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Determining feasible design parameter domains of impinging jet ventilation and passive chilled beam combined systems using an integrated CFD-data-driven framework

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Abstract: Impinging jet ventilation (IJV) and passive chilled beam (PCB) combined (IPC) systems have been recognized as an efficient air distribution strategy for public buildings. However, the feasible design parameter domains of IPC systems under varying cooling load conditions remain unclear because the system performance is jointly affected by IJV supply parameters (v_s , T_s) and the PCB cooling ratio (η). An integrated framework combining CFD simulations, Sobol sensitivity analysis, a backpropagation neural network (BPNN), and the non-dominated sorting genetic algorithm III (NSGA-III) is proposed to determine the feasible design parameter domains. The results indicate that, with increasing cooling loads from 100 to 250 W/m², the indoor airflow pattern changes from a downward cold jet dominated flow to a buoyancy-driven turbulent flow, resulting in heat and contaminant accumulation in the occupied zone. Accordingly, the feasible design parameter domains initially expand and subsequently shrink, accompanied by a shift toward higher supply velocities and larger η . Sobol sensitivity analysis reveals that η exhibits significant nonlinear interactions with energy efficiency (E_r) and ventilation efficiency (ε), indicating its critical role in improving system performance. A BPNN surrogate model of IPC systems is established, and prediction accuracy with $R^2 > 0.98$ is achieved for eight key performance indicators. Finally, the optimal operating solutions are obtained using NSGA-III combined with entropy-weight TOPSIS. Validation results confirm that the optimized solutions effectively alleviate overcooling and overheating under different cooling load conditions, maintain draft dissatisfaction below 20%, and achieve a balanced improvement in thermal comfort, indoor air quality, and energy efficiency.

Keywords: IPC systems; Feasible design parameter domains; CFD-data-driven framework; Sobol sensitivity analysis; Multi-objective optimization

1. Introduction

With the continuous expansion of large public buildings, the energy consumption associated with building operation has increased substantially [1,2]. During full-load operation, centralized air-conditioning and ventilation systems are generally relied upon to deliver the required levels of thermal comfort and indoor air quality [3]. Variations in occupant number can induce rapid changes in cooling loads, causing the operating conditions of systems to deviate from the design conditions. Conventional ventilation and cooling strategies are unable to respond promptly to such dynamic changes, which may result in local thermal discomfort, uneven temperature distributions, and reduced energy efficiency [4]. Therefore, the rational determination of supply parameters to accommodate variations in occupant-

related cooling loads and achieve coordinated optimization of thermal environment, indoor air quality, and energy consumption represents a critical issue in ventilation control of high-occupancy public buildings.

Impinging jet ventilation (IJV) is a novel air distribution strategy that supplies conditioned air from the low-level of the room. After impacting the floor surface, the supply jet forms a wall-attached spreading flow and interacts with the upward thermal plumes generated by indoor heat sources, resulting in a stable thermal stratification environment [5]. Under thermally stratified conditions, the occupied zone can maintain a comfortable average temperature while achieving considerable energy-saving potential and ventilation efficiency [6,7]. Previous studies have demonstrated that the stability of indoor thermal stratification is strongly affected by the cooling load [8]. With increasing cooling loads, the feasible supply parameter range that simultaneously satisfies thermal comfort, energy efficiency, and contaminant removal requirements becomes substantially narrowed [8]. For example, under low-to-moderate cooling load conditions below 50 W/m^2 , the supply parameters of IJV systems can be flexibly selected within the recommended range. However, under high cooling load scenarios exceeding 100 W/m^2 , higher supply momentum or lower supply temperature is generally required to meet the instantaneous cooling demand, which may increase local air velocity and intensify draft sensation beyond the acceptable thermal comfort threshold [9]. Therefore, simply increasing the supply airflow rate or reducing the supply temperature cannot simultaneously achieve thermal comfort and high system efficiency.

To enhance the applicability of IJV systems under demanding high cooling conditions, the integration of IJV with passive chilled beams (PCB) to form impinging jet ventilation and passive chilled beam combined (IPC) systems has gradually emerged as an effective solution [10]. In IPC systems, the treated fresh air is mixed with return air and discharged to the occupied zone by the IJV system, while the remaining sensible cooling load is removed by PCB through convective heat transfer [10,11]. Previous studies have demonstrated that IPC systems can preserve the high ventilation efficiency of IJV while reducing vertical temperature gradients and expanding the feasible operating range of supply parameters. Furthermore, considerable potential has been observed in improving indoor thermal conditions and reducing energy consumption [10-13]. As reported in the previous study [13], approximate recommended ranges of the PCB cooling ratio (η) are provided under different high cooling load conditions. For example, when the indoor cooling load is 150 W/m^2 ($q^* = 5.00$), the recommended range of η is $0.4 - 0.5$. However, this range is relatively broad and is provided in a discrete manner. During further investigation, such discrete design parameter ranges are found to be insufficient to meet the practical design requirements of IPC systems. Moreover, multiple design variables, including supply parameters, cooling load allocation, and operating conditions, are introduced in IPC systems, and the complex coupling mechanisms governing system performance remain insufficiently understood.

Recent advances in IPC systems have highlighted the importance of supply conditions and airflow characteristics in determining thermal stratification and system performance. Yang et al. [14] demonstrated that supply parameters modify jet development behavior, which subsequently affects the formation of thermal stratification and occupant comfort. Shan and Rim [15] found that increasing the cooling load ratio undertaken by PCB can reduce the vertical temperature difference, but may weaken the stratification structure and intensify draft sensation. Hu et al. [16] further reported that the thermal stratification height is primarily governed by supply parameters, while the indoor thermal environment is jointly affected by cooling load allocation and supply temperature. These studies indicate that the performance of IPC systems is determined by the coupled effects of multiple design parameters and

1 exhibits pronounced nonlinear characteristics. However, existing investigations have mainly focused on
2 individual parameters or limited parameter combinations, making it difficult to reveal the overall
3 performance characteristics. Therefore, establishing feasible design parameter domains for IPC systems
4 is essential for system performance evaluation and optimization design.

5 Although CFD methods can accurately reveal the airflow and heat transfer mechanisms of IPC systems,
6 their applications usually require a large number of operating conditions and high-resolution mesh
7 calculations, resulting in considerable computational costs [17-19]. Moreover, CFD simulations are
8 generally performed under discrete operating conditions, which limits the establishment of continuous
9 mappings between system design parameters and performance responses, particularly in high-
10 dimensional design spaces [20]. Data-driven approaches provide an effective solution by constructing
11 rapid surrogate models between design variables and performance responses, thereby significantly
12 reducing the computational burden associated with large-scale parameter analyses using conventional
13 CFD methods [21]. Therefore, data-driven approaches have gradually become important tools for
14 performance prediction and optimization of building environments and HVAC systems.

15 Data-driven surrogate modeling has become an effective strategy for optimizing building
16 environmental systems, offering rapid performance prediction while avoiding computationally intensive
17 numerical simulations. Machine learning methods, such as support vector regression (SVR), artificial
18 neural networks (ANN), and backpropagation neural networks (BPNN), have been widely adopted for
19 building energy consumption prediction [20,22,23]. Among these methods, BPNN exhibits strong
20 nonlinear approximation capability and adaptive learning ability, allowing complex nonlinear
21 relationships between performance indicators and design parameters to be effectively captured in
22 engineering systems. Therefore, BPNN has been extensively applied in complex system modeling and
23 performance prediction [24,25]. By developing a BPNN-based surrogate model for IPC systems, rapid
24 performance prediction under various design parameter combinations can be achieved, providing an
25 efficient evaluation tool for subsequent optimization.

26 However, surrogate models alone can only provide rapid predictions of system performance and
27 cannot directly identify optimal design parameter combinations satisfying multiple performance
28 objectives. Therefore, optimization algorithms are further required to explore the design space and
29 determine appropriate solutions. Multi-objective optimization methods have emerged as effective tools
30 for designing indoor thermal environments and HVAC systems, enabling the simultaneous optimization
31 of conflicting objectives, such as thermal comfort, and energy consumption [26-28]. Among these
32 methods, the NSGA algorithm combined with surrogate models can efficiently search a wide range of
33 feasible solutions with reduced computational costs and obtain Pareto-optimal solution sets under
34 multiple performance constraints [29-31]. Since multiple non-dominated solutions are usually included
35 in the Pareto front, further screening using multi-criteria decision-making methods is required. The
36 entropy-weight TOPSIS method provides an objective weighting and comprehensive evaluation
37 approach for ranking alternative solutions and has demonstrated good applicability in complex
38 engineering optimization problems [32,33]. Therefore, the integration of surrogate models, multi-
39 objective optimization algorithms, and decision-making methods enables efficient exploration of IPC
40 system design parameter spaces and identification of optimal operating strategies.

41 In this study, a CFD simulation database is established based on a full-factorial design method to
42 systematically investigate the influence of different design parameters on the performance of IPC systems
43 under different cooling load conditions. Subsequently, a BPNN surrogate model is developed for rapid
44 prediction of system performance, and optimal design parameter combinations are determined by

integrating multi-objective optimization with the entropy-weight TOPSIS method. Finally, the feasible design parameter domains of IPC systems under different cooling load conditions are identified. The findings provide valuable references for the data-driven design and optimization of mechanical ventilation systems in high cooling load environments.

2. IPC Model setup and numerical settings

2.1. IPC Model introduction

Fig. 1 gives the numerical model of the impinging jet ventilation and passive chilled beam combined (IPC) system, which represents a typical occupied scenario in public buildings. A rectangular computational domain with sizes of 6.0 m (x) $\times$ 6.0 m (y) $\times$ 3.6 m (z) is established. Four PCB units are arranged in the room, with each unit measuring 0.4 m (x) $\times$ 2.0 m (y) $\times$ 0.2 m (z). The PCB units are installed at a horizontal height of $z = 3.0$ m, with a vertical spacing of 0.4 m between the upper surface and the ceiling. Four IJV supply inlets (sizing 0.2 m $\times$ 0.2 m) are positioned at the four room corners, with an installation height of 0.5 m above the floor. A return air outlet (sizing 0.6 m $\times$ 0.6 m) is located at the ceiling center.

Thirty-six simplified human heat sources are uniformly arranged in the room, with sizes of 0.4 m (x) $\times$ 0.4 m (y) $\times$ 1.1 m (z). A CO₂ release source is defined at a height of 0.1 m above each heat source to represent occupant-generated contaminants. To analyze the simulation results, two typical cross-sections are selected for visualization of the numerical contours: the transverse plane normal to the primary orientation of the PCB units ($x = 1.8$ m) and the longitudinal center symmetry plane ($y = 1.8$ m).

