., 2026. However, existing data-driven modeling methods for data centers have not fully considered the physical characteristics of thermal management.

Methods.

Preliminary.

The theoretical foundation of PINNs is the universal function approximation theorem, which states that neural networks have the ability to approximate any continuous function, providing a theoretical basis for solving partial differential equations (PDEs) using neural networks (Hornik et al., 1990). Standard PINN (SPINN) formulates a loss function that includes physical residuals, transforming PDE solving into an optimization problem of neural network parameters. Specifically, the approximate solution output by the neural networks for a physical problem is computed based on the loss function:

$$\mathcal{L}_r = \frac{1}{N_r}\sum_{k=1}^{N_r}[\mathcal{F}(\widehat{u_k}) - f(X_k)] \qquad (1)$$

$$\mathcal{L}_b = \frac{1}{N_b}\sum_{k=1}^{N_b}[\mathcal{G}(\widehat{u_k}) - g(X_k)] \tag{2}$$

$$\mathcal{L}_{data} = \frac{1}{N_{data}}\sum_{k=1}^{N_r}[\widehat{u_k} - u_k] \tag{3}$$

$$\mathcal{L}_t = \mathcal{L}_r + \mathcal{L}_b + \mathcal{L}_{data} \tag{4}$$

where the physics loss $\mathcal{L}_r$ ensures physical consistency, the boundary loss $\mathcal{L}_b$ enforces the boundary conditions, and the data loss $\mathcal{L}_{data}$ is used to fit the observed data. N_r, N_b and N_{data} denote the numbers of sampling points for each term, respectively; u_k represents the observed data, and u_k represents the predicted solution; $\mathcal{F}$ and $\mathcal{G}$ and denote the operator in interior and boundary domain. PINN achieves a deep integration of physical laws and data-driven learning through the cyclic process of neural network forward propagation, residual calculation via automatic differentiation, loss function construction, and backpropagation optimization.

Dual-branch physical information neural networks

As shown in Figure 1, we improve the SPINN architecture. Dual-PINN adopt the same input as the SPINN and use a multi-layer perceptron (MLP) structure.

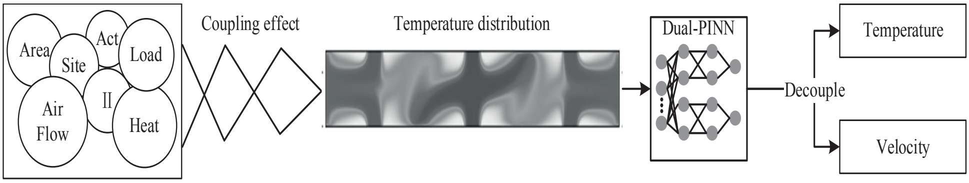


Figure 2 – Coupling mechanism of data center thermal management

Data center thermal management involves multiple coupled factors, such as computing load, operating behavior, and airflow distribution. In Figure 2, we use a dual-branch PINN to decouple thermal management into airflow velocity and temperature, which facilitates the analysis of the physical laws inside the data center. To alleviate the convergence conflict between the two branches during training, the branches share the input layer of the network and employ a shared hidden layer. To avoid additional redundancy caused by the dual-branch structure, the number of hidden neurons in each branch is set to half of that in the shared hidden layer.

Reconstruction of loss function.

We employ a hybrid modeling approach, where the model input is the coordinate position, and the outputs are the predicted values of temperature and velocity. In the training phase, labeled data are used, and the residuals between the predicted and observed values of temperature and velocity are adopted to compute the data losses and . The physics-consistent loss uses the Pearson correlation coefficient to measure the correlation between temperature and velocity. In the airflow thermal management of data centers, to improve heat dissipation efficiency, positions with higher flow velocity in the cold aisle usually correspond to lower temperatures. Therefore, we use the Pearson correlation coefficient to quantify the negative correlation between temperature and velocity, so as to characterize the underlying physical information. We improve the loss function by introducing an adaptive loss re-weighting mechanism. is transformed by the Sigmoid function and then multiplied by to guide the gradient descent of temperature and velocity. Notably, the Sigmoid function yields a positive output even when the input is zero, which prevents the model from neglecting the velocity gradient. As an additional regularization term, imposes a constraint on the loss function and guides the model to converge while considering the physically consistent negative correlation between temperature and velocity. Accordingly, our final loss function is given as follows:

$$\mathcal{L}_u = \frac{1}{N}\sum_{k=1}^{N}[\widehat{u_k} - u_k] \tag{5}$$

$$\mathcal{L}_s = \frac{1}{N}\sum_{k=1}^{N}[\widehat{u_s} - u_s] \tag{6}$$

$$\mathcal{L}_p = \frac{\sum_{k=1}^{N_r}[\widehat{u_k} - \overline{u_k}][\widehat{u_k} - \overline{u_k}]}{\sqrt{\sum_{k=1}^{N_r}[\widehat{u_k} - u_k]^2}\sqrt{\sum_{k=1}^{N_r}[\widehat{s_k} - s_k]^2}} \tag{7}$$

$$w = sigmoid(\mathcal{L}_u) \tag{8}$$

$$\mathcal{L}_t = w\mathcal{L}_s + \mathcal{L}_p \tag{9}$$

Experiments

Problem description.