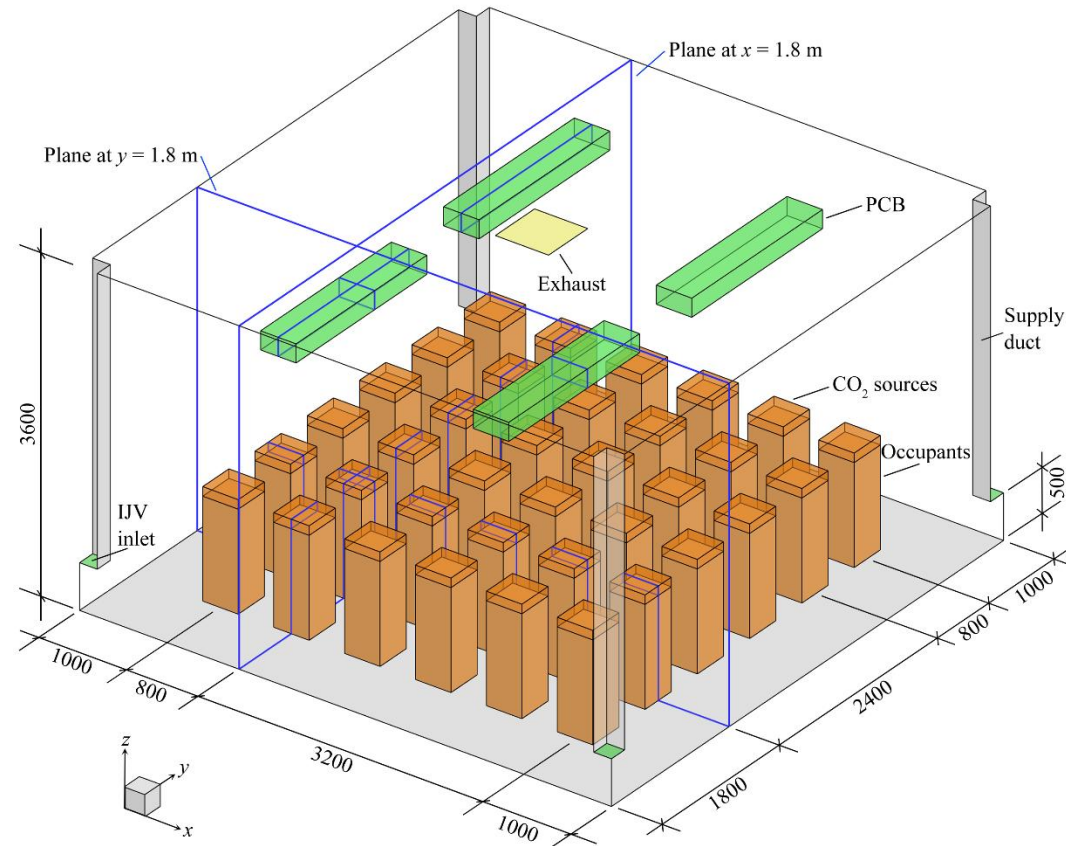


Fig. 1. Schematic of the numerical model for the IPC system.

2.2. Full Factorial Case Design

A numerical simulation database is established based on the full factorial design (FFD) method to systematically evaluate the influence of different design parameters on the system performance of IPC. Four key design parameters, including supply velocity (v_s), supply temperature (T_s), the PCB cooling ratio (η), and indoor cooling loads (q), are selected. The values of η is defined as: $\eta = q_{PCB} / q$, representing the ratio of indoor cooling loads for PCB removing.

The ranges of these parameters are determined according to the practical operating characteristics of IPC systems and relevant building ventilation design standards [13,34]. As listed in Table 1, four uniformly distributed levels are assigned to each parameter, resulting in a total of $4 \times 4 \times 4 \times 4 = 256$ independent numerical simulation cases. The full-factorial design provides a supervised learning dataset covering the parameter space for the subsequent BPNN model, thereby improving the prediction accuracy and generalization capability of the model in multidimensional design spaces.

Table 1 Range and values of design parameters.

Structural parameters	Values			
Supply velocity V_s (m/s)	1.5	1.9	2.3	2.7
Supply temperature T_s (°C)	17	18	19	20
PCB cooling ratio η (—)	0.2	0.3	0.4	0.5
Indoor cooling loads q (W/m ²)	100	150	200	250

To comprehensively investigate the performance of IPC systems, four categories of evaluation indicators are selected, including thermal stratification characteristics, thermal comfort, energy utilization coefficient (E_T), and ventilation efficiency (ε). Two indicators are applied to characterize the thermal stratification characteristics [35], namely the occupied zone air temperature at 1.8 m height ($T_{1.8}$) and the vertical temperature difference between 1.7 m (head level) and 0.1 m (ankle level) ($\Delta T_{1.7-0.1}$). Thermal comfort is evaluated using the predicted mean vote (PMV) and percentage dissatisfied of draft sensation (PD) [36], which jointly represent the overall thermal sensation and local discomfort caused by draft. The energy utilization coefficient (E_T) and ventilation efficiency (ε) are calculated as follows [13]:

$$E_T = \frac{T_e - T_s}{T_{oz} - T_s}, \varepsilon = \frac{C_e - C_s}{C_{oz} - C_s} \quad (1)$$

where T and C denote temperature and CO₂ concentration, respectively. The subscripts s , e , and oz represent supply air, exhaust air, and the occupied zone, respectively.

2.3. Simulation settings

2.3.1. Simulation model and specific equation setup

Numerical simulations of the IPC system are conducted using ANSYS Fluent 2023 R2. The indoor airflow and heat transfer processes are described using the Reynolds-Averaged Navier-Stokes (RANS) equations. Considering the coexistence of confined jets and buoyancy-driven flows within the system, the RNG k - ε turbulence model is applied for turbulence closure. This model incorporates a modified turbulent viscosity term compared to the standard k - ε model, thereby improving the prediction capability for flows with high strain rates and strong streamline curvature. The model has been widely validated and applied in simulating the indoor airflow, thermal stratification, and buoyancy-driven ventilation [4,8,37]. Considering the buoyancy effects induced by the mixing of cold and warm airflows, the Boussinesq approximation is adopted to account for the momentum exchange caused by density

variations [38]. Specifically, the equations for the RNG k - ε turbulence model are expressed as [39]:

$$\frac{\partial u_i}{\partial x_i} = 0 \quad (2)$$

$$u_j \frac{\partial u_i}{\partial x_j} = -\frac{1}{\rho} \frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j} \left(\left(\nu + \nu_t \right) \left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) \right) + g_i \beta_T (T - T_0) \quad (3)$$

$$u_i \frac{\partial k}{\partial x_i} = \frac{\partial}{\partial x_j} \left(\left(\nu + \frac{\nu_t}{\sigma_k} \right) \frac{\partial k}{\partial x_j} \right) - G_k + G_b - \varepsilon \quad (4)$$

$$u_i \frac{\partial \varepsilon}{\partial x_i} = \frac{\partial}{\partial x_j} \left(\left(\nu + \frac{\nu_t}{\sigma_\varepsilon} \right) \frac{\partial \varepsilon}{\partial x_j} \right) + C_{1\varepsilon} \frac{\varepsilon}{k} (G_k + C_{3\varepsilon} G_b) - C_{2\varepsilon}^* \frac{\varepsilon^2}{k} \quad (5)$$

$$G_k = \nu_t \left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) \frac{\partial u_i}{\partial x_j}, \quad G_b = g_i \beta_T \frac{\nu_t}{Pr_i} \frac{\partial T}{\partial x_i}, \quad \mu_t = C_\mu \frac{k^2}{\varepsilon} \quad (6)$$

$$C_{2\varepsilon}^* = C_{2\varepsilon} + \frac{C_\mu \eta^3}{1 + \beta \eta^3} \left(1 - \frac{\eta}{\eta_0} \right), \quad \eta = \frac{Sk}{\varepsilon}, \quad S = \sqrt{2S_{ij}S_{ij}} \quad (7)$$

$$\{C_\mu, C_{1\varepsilon}, C_{2\varepsilon}, \sigma_k, \sigma_\varepsilon, \eta_0, \beta\} = \{0.0845, 1.42, 1.68, 0.7178, 0.7178, 4.38, 0.012\} \quad (8)$$

where u_i is the x_i direction time-averaged velocity component, ν and ν_t are the molecular and turbulent kinematic viscosities, respectively. k and ε are the turbulent kinetic energy and turbulent dissipation rate, respectively. β_T is the thermal expansion coefficient, g_i is the gravitational acceleration component. T and T_0 is the local air temperature and the reference temperature, respectively. S is the modulus of the mean strain rate tensor. The model constants are presented in Eq. (8).

During the numerical solution process, the pressure-velocity coupling is treated using the SIMPLE algorithm. The simulations are performed under steady-state conditions. The convective terms are discretized using the second-order upwind scheme, while the pressure terms are discretized using the standard scheme. The convergence criteria are defined as residuals below 10^{-6} for the energy equation and below 10^{-4} for the remaining equations, including the k , ε , continuity, and momentum. In addition, the temperature and velocity variations at representative indoor locations are monitored. The solution is considered converged when both the residual criteria are satisfied and the monitored parameters reach stable values.

The Surface-to-Surface (S2S) radiation model is applied to study the influence of thermal radiation exchange on the indoor thermal environment [39-41]. The model assumes that the air medium is transparent to thermal radiation, and only radiative heat exchange between enclosure surfaces is considered, while the absorption, emission, and scattering effects of the medium are neglected. All indoor surfaces, including heat sources, building envelopes, and ceilings, are treated as diffuse-gray surfaces. The view factors are determined using the ray-tracing method according to spatial geometric relationships. Given that typical building envelope materials generally have high emissivity values, the emissivity of all radiative surfaces is uniformly given as 0.95.

2.3.2. Meshing and grid independence test

A series of mesh generation and independence tests were performed to evaluate the influence of mesh resolution on the simulation results. The domain was discretized using structured hexahedral meshes.

Considering the complexity of indoor airflow organization, local mesh refinement was performed in regions with large flow and heat transfer gradients, including the vicinity of heat sources, supply inlets, and PCB surfaces, to ensure adequate solution accuracy with reasonable computational cost. The first-layer mesh height near the walls was set to 0.01 m, the maximum mesh size was controlled below 0.05 m, and the mesh growth rate was maintained lower than 1.2. All generated meshes achieved a quality value above 0.99. Fig. 2 presents the overall mesh distribution of the computational domain and the refined meshes in key local regions.

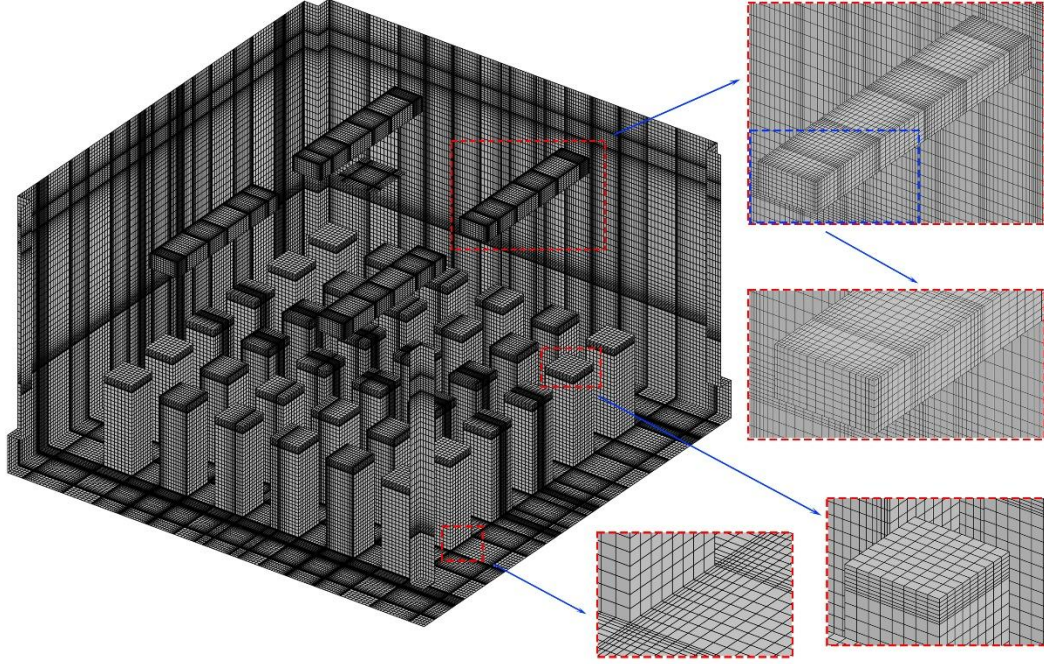


Fig. 2. Computational mesh of the IPC system.

Six mesh configurations with different resolutions were generated in this study, containing 1.88, 2.73, 3.72, 4.71, 5.85, and 7.23 million cells, respectively. To evaluate mesh independence, the temperature, velocity, and CO₂ mass fraction in the occupied zone were selected as monitoring parameters. Their variations with increasing mesh numbers are presented in Fig. 3. The results indicated that all monitored parameters remained nearly unchanged when the mesh number reached 4.71 million cells or higher, and further mesh refinement had a negligible influence on the simulation results. Therefore, the mesh configuration containing approximately 4.71 million cells was adopted for subsequent simulations.

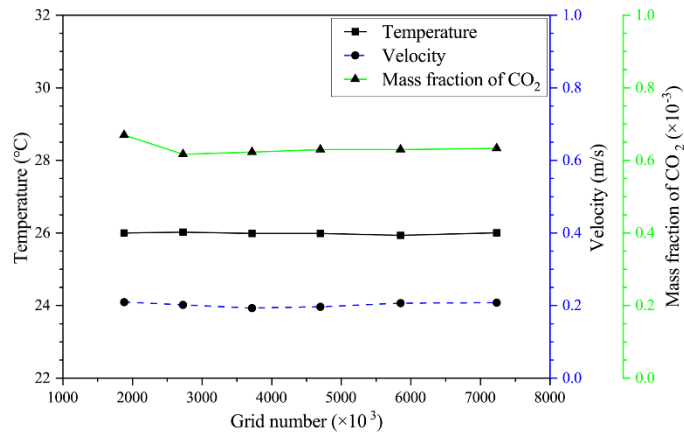


Fig. 3. Verification curves for the six mesh configurations.

2.3.3 Model validation

The IPC system consists of an IJV system and PCB units, and its airflow and thermal characteristics are determined by the coupled effects of both components. Therefore, the reliability of the CFD model is evaluated through the validation of the two subsystems. The IJV system under cooling conditions was experimentally validated in our previous study using a full-scale laboratory, where good agreement between the simulated and experimental airflow and temperature distributions was obtained [4]. The PCB units were validated against the full-scale experimental data obtained by Nelson et al. [42,43] to evaluate its capability of the PCB model in simulating the indoor airflow and thermal environment. The experiments were conducted in test chamber with sizes of 4.22 m × 4.22 m × 3.02 m (Figs. 4(a) and 4(b)). Twelve thermal manikins conforming to the EN 14518 standard [44] were arranged inside the chamber, generating an indoor cooling load of approximately 2300 W. During the validation process, identical measurement locations were applied in both the experiments and simulations. The prediction performance of the PCB model was evaluated by comparing the temperature and velocity profiles along the four representative paths ($l_1 - l_4$).

The comparisons between the simulation and experimental results are presented in Figs. 4(c) – 4(f). In the region below the PCB outlet, Fig. 4(c) shows that the simulated results reproduced the symmetrical “V-shaped” temperature distribution near the outlet center. Although the numerical predictions exhibited an underestimation of approximately 1 °C compared with the experimental data, consistent variation trends were observed between the two results. As shown in Fig. 4(e), the velocity distributions also exhibited good agreement, and the airflow velocity in the jet core region beneath the PCB unit was reasonably captured by the CFD model. A difference of approximately 0.1 m/s was observed between the simulated and measured velocities, which may be attributed to local airflow fluctuations during the experiments and measurement uncertainties.

For the prediction of the indoor thermal environment, Fig. 4(d) presents the comparison of vertical temperature profiles between the numerical and experimental results. In the region of $z > 2$ m, good agreement was observed between the two temperatures. Within the occupied zone ($z < 2$ m), the simulated temperatures were slightly lower than the experimental measurements, while the overall deviation remained small. Fig. 4(f) further compares the reference temperatures at different measurement locations, and the results indicated that the CFD model was capable of reproducing the characteristics and variation trends of the indoor temperature distribution. Overall, good consistency was achieved between the CFD predictions and experimental data, demonstrating that the developed numerical model could reasonably represent the airflow and heat transfer characteristics of the IPC system and could be further applied for subsequent parameter analysis and optimization studies.

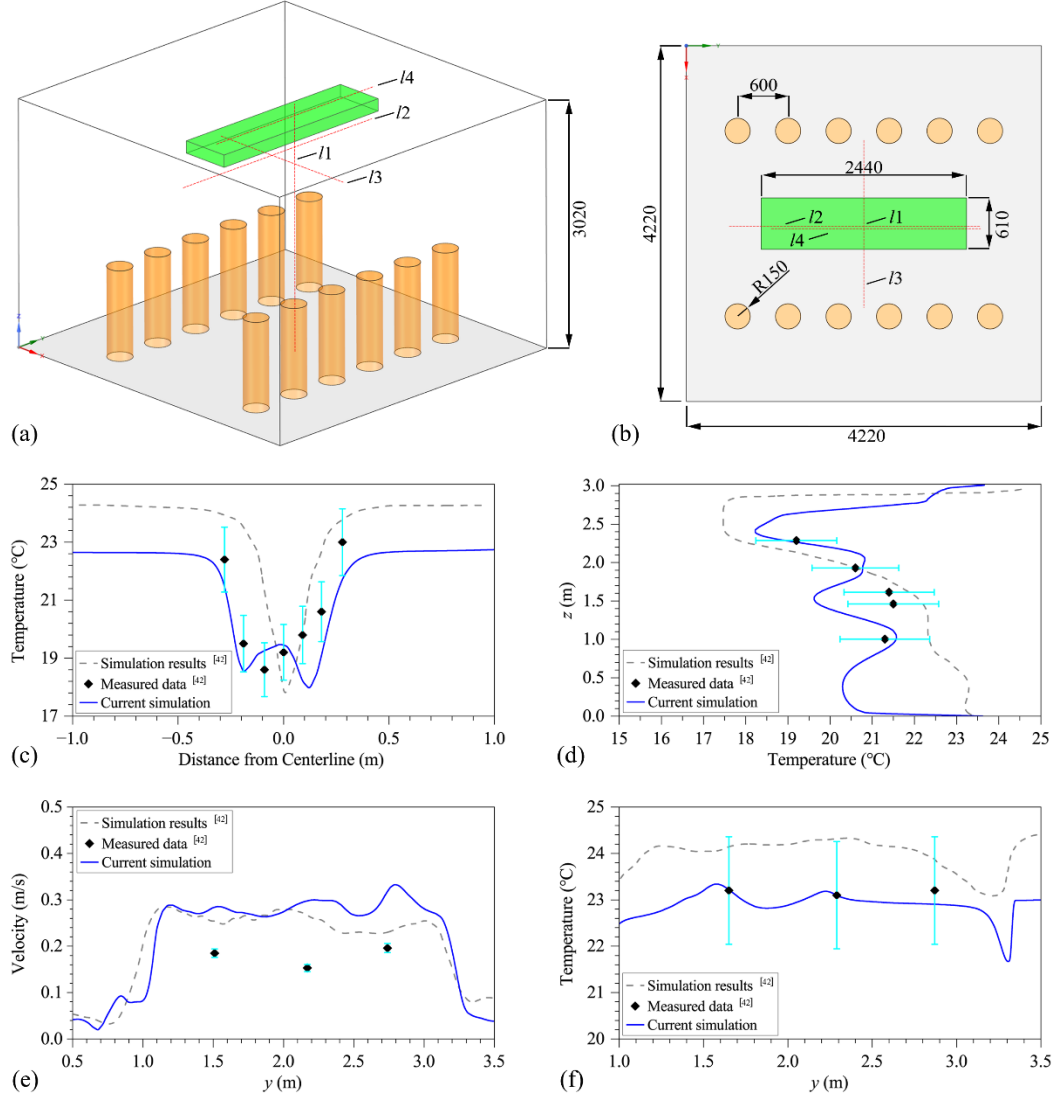


Fig. 4. Validation of temperature and velocity predictions against experimental measurements: (a) perspective of the CFD model; (b) plan layout; (c) vertical temperature profile; (d) outlet velocity of PCB; (e) outlet temperature of PCB; (f) reference temperature.

2.4. Surrogate-based multi-objective optimization framework

2.4.1. BPNN construction

The performance indicators of the IPC system, including $T_{1.8}$, $T_{1.7-0.1}$, T_{oz} , T_e , C_{oz} , C_e , $PMV_{0.1}$, $PD_{0.1}$, exhibits complex nonlinear relationships with the four design parameters (v_s , T_s , η , and q). Several machine learning algorithms are assessed for their capability to capture the nonlinear relationship between design variables and system responses. The results demonstrate that the backpropagation neural network (BPNN) exhibits superior prediction performance for the present dataset and is therefore selected to develop the data-driven prediction model.

The prediction model is developed based on the PyTorch framework and the scikit-learn toolkit [45,46]. Considering both prediction performance and computational cost, a network architecture of $4 \times 128 \times 64 \times 8$ is adopted (see Fig. 5), consisting of four input neurons, two hidden layers with 128 and 64 neurons, and eight output neurons. The ELU activation function is selected to introduce nonlinear mapping capability, and the mean squared error (MSE) is defined as the objective function for model training. The

2.4.2. Configuration of NSGA-III

For the parameter optimization of the IPC system, multiple objectives, including indoor thermal environment quality, system energy efficiency, and thermal comfort, are conflicting with each other, and the optimization problem exhibits high-dimensional characteristics. Therefore, traditional single-objective optimization methods are difficult to apply to such problems. The NSGA-II algorithm based on crowding distance [47] is widely used for multi-objective optimization problems (MaOPs). However, the selection pressure of NSGA-II may be weakened, with an increasing number of non-dominated solutions, thereby affecting its convergence performance. Conversely, the NSGA-III algorithm [48,49] introduces a reference point based environmental selection mechanism, in which uniformly distributed reference points are predefined in the objective space to guide the population toward the Pareto Front while maintaining solution diversity. To address the nonlinear trade-offs among thermal comfort, ventilation performance, and energy efficiency, the NSGA-III algorithm is employed to explore the feasible solution space of the IPC system. For each prescribed cooling load scenario, the corresponding IPC supply parameters are optimized separately. Accordingly, the multi-objective optimization problem is defined as follows:

$$\begin{cases} \min F(x) = [-E_T(x), -\varepsilon(x), PD_{0.1}(x)] \\ s.t. \quad |T_{1.8} - 26| \leq 2 \\ \quad \Delta T_{1.7-0.1} \leq 3 \\ \quad |PMV_{0.1}| \leq 0.5 \end{cases} \quad (10)$$

where the decision variable vector is defined as $x = [v_s, T_s, \eta]^T$, with the corresponding ranges of $1.5 \text{ m/s} \leq v_s \leq 2.7 \text{ m/s}$; $17 \text{ }^\circ\text{C} \leq T_s \leq 20 \text{ }^\circ\text{C}$; $0.2 \leq \eta \leq 0.5$. The cooling load q is prescribed as a scenario parameter, with a range of $100 \text{ W/m}^2 \leq q \leq 250 \text{ W/m}^2$, and is fixed at each optimization condition. Meanwhile, the air temperature at the occupied level (1.8 m height) is constrained within $24 - 28 \text{ }^\circ\text{C}$, the vertical temperature difference between 1.7 m and 0.1 m is limited to below $3 \text{ }^\circ\text{C}$, and the PMV value is maintained within ± 0.5 [34].

Table 3 lists the key hyperparameters adopted in NSGA-III. The population size is set to 600, and the maximum number of iterations is set to 1000. The distribution of reference points is determined by the number of objectives and divisions, ensuring uniform coverage of the objective space. The genetic operators include simulated binary crossover (SBX) and polynomial mutation (PM), with both distribution indices set to 20. The initial population is generated using Latin hypercube sampling to enhance the coverage of the design space. During each iteration, candidate solutions are normalized, and perpendicular distances to reference points are evaluated for environmental selection, allowing the Pareto-optimal solutions to be progressively identified.

Table 3 NSGA-III algorithm configuration.

Algorithm parameter	Setting
Population size / Max iterations	600 / 1000
Initial sampling	Latin Hypercube (LHS)
Genetic operators	SBX & Polynomial Mutation
Distribution index (η_c, η_m)	20, 20
Crossover / Mutation prob.	0.9 / 0.25
Reference point method	Das and Dennis (H=30)
Selection mechanism	Reference point-based selection

2.4.3. Entropy-weighted TOPSIS

The Pareto solution set obtained by the NSGA-III algorithm contains a series of non-dominated solutions that represent trade-offs among multiple objectives. In practical engineering applications, a multi-criteria decision-making (MCDM) method is further required to screen the solution set and determine the optimal solution with comprehensive performance. In this study, the entropy-weighted TOPSIS method is adopted for decision analysis. The TOPSIS method [50] is adopted to identify the optimal compromise solution from the Pareto front by measuring the relative closeness of each candidate solution to the positive ideal solution (PIS) and negative ideal solution (NIS). To reduce the influence of subjective weighting, entropy weighting is employed to derive objective weights for the evaluation indicators. The information entropy is calculated based on the dispersion degree of indicator data to reflect the information contribution of each indicator. The combination of these two methods reduces human-induced bias to some extent and improves the objectivity of the evaluation results, thereby enabling the selection of optimal parameter schemes for the IPC system. The detailed procedures of the entropy-weighted TOPSIS method are described as follows:

1. Construction and normalization of the decision matrix. A decision matrix $X = (x_{ij})_{mn}$ is constructed by extracting m candidate solutions and n evaluation indicators from the Pareto solution set. To eliminate the influence of different dimensions, the decision matrix is normalized to obtain the standardized matrix $R = (r_{ij})_{mn}$.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (11)$$

2. Entropy-weight calculation. The entropy weight method is applied to quantify the variation degree of each evaluation indicator based on information entropy theory. A smaller information entropy value indicates a larger amount of information provided by the corresponding indicator, resulting in a higher weight coefficient w_j . The information entropy e_j and weight coefficient w_j are calculated as follows:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (12)$$

$$p_{ij} = r_{ij} / \sum_{i=1}^m r_{ij} \quad (13)$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^n (1 - e_j)} \quad (14)$$

3. Weighted decision matrix and ideal solutions. The weighted normalized matrix $Z = (z_{ij})_{mn}$ is constructed by incorporating the entropy weights, where $z_{ij} = w_j \cdot r_{ij}$. Based on the weighted normalized matrix, the positive ideal solution Z^+ and negative ideal solution Z^- are determined.

$$Z^+ = (\max z_{i1}, \max z_{i2}, \dots, \max z_{in}), Z^- = (\min z_{i1}, \min z_{i2}, \dots, \min z_{in}) \quad (15)$$

4. Calculation of the relative closeness. The Euclidean distances between each alternative and the positive and negative ideal solutions are calculated as d_i^+ and d_i^- , respectively. The relative closeness C_i is then obtained based on these distances, where $0 \leq C_i \leq 1$. A larger value of C_i indicates that the alternative is closer to the optimal solution.

$$d_i^+ = \sqrt{\sum_{j=1}^n (z_{ij} - z_j^+)^2}, d_i^- = \sqrt{\sum_{j=1}^n (z_{ij} - z_j^-)^2} \quad (16)$$

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (17)$$

2.4.4 Integrated framework

The framework of this study is illustrated in Fig. 6, and the detailed procedures are described as follows:

1. Data preparation. The design parameters (V_s , T_s , η and q) are determined, and the evaluation indicators ($T_{1.8}$, $T_{1.7-0.1}$, PD, E_t , PMV, and ε) are obtained through CFD simulations. The original data are subsequently cleaned and normalized for further analysis.

2. BPNN construction. The optimal BPNN architecture is determined, and the preprocessed dataset is used for model training. The coefficient of determination (R^2) and root mean square error (RMSE) are adopted to evaluate the nonlinear fitting capability and prediction accuracy of the model.

3. Pre-optimization analysis. Sobol global sensitivity analysis is conducted using the original CFD dataset to quantify the contribution of each design parameter to the evaluation indicators and provide physical insights for subsequent optimization.

4. Multi-objective optimization. The trained BPNN model is employed as the fitness evaluation function, and the NSGA-III algorithm is applied for global optimization. The Pareto optimal solution sets representing trade-offs among multiple objectives are obtained under different cooling load conditions.

5. Post-optimization analysis. The entropy-weighted TOPSIS method is introduced to objectively evaluate and rank the Pareto solution sets. The global optimal solutions under different cooling load levels are determined, and the optimization results are further validated through CFD simulations.

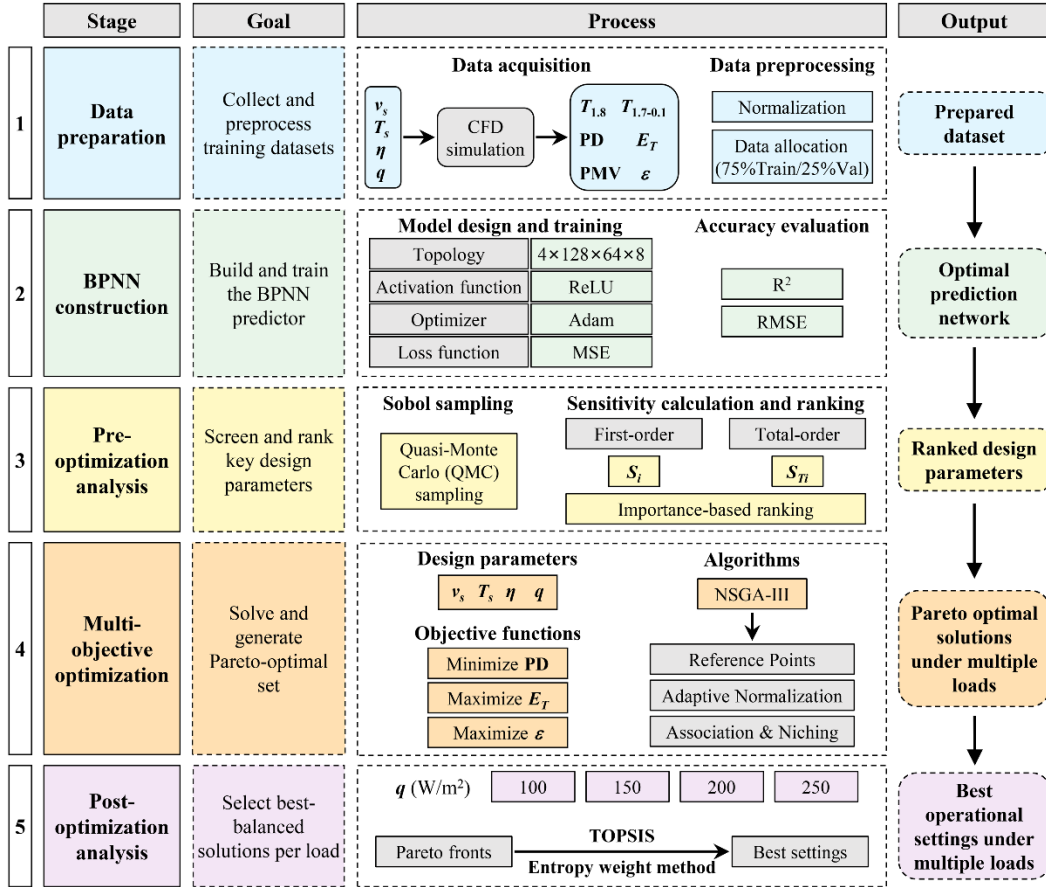


Fig. 6. Study framework of the investigation.

3. Results and discussion

3.1. Indoor air distribution and thermal environment characteristics

Fig. 7 illustrates the variations in temperature fields and streamline distributions on the vertical section ($y = 1.8$ m) of the IPC system under different indoor cooling load levels (q) at the same cooling load ratio ($\eta = 0.4$). As shown in Fig. 7(a) and Fig. 7(b), when $q = 100$ and 150 W/m², the indoor average temperature remains relatively low. The descending cold jet induced by the PCB units maintains a clear and stable trajectory, which smoothly penetrates the central region of the room and interacts with the near-floor cold airflow generated by the IJV system. Consequently, a relatively uniform temperature distribution is achieved in the occupied zone. At these conditions, the upward buoyancy flow generated by the heat sources is relatively weak, resulting in a simple indoor airflow structure with small recirculation zones formed near the room corners.

As q increases (Fig. 7(c) and Fig. 7(d)), noticeable variations in indoor temperature distribution and thermal stratification are observed. The enhanced thermal plumes generated by the heat sources intensify airflow disturbances, resulting in more complex streamline distributions. Particularly under the high-load condition (Fig. 7(d)), strong momentum shear is generated between the upward thermal flows and the descending cold jets from the PCB units. Consequently, multiple recirculation zones with different scales are formed in the upper-middle region of the room. These recirculation structures not only enhance air mixing but also disturb the originally stable thermal stratification.