In data center thermal management, the horizontal supply of cold air can force the hot air to be exhausted laterally, thereby reducing the influence of vertical buoyancy on the cooling performance. Thus, the airflow circulation can be described by a two-dimensional model(Hashemi et al., 2025)requiring accurate airflow and temperature predictions. This study pioneers the application of physics-informed neural networks (PINNs, which is suitable for evaluating the performance of the PINNs framework.

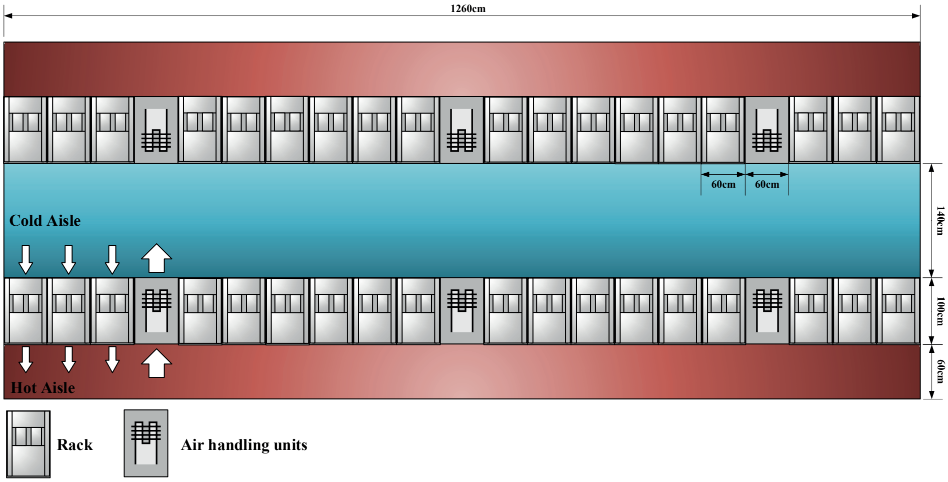


Figure 3 – Schematic of the air-cooled data center

As shown in Figure 3, this study adopts the layout from case in the literature(Hashemi et al., 2025)requiring accurate airflow and temperature predictions. This study pioneers the application of physics-informed neural networks (PINNs. The data center is equipped with two rows of 36 server racks and six air handling units (AHUs). Air in the hot aisle enters the cold aisle through the AHUs, and the air in the cold aisle passes through the racks into the hot aisle, realizing air circulation. The entire data center is symmetrically distributed.

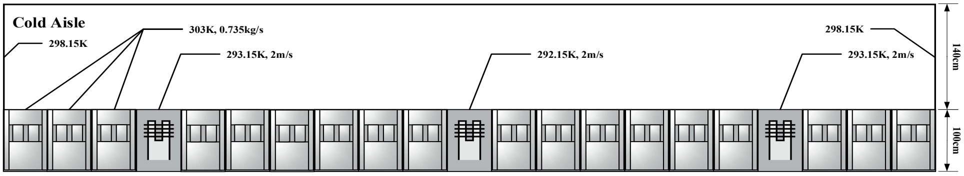
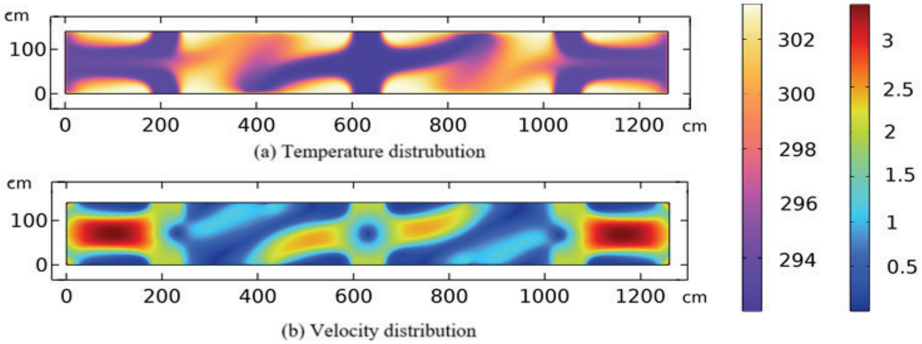


Figure 4 – Conditions for the Cold Aisle

In this case, heat exchange mainly occurs in the cold aisle. Taking the cold aisle as the research object, we impose the boundary conditions as shown in Figure 4. As the cold aisle is symmetrically distributed, we present the boundary conditions for the lower half. To meet practical requirements, the boundary conditions at both ends are set to ambient temperature. The supply air temperature of the air handling units in the middle region is lower than that on both sides. The boundary condition for the air handling units is velocity inflow, while that for the server racks is mass flow rate.



(a) Temperature distrubution

(b) Velocity distribution

Figure 5 – Temperature and velocity numerical simulation results

Notably, we modified the boundary conditions to be more realistic, as shown in Figure 4, which differs from the original literature. All raw data were recalculated using the scientific numerical simulation software COMSOL 6.3, which has been widely adopted for thermal management simulations. The simulation results are shown in Figure 5.

Dataset preparation.

The simulation dataset has 6049 data points, including 228 boundary points and 5821 internal points. Since the length of data center is 1260 cm and symmetric about its central axis, we select the first 80% of the horizontal distance as the training set (i.e., points with) and the remaining 20% as the test set. The training set contains 4839 points, and the test set contains 1210 points.

Experimental settings.

We compare four models: the proposed Dual-PINN, the SPINN, standard neural network (SNN), and random forest (RF). SPINN was used to evaluate the effectiveness of the dual-branch architecture, and SNN was adopted to verify the role of the adaptive physics-informed loss. RF, which is widely used in prediction tasks, represents the baseline performance of traditional machine learning models. The learning rate for all neural network models was set to 0.01, with 4 hidden layers and 30 neurons per layer, except for the branch neurons of the Dual-PINN, which were set to 15. For the RF model, the number of decision trees was set to 100 and the maximum depth to 10. Notably, SPINN adopts the traditional single network structure with loss function as shown in Eq. (9). However, the SNN does not employ any physical constraints with loss function as shown in Eq. (10).

$$\mathcal{L}_t = \mathcal{L}_s + \mathcal{L}_u \tag{10}$$

RMSE and MAE are used as evaluation metrics to quantify the prediction performance in Eq. (11) and Eq. (12). Furthermore, to comprehensively evaluate the parameter characteristics of each model, we statistically analyzed the number of trainable parameters for different neural network models.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{11}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{12}$$

Results. As shown in Figure 6, Dual-PINN and PINN converge faster than SNN, indicating that the embedding of physical information is effective. Meanwhile, Dual-PINN converges slower than SPINN in the early stage, which is attributed to the need for coordinating the convergence pace of the two branches. Although no significant difference in loss variation is observed between SPINN and Dual-PINN, Dual-PINN achieves better prediction performance and exhibits stronger generalization ability, as shown in Table 1. The final results demonstrate that Dual-PINN achieves the best performance in both temperature and velocity prediction with the fewest trainable parameters. Compared with SPINN, Dual-PINN reduces the MAE and RMSE by 19.95% and 15.79% for temperature prediction, and by 34.01% and 31.86% for velocity prediction, respectively, demonstrating the significant effectiveness of the dual-branch structure. The improvement of performance is even more pronounced compared with SNN, which showing a MAE decrease in temperature by 24.51% and in velocity by 25.89%. The prediction performance of RF is between that of SNN and SPINN. In particular, although the architecture of Dual-PINN is more complex, we reduce the number of neurons in each branch. As a result, the number of trainable parameters in Dual-PINN is reduced by 16.32% compared with other neural network models with the same number of hidden layers.

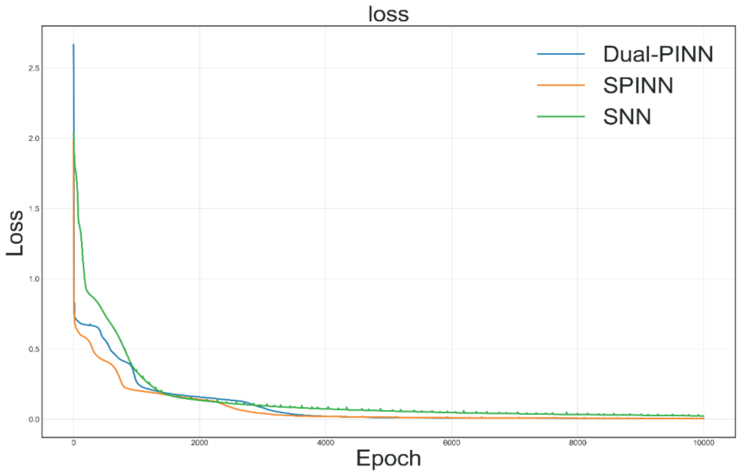
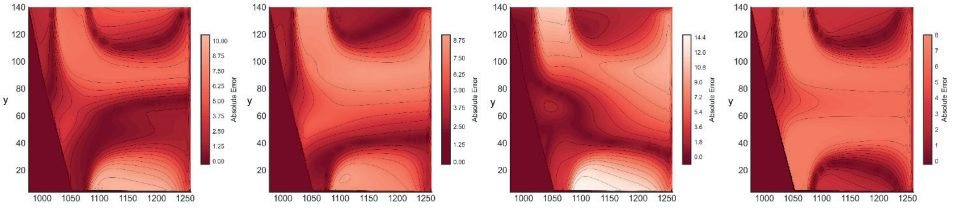