As observed from the temperature contours, the high-temperature region gradually expands downward from the ceiling with increasing cooling load. This phenomenon becomes more pronounced at $q = 250$ W/m², where significant heat accumulation occurs around the occupants. Meanwhile, the cold airflow beneath the PCB units is strongly entrained by the surrounding warm air, leading to a limited cooling coverage area. The coupled variations in airflow and temperature fields indicate that the cooling load intensity is a critical factor governing the airflow stability of the IPC system. The buoyancy-driven effect under high cooling load conditions serves as the dominant physical mechanism responsible for the deterioration of thermal stratification and the disturbance of indoor airflow structures.

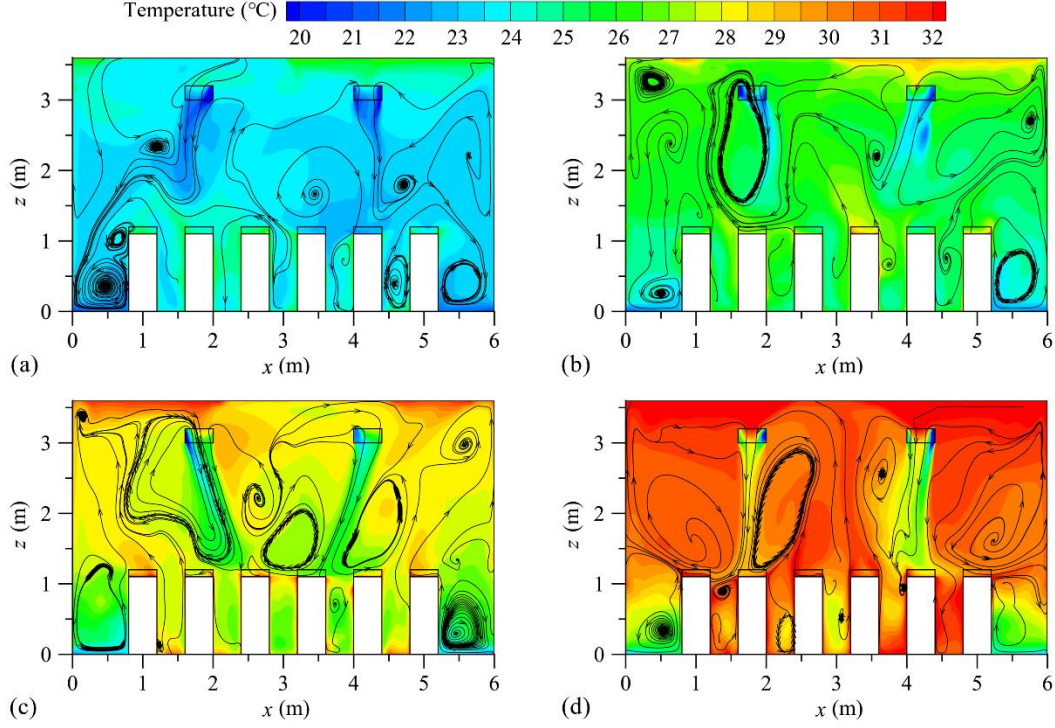


Fig. 7. Indoor temperature and streamline distributions under four cooling load conditions. (a) $q = 100\text{W/m}^2$; (b) $q = 150\text{W/m}^2$; (c) $q = 200\text{W/m}^2$; (d) $q = 250\text{W/m}^2$.

3.2. Analysis of feasible design parameter domains

To quantitatively characterize the influence of design parameters on system performance within the multi-dimensional parameter space, three-dimensional feasible design parameter domains under different cooling load conditions are constructed (see Fig. 8). The colored envelope represents the combinations of design parameters that satisfy the indoor thermal environment criteria, namely, the feasible domains of v_s , T_s , and η . These feasible domains are established within the predefined ranges of the three design parameters, which are determined based on relevant standards and practical engineering requirements [13,34]. Therefore, the resulting domains represent the feasible operating space within the specified parameter ranges rather than universally applicable design rules. The detailed coordinates of the vertices of these domains are summarized in Table 4.

As shown in Fig. 8, the feasible design parameter domains of the IPC system exhibit a non-monotonic variation with the increase in indoor cooling load (q), characterized by an initial expansion followed by a subsequent contraction. Notably, under the condition of $q = 150\text{ W/m}^2$ (see Fig. 8(b)), the volume of the feasible domain reaches the maximum value among all investigated cases. This phenomenon indicates that an optimal balance is achieved between the IJV supply parameters and the PCB cooling ratio at this load level, providing the IPC system with the largest operational flexibility and robustness. As the cooling load further increases to 250 W/m^2 (Fig. 8(d)), the feasible domain shrinks significantly and shifts toward the region with higher supply velocity and higher PCB cooling ratio.

The data presented in Table 4 further confirm that, under high cooling load conditions, the IPC system requires relatively high supply velocity (e.g., $v_s = 1.98\text{ m/s}$ at point D8) and PCB cooling ratio (e.g., $\eta = 0.308$ at point D1) to compensate for the intensified disturbance induced by thermal plumes. Since the investigated parameter ranges are selected based on commonly used engineering conditions, the envelope of the feasible design parameter domain shown in Fig. 8 exhibits truncated boundaries in some regions

(e.g., near $v_s = 2.7$ m/s or $T_s = 17$ °C). This feature suggests that the theoretical optimal solution under such high-load conditions may exist beyond the current parameter range. Therefore, the present results demonstrate that the feasible design parameter domain of the IPC system gradually shifts from a state dominated by operational flexibility toward one constrained by extreme performance requirements as the cooling load increases.

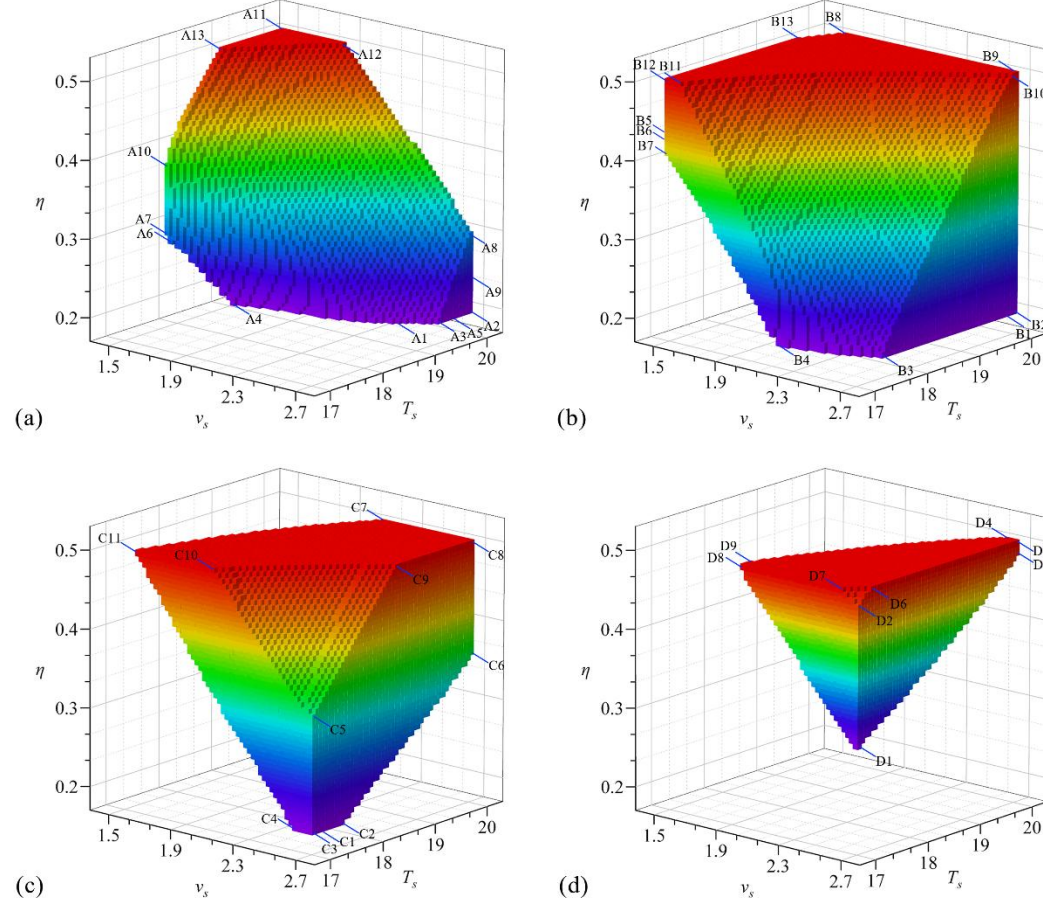


Fig. 8. 3D range plots of design parameters as required by the four cooling load conditions. (a) $q = 100$ W/m²; (b) $q = 150$ W/m²; (c) $q = 200$ W/m²; (d) $q = 250$ W/m².

Table 4 Detailed parameters of the data points in Fig. 8.

Points	v_s (m/s)	T_s (°C)	η (-)	Points	v_s (m/s)	T_s (°C)	η (-)
A1	1.74	20.00	0.200	B1	2.63	20.00	0.200
A2	2.70	20.00	0.200	B2	2.70	20.00	0.200
A3	2.70	19.40	0.200	B3	2.70	17.48	0.200
A4	1.74	18.38	0.200	B4	2.20	17.06	0.200
A5	1.50	19.46	0.278	B5	1.50	17.54	0.404
A6	1.50	17.90	0.278	B6	1.50	17.36	0.404
A7	1.50	17.84	0.290	B7	1.50	17.00	0.410
A8	2.70	20.00	0.296	B8	1.62	20.00	0.500
A9	1.50	20.00	0.326	B9	2.70	20.00	0.500
A10	1.50	17.84	0.374	B10	2.70	19.94	0.500
A11	1.50	20.00	0.500	B11	1.58	17.00	0.500
A12	1.88	20.00	0.500	B12	1.50	17.00	0.500

A13	1.50	18.86	0.500	B13	1.50	19.46	0.500
C1	2.61	17.18	0.200	D1	2.70	17.00	0.308
C2	2.70	17.54	0.200	D2	2.70	17.00	0.482
C3	2.70	17.00	0.200	D3	2.70	20.00	0.488
C4	2.61	17.00	0.200	D4	2.65	20.00	0.500
C5	2.70	17.00	0.344	D5	2.70	20.00	0.500
C6	2.70	20.00	0.362	D6	2.70	17.24	0.500
C7	2.15	20.00	0.500	D7	2.61	17.00	0.500
C8	2.70	20.00	0.500	D8	1.98	17.00	0.500
C9	2.70	18.56	0.500	D9	1.98	17.12	0.500
C10	2.08	17.00	0.500	—	—	—	—
C11	1.60	17.00	0.500	—	—	—	—

The planar slices of Fig. 9 further illustrate the evolution characteristics of the feasible design parameter domain. The green regions represent the parameter ranges that satisfy the thermal comfort requirements of the IPC system. A comparison among four cooling load conditions indicates that the green feasible regions maintain clear continuity and topological similarity in terms of shape, while a significant overall translation occurs in the parameter space. Specifically, the centroid of the feasible region gradually shifts from the upper-left region (low supply velocity and high supply temperature) toward the lower-right region (high supply velocity and low supply temperature). This “domain shifting” phenomenon reflects the inherent thermal compensation mechanism of the system, where an increase in supply velocity combined with a reduction in supply temperature is required to restore the thermal balance under high cooling load conditions.

A horizontal comparison reveals that increasing the PCB cooling ratio (η) provides a significant compensatory effect on the shift of the feasible design parameter domain. Under the same cooling load condition, an increase in η drives the feasible region toward the lower supply velocity direction and expands the acceptable parameter range, effectively reducing the operational burden of the IJV system. However, when the cooling load further increases to the extreme condition ($q = 250 \text{ W/m}^2$), the feasible domain is compressed into a narrow band located near the boundary of the design parameter space. This result indicates that the parameter tolerance of the IPC system is substantially reduced under extreme operating conditions. Maintaining indoor thermal comfort can no longer be achieved through the adjustment of a single parameter, but requires precise coupling among multiple design parameters within a limited range. Such complex evolution characteristics of the feasible design parameter domain reveal the nonlinear operational boundaries of the IPC system in the multi-dimensional parameter space.

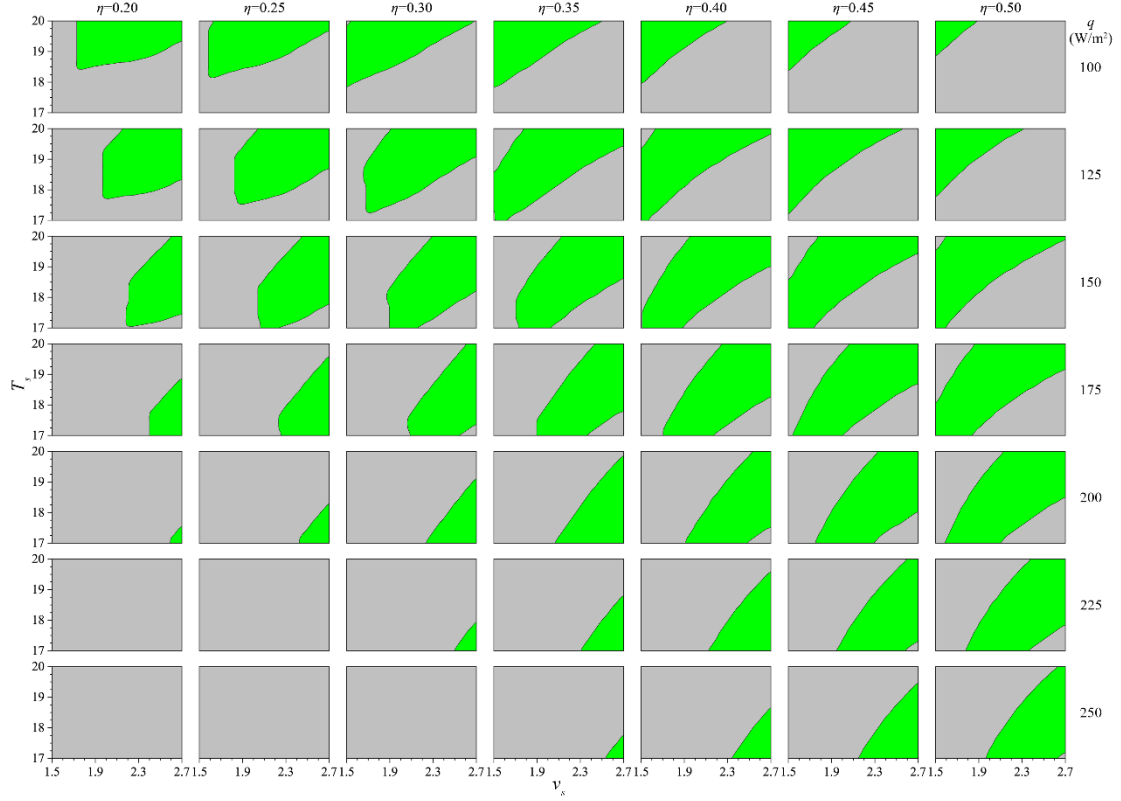


Fig. 9. Planar slices of the evolution characteristics for the feasible design parameter domain.

3.3. Sobol sensitivity analysis results

To quantify the effects of design parameters and their interactions on multiple IPC performance indicators, the variance-based Sobol global sensitivity analysis method [51,52] is employed. The Sobol method decomposes the total variance $V(Y)$ of the model output into the contributions caused by individual input parameters and their interactions:

$$V(Y) = \sum_{i=1}^d V_i(Y) + \sum_{i < j} V_{ij}(Y) + \dots + V_{12\dots d}(Y) \quad (18)$$

where V_i represents the first-order variance contribution of parameter x_i , and V_{ij} denotes the variance contribution induced by the interaction between parameters x_i and x_j . Based on this decomposition, the first-order sensitivity index (S_i) and total-order sensitivity index (S_{Ti}) are defined as follows:

$$S_i = \frac{V_i(Y)}{V(Y)} \quad (19)$$

$$S_{Ti} = 1 - \frac{V_{\sim i}(Y)}{V(Y)} \quad (20)$$

The results of the Sobol sensitivity analysis are presented in Fig. 10 and Fig. 11. As shown in Fig. 10, the indoor cooling load (q) is the dominant factor affecting the average air temperature at 1.8 m height ($T_{1.8}$) and the thermal comfort index ($PMV_{0.1}$). Its sensitivity indices are significantly larger than those of other design parameters, indicating that the indoor thermal equilibrium state undergoes substantial shifts with variations in cooling load. This dominant effect is physically associated with the strength of buoyancy-driven thermal plumes, which changes with the cooling load and consequently modifies the indoor thermal stratification. Correspondingly, the supply velocity v_s exhibits a dominant influence on

the draft discomfort index at 0.1 m height ($PD_{0.1}$), which can be attributed to the increase in jet momentum and the resulting stronger local air movement in the occupied zone.

Furthermore, for the energy utilization coefficient (E_T) and contaminant removal efficiency (ε) (see Fig. 10(e) and Fig. 10(f)), the total-order sensitivity index S_{Ti} of the PCB cooling ratio (η) is considerably higher than its first-order sensitivity index S_i . This indicates that η not only has a significant direct influence on system energy efficiency and contaminant removal performance but also exhibits strong nonlinear interactions with other design parameters. Physically, increasing η strengthens the PCB-induced downdraft, thereby modifying the interaction between the downward cold airflow and the upward buoyancy-driven flow and consequently affecting both thermal stratification and contaminant transport.

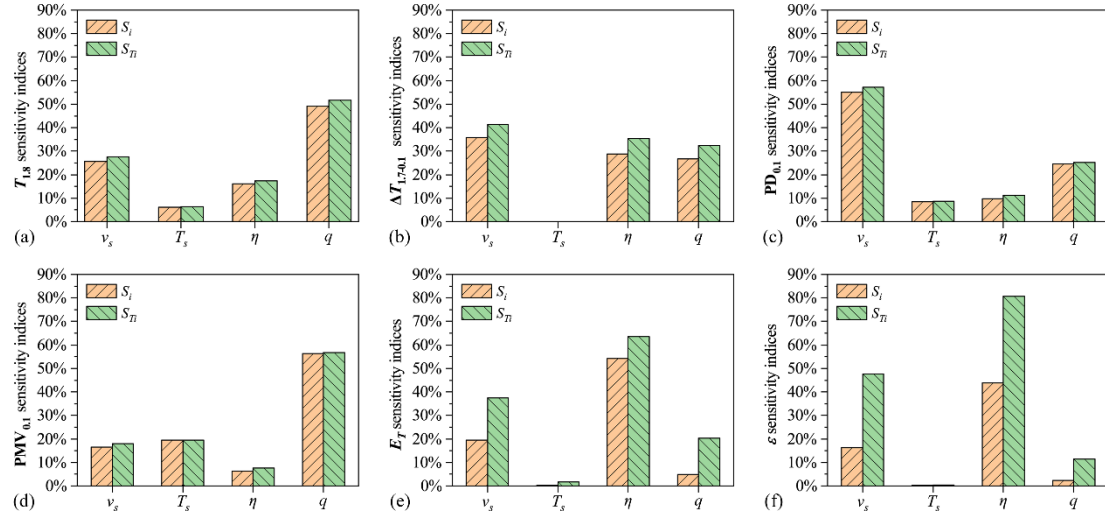


Fig. 10. Sobol sensitivity indexes of design parameters based on S_i and S_{Ti} for six performance indicators.

Fig. 11 further illustrates the first-order and higher-order Sobol indices, revealing the individual and interactive effects of design parameters on the six performance indicators. The results indicate that parameter interactions, such as those between v_s and η , and between v_s and q , have significant impacts on system performance. The interaction between v_s and η reflects the competition between the momentum of the IJV supply jet and the PCB-induced downdraft, while the interaction between v_s and q is related to the balance between jet momentum and buoyancy-driven flow under different cooling load conditions. For thermal environment evaluation, $T_{1.8}$ and $PMV_{0.1}$ exhibit clear single-factor-driven characteristics, which are mainly governed by the first-order effect of q , while the influence of higher-order interactions remains limited. However, coupling effects become more pronounced in the analyses of local thermal conditions and energy performance. Both $\Delta T_{1.7-0.1}$ and E_T show high sensitivity to the interaction effects among η , v_s , and q , demonstrating that coordinated regulation among multiple parameters provides greater potential for performance improvement than single-parameter adjustment under high cooling load conditions. These interactions also determine the balance between thermal stratification and local air movement, which is closely related to draft risk in the occupied zone. In addition, although the variation of ventilation efficiency (ε) is dominated by η , strong interaction effects are also observed, indicating that the airflow induced by the PCB units plays a critical role in enhancing parameter coupling and improving airflow uniformity. The resulting redistribution of airflow further influences the transport and removal of contaminants within the occupied zone, explaining the strong

interaction effects observed for ε . These multi-dimensional sensitivity characteristics provide physical insights for developing a high-accuracy nonlinear prediction model.

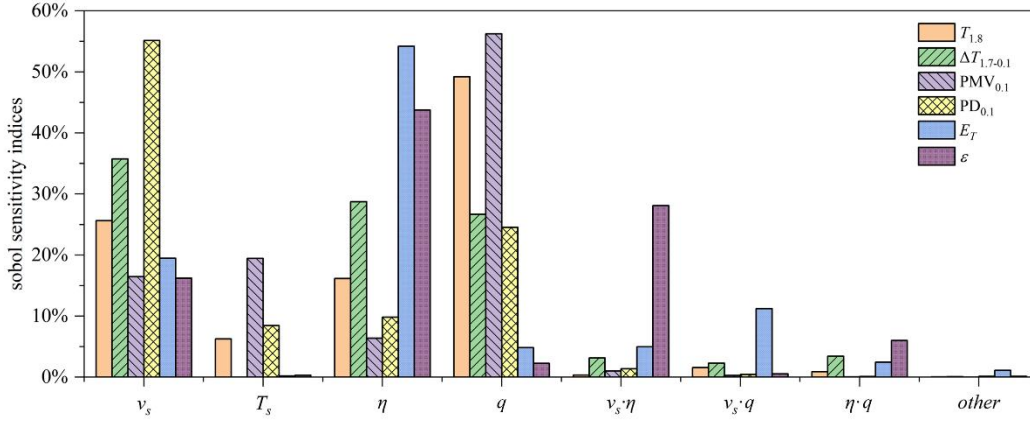


Fig. 11. First-order and high-order sensitivity indexes of design parameters on six performance indicators.

3.4. Predictive performance evaluation of the BPNN model

To validate the predictive capability of the BPNN model in capturing the multi-parameter nonlinear mappings of the IPC system, Fig. 12 presents the prediction performance of the model for eight performance indicators ($T_{1.8}$, $T_{1.7-0.1}$, T_{oz} , T_e , C_{oz} , C_e , $PMV_{0.1}$, and $PD_{0.1}$) on the training and testing datasets. The coefficient of determination (R^2) and root mean square error (RMSE) are adopted for quantitative evaluation. As shown in Fig. 12(a), the BPNN model achieves high prediction accuracy for all evaluated indicators. The R^2 values of both the training and testing datasets exceed 0.98, and those of some indicators (e.g., $T_{1.8}$ and T_{oz}) approach 1.00. The close agreement between the predicted and CFD-derived results confirms that the developed BPNN surrogate model accurately captures the complex nonlinear mapping between the input parameters (v_s , T_s , η , and q) and the performance indicators.

As further demonstrated by the RMSE distributions in Fig. 12(b), the overall prediction errors of the model remain within a low range during the testing process, indicating excellent generalization capability. Although the prediction error of $PD_{0.1}$ in the testing dataset is slightly higher than that in the training dataset due to the stochastic characteristics of airflow and local turbulence effects, its RMSE value remains within an acceptable range for engineering applications. The high symmetry and overlap observed in the radar charts further indicate that no evident overfitting occurs during model training. To further evaluate the robustness and generalization capability of the BPNN model, five-fold cross-validation and repeated training with different random seeds are also conducted. The results are presented in Tables 5 and 6, respectively. The relatively small variations in R^2 and RMSE across different folds and random seeds further confirm the stability of the model performance.

In addition, RSM, Kriging, and SVR models were developed using the same dataset for comparison, and the results are presented in Table 7. BPNN and Kriging show high predictive accuracy, while RSM and SVR generally exhibit lower performance for several output variables. Although Kriging slightly outperforms BPNN for some individual outputs, BPNN demonstrates comparable and consistently high performance across the multiple output variables. Overall, the BPNN-based surrogate model provides an efficient alternative to time-consuming CFD simulations with significantly reduced computational costs and can be applied for performance prediction and multi-objective parameter optimization of IPC systems under practical operating conditions.

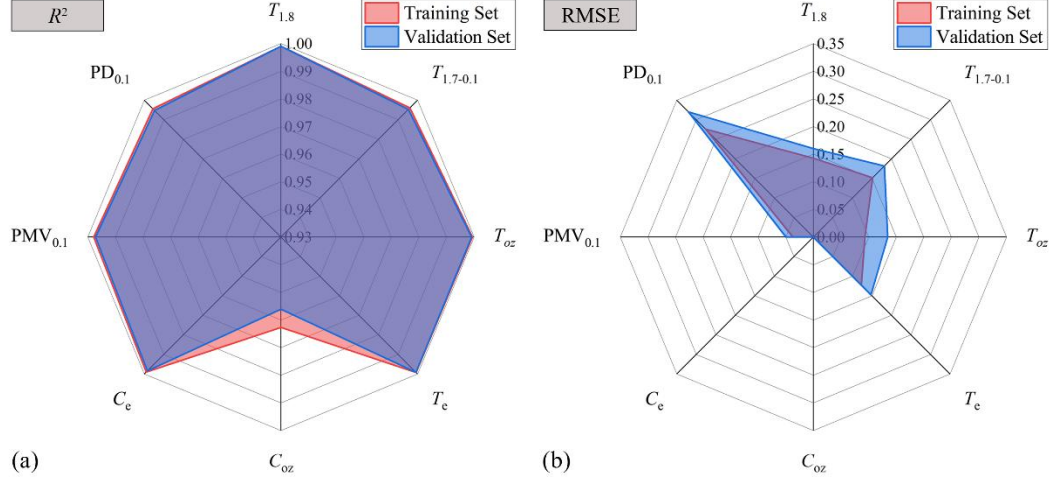


Fig. 12. Predictive performance of the BPNN model characterized by R^2 and RMSE.

Table 5 Performance of the BPNN model using 5-fold cross-validation.

Output	Fold1		Fold2		Fold3		Fold4		Fold5	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
$T_{1.8}$	0.9977	0.2058	0.9993	0.1237	0.9988	0.1627	0.9993	0.1315	0.9985	0.1614
$T_{1.7-0.1}$	0.9926	0.2232	0.9945	0.1767	0.9911	0.2194	0.9961	0.1738	0.9939	0.1718
T_{oz}	0.9986	0.1327	0.9989	0.1298	0.9991	0.1224	0.9991	0.1327	0.9988	0.1260
T_e	0.9988	0.1514	0.9995	0.1120	0.9994	0.1184	0.9992	0.1531	0.9991	0.1329
C_{oz}	0.9574	3.895×10^{-5}	0.9536	4.8653×10^{-5}	0.9591	3.8294×10^{-5}	0.9611	3.7515×10^{-5}	0.9541	4.2484×10^{-5}
C_e	0.9992	6.2412×10^{-6}	0.9986	6.9697×10^{-6}	0.9978	1.0122×10^{-6}	0.9992	6.4330×10^{-6}	0.9988	7.3406×10^{-6}
$PMV_{0.1}$	0.9963	0.0428	0.9966	0.0484	0.9962	0.0588	0.9970	0.0490	0.9979	0.0371
$PD_{0.1}$	0.9924	0.3565	0.9944	0.2757	0.9934	0.3733	0.9933	0.3605	0.9948	0.3098

Table 6 Prediction performance of the BPNN model under different random seeds.

Output	42		98		26		784		2026	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
$T_{1.8}$	0.9977	0.2058	0.9990	0.1466	0.9983	0.1774	0.9987	0.1492	0.9983	0.1672
$T_{1.7-0.1}$	0.9926	0.2232	0.9936	0.1796	0.9947	0.1764	0.9918	0.1988	0.9929	0.1826
T_{oz}	0.9986	0.1327	0.9993	0.1079	0.9988	0.1285	0.9989	0.1208	0.9988	0.1229
T_e	0.9988	0.1513	0.9990	0.1522	0.9990	0.1438	0.9992	0.1224	0.9993	0.1156
C_{oz}	0.9574	3.8985×10^{-5}	0.9543	4.1372×10^{-5}	0.9607	4.8368×10^{-5}	0.9552	4.8551×10^{-5}	0.9594	4.2092×10^{-5}
C_e	0.9992	6.2400×10^{-6}	0.9983	8.2812×10^{-6}	0.9978	9.4128×10^{-6}	0.9982	9.2349×10^{-6}	0.9979	9.7190×10^{-6}
$PMV_{0.1}$	0.9963	0.0428	0.9979	0.0401	0.9964	0.0456	0.9955	0.0544	0.9972	0.0405
$PD_{0.1}$	0.9924	0.3565	0.9952	0.285	0.9927	0.3405	0.9954	0.2876	0.9925	0.3359

Table 7 Prediction performance of different surrogate models for the output variables.

Output	BPNN	RSM	Kriging	SVR
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	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
$T_{1.8}$	0.9979	0.1998	0.9976	0.2156	0.9978	0.2060	0.9955	0.2923
$T_{1.7-0.1}$	0.9929	0.2131	0.9930	0.2111	0.9943	0.1911	0.9731	0.4140
T_{oz}	0.9985	0.1405	0.9968	0.2100	0.9990	0.1167	0.9977	0.1751
T_e	0.9990	0.1470	0.9974	0.2320	0.9995	0.1000	0.9943	0.3460
C_{oz}	0.9510	4.015×10^{-5}	0.9206	5.109×10^{-5}	0.9476	4.152×10^{-5}	0.6771	1.031×10^{-5}
C_e	0.9992	5.804×10^{-6}	0.9988	7.208×10^{-6}	0.9993	5.472×10^{-6}	0.9917	1.917×10^{-6}
PMV _{0.1}	0.9963	0.0465	0.9934	0.0621	0.9962	0.0471	0.9820	0.1023
PD _{0.1}	0.9928	0.3567	0.9900	0.4208	0.9945	0.3102	0.9715	0.7093

3.5. Multi-objective optimization results

To quantitatively evaluate the quality and stability of the NSGA-III Pareto fronts, HV, GD, IGD, and diversity metrics are calculated from ten independent runs with different random seeds. The results are summarized in Table 8. The high HV and low GD and IGD values indicate good convergence and coverage, while the small standard deviations demonstrate stable optimization performance.

To balance the conflicting objectives among thermal comfort, ventilation performance, and energy utilization efficiency of the IPC system, the NSGA-III algorithm is employed to obtain the Pareto fronts under four cooling load conditions, as shown in Fig. 13. Each data point represents a non-dominated solution under the corresponding cooling load condition, where further improvement of one objective cannot be achieved without sacrificing other objectives. The color scale indicates the corresponding PCB cooling ratio (η).

As observed from Fig. 13, significant trade-offs and coordinated variation patterns exist among E_T , ε , and PD. Under all investigated cooling load conditions, E_T and ε exhibit an overall positive correlation, indicating that improved ventilation efficiency is generally accompanied by enhanced energy utilization efficiency. However, the draft discomfort index PD shows an evident conflicting relationship with these two objectives. To achieve higher energy utilization efficiency or ventilation efficiency, the supply velocity needs to be increased, which inevitably increases PD and consequently compromises local thermal comfort.

A comparison among different cooling load conditions reveals that the spatial distribution and morphology of the Pareto solution sets undergo significant shifts with increasing q . Under low cooling load conditions (see Fig. 13(a) and Fig. 13(b)), the Pareto fronts are relatively sparse and mainly distributed in the low- η region (purple and dark blue regions). Under these conditions, the system exhibits high energy utilization potential ($E_T > 1.25$) and a low risk of draft discomfort. As the cooling load increases to 250 W/m² (see Fig. 13(d)), the optimal solution set satisfying thermal comfort constraints shifts toward the high supply velocity region due to severe heat accumulation. Consequently, the overall PD value increases significantly, from approximately 10% to above 15%, while the E_T value decreases and the Pareto front becomes flatter and more concentrated.

Furthermore, the color variation reveals the decision importance of η in the multi-objective optimization process. Under high cooling load conditions (see Fig. 13(d)), the Pareto optimal solutions are mainly distributed in the high- η region (red region), indicating that enhanced heat transfer induced by the PCB units becomes a critical strategy for compensating for the reduction in energy utilization efficiency of the IJV system and maintaining the overall system performance under extreme operating conditions. The distribution characteristics of the Pareto fronts provide intuitive guidance for selecting optimal operating parameters according to different engineering priorities, such as energy efficiency-

oriented or thermal comfort-oriented operation. The Pareto-optimal solutions are further evaluated using the entropy-weight TOPSIS method, and the optimal design parameters identified under different cooling load conditions are summarized in Table 9.

Based on the feasible design domains and optimization results, a practical parameter-selection procedure can be established for IPC system design. First, the design scenario is determined according to the required cooling load. Then, an appropriate PCB cooling ratio (η) is selected according to the corresponding feasible domain, followed by the determination of the supply velocity (v_s) and supply temperature (T_s) within their feasible ranges. Finally, the parameter combination can be selected according to the specific requirements for thermal comfort, indoor air quality, and energy efficiency, with the parameter priority informed by the Sobol sensitivity results. This procedure provides a clear and systematic sequence for translating the identified feasible design domains into practical engineering design guidance.

Table 8 Performance evaluation metrics of NSGA-III obtained from ten independent runs.

Algorithm	Number of runs	HV	GD	IGD	Diversity
NSGA-III	10	0.8819 ± 0.0032	0.0028 ± 0.0008	0.0247 ± 0.0021	0.7516 ± 0.0406

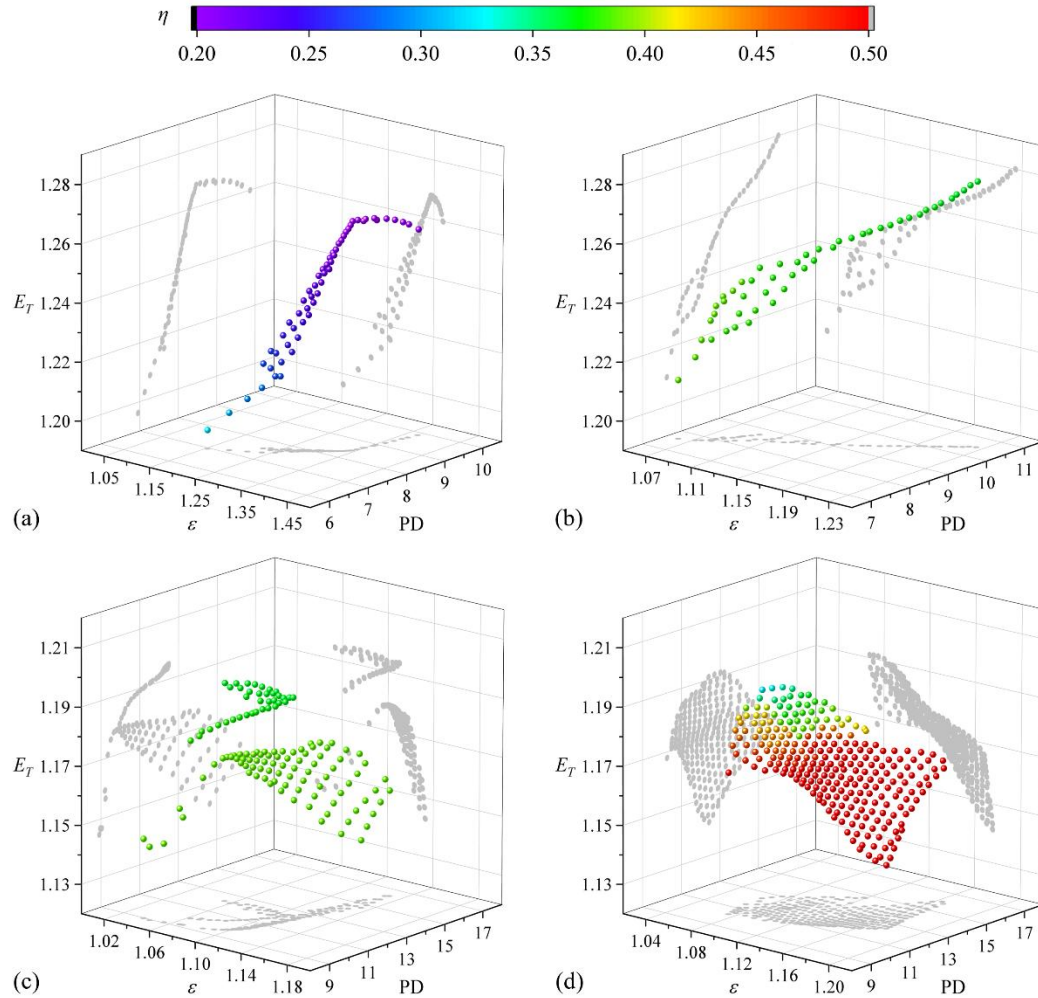


Fig. 13. Comparison of Pareto fronts under four different cooling load conditions. (a) $q = 100\text{W/m}^2$; (b) $q = 150\text{W/m}^2$; (c) $q = 200\text{W/m}^2$; (d) $q = 250\text{W/m}^2$.

Table 9 Optimal design parameters under different cooling loads

q (W/m ²)	v_s (m/s)	T_s (°C)	η (–)
100	1.50	19.54	0.28
150	1.52	19.56	0.50
200	1.77	18.09	0.49
250	2.12	17.97	0.50

3.6. Performance verification and contour analysis of optimized cases

To demonstrate the improvement of indoor thermal environment achieved by the multi-objective optimization model, the highest cooling load condition ($q = 250$ W/m²) is selected as a representative and most demanding scenario. The baseline case is defined using the midpoint values of the prescribed design parameter ranges ($v_s = 2.10$ m/s; $T_s = 18.50$ °C; $\eta = 0.35$), providing a representative reference condition for comparison with the optimized solution. The airflow and temperature distributions of the baseline case and the Pareto optimal solution (optimized case) ($v_s = 2.12$ m/s; $T_s = 17.97$ °C; $\eta = 0.5$) are compared, as shown in Fig. 14.

As shown in Fig. 14, the baseline case exhibits apparent thermal accumulation and insufficient contaminant removal capacity due to the lack of coordinated regulation among design parameters. Most of the indoor region exceeds 28 °C, accompanied by noticeable CO₂ accumulation within the occupied zone. In contrast, the optimized case achieves a more uniform temperature distribution through the coordinated adjustment of the v_s and η . The induced airflow generated by the PCB units interacts effectively with the fresh air supplied by the IJV system, promoting enhanced air mixing and eliminating local thermal stagnant regions. Meanwhile, the contaminant concentration within the occupied zone is maintained at a lower level. These results demonstrate that the proposed optimization framework effectively identifies indoor airflow organization and environmental control performance under high cooling load conditions.

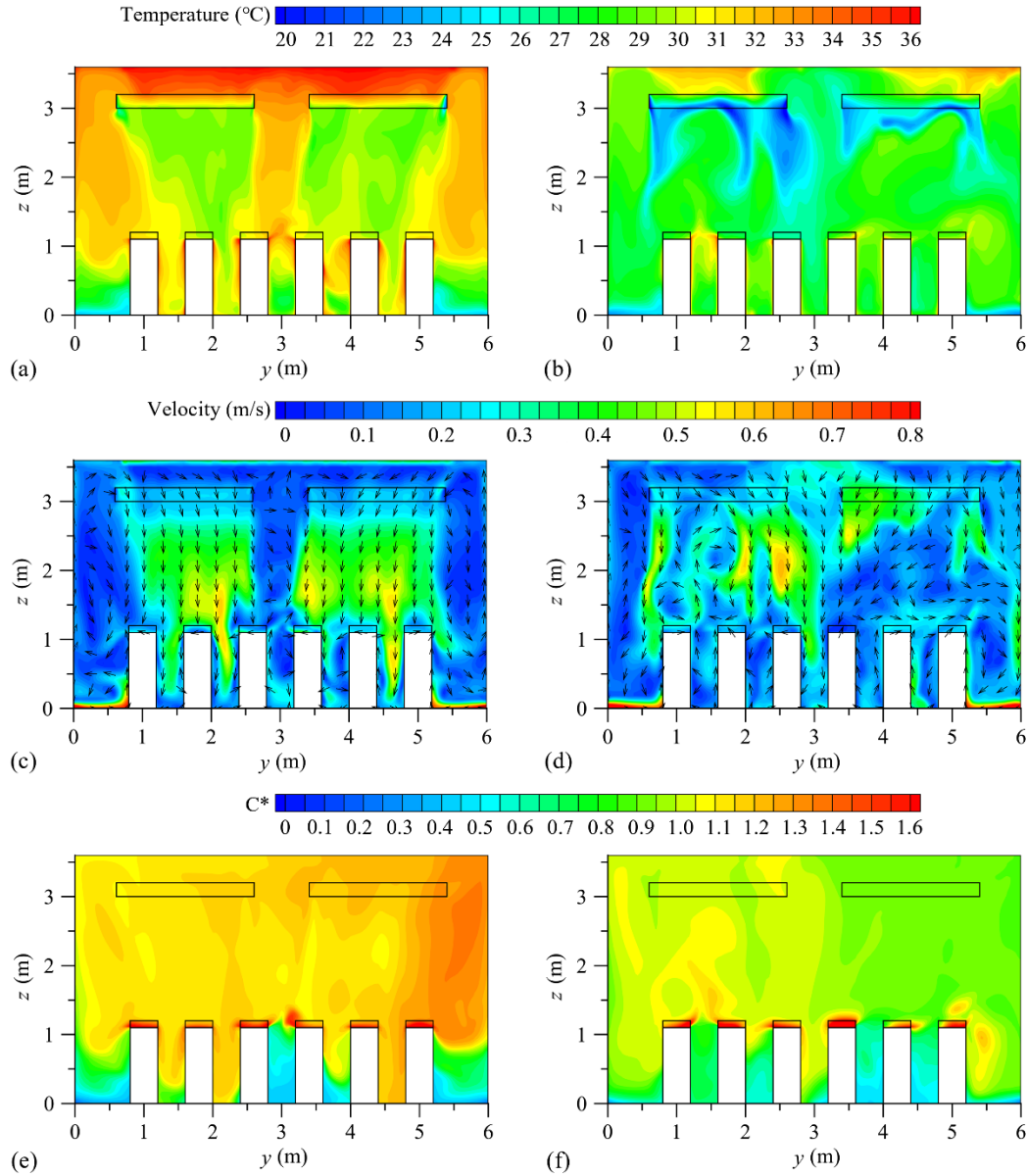


Fig. 14. Comparison of indoor temperature, velocity, and CO₂ concentration contours the initial and optimized cases. (a)(c)(e) baseline case; (b)(d)(f) optimized case.

Fig. 15 further compares the variations of the evaluation indicators, demonstrating the stable prediction capability and performance improvements of the proposed optimization model across the entire range of cooling load conditions. As shown in Fig. 15, in terms of thermal environment control, the optimized solutions maintain the average air temperature at 1.8 m height ($T_{1.8}$) within the design threshold under different cooling load conditions. The excessive temperature deviations observed in the baseline cases, including overcooling under low cooling loads and overheating under high cooling loads, are effectively corrected.

Although the supply velocity needs to be moderately increased under high cooling load conditions to satisfy the temperature requirements, the optimized design solutions still maintain the draft rate (PD) within the acceptable comfort criterion of 20%. Moreover, the optimized cases consistently achieve higher ventilation efficiency (ε) than the baseline cases. The good agreement between the quantitative

performance indicators and the qualitative flow field distributions demonstrates that the proposed optimization framework based on the BPNN surrogate model and evolutionary algorithm can effectively balance thermal comfort, ventilation efficiency, and energy utilization efficiency in complex ventilation environments