Figure 6 – Loss with epochs of different neural networks

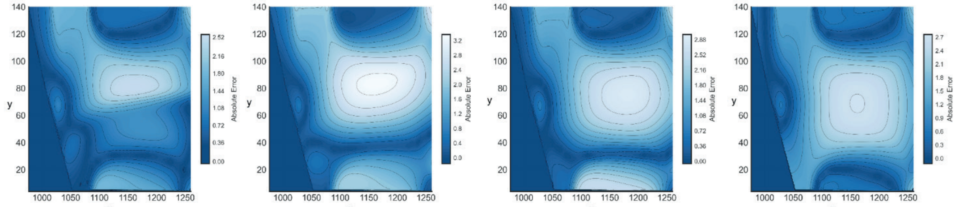
Table 1 – Evaluation metrices of different models. Here '–' denotes that the trainable parameters cannot be counted as the same as neural networks models.

Models	MAE		RMSE		Trainable parameters
	Temperature	Velocity	Temperature	Velocity	
Dual-PINN	3.6793	0.9455	4.5589	1.1703	2462
SPINN	4.5962	1.4326	5.4140	1.7175	2942
SNN	4.8742	1.3050	6.1515	1.5737	2942
RF	4.6052	1.2675	5.1360	1.4995	–

Figure 7 shows the prediction error distributions of different models. It can be observed that all models reasonably capture the characteristics of temperature distribution and airflow velocity. In the temperature prediction error distribution, SNN yields the largest error, with the boundary error reaching 14.4. Random Forest exhibits the most uniform error distribution. Dual-PINN and SPINN achieve a good balance between error distribution and error range. In particular, as shown in Figure 7(a), Dual-PINN provides superior prediction performance at the airflow intersection in the middle of the aisle compared with other models. For airflow velocity prediction, SPINN has the largest error, while Dual-PINN performs the best. Meanwhile, from the error distribution, Dual-PINN has the smallest high-error region. Furthermore, the velocity error distribution is consistent with the temperature error distribution for all models except Dual-PINN. Benefiting from its dual-branch structure, Dual-PINN avoids introducing erroneous guidance from temperature prediction into velocity prediction, demonstrating the effectiveness of the proposed decoupling strategy.



(a) Temperature error of Dual-PINN (b) Temperature error of SPINN (c) Temperature error of SNN (d) Temperature error of RF



(e) Velocity error of Dual-PINN (f) Velocity error of SPINN (g) Velocity error of SNN (f) Velocity error of RF

Figure 7 – Temperature and velocity errors distribution of different models

Discussion. PINNs provide a novel solution for data center modelling. The performance of data-driven PINNs models can be significantly enhanced. Under the guidance of physical information, the modelling error of data centers is reduced, and the error distribution becomes more uniform, which provides valuable references for thermal management of data center. In addition, architecture optimization of PINNs should be emphasized in multi-physics modelling of data centers. Multi-branch architectures can better decouple physical quantities and improve modelling performance. However, PINNs still face challenges. For instance, in temperature prediction, the maximum error of Dual-PINN is not the smallest, even though its error distribution is more uniform. In the future, how to optimize the convergence performance of branch-structured PINNs and further improve prediction accuracy deserves more attention. Furthermore, we plan to further optimize architecture of Dual-PINN to balance the number of branches and multi-physics field prediction. Meanwhile, transient modeling of data centers in three-dimensional scenarios will also be considered to meet the requirements of complex energy operation control.

Conclusion. This paper presents a Dual-PINN for modeling temperature and airflow velocity in data center. We adopt a hybrid modeling approach and embed the Pearson correlation coefficient between predicted temperature and airflow velocity into the loss function as a soft physical constraint. Meanwhile, an adaptive loss reweighting mechanism is designed, in which the temperature residual is nonlinearly transformed via the Sigmoid function and then multiplied by the velocity residual. In the experiments, we compare the proposed method with SPINN, SNN, and RF. The results demonstrate that Dual-PINN achieves the best prediction performance. This study explores the application of Dual-PINN in data centers, providing a reference for the use of PINNs in modeling within the data center energy domain.

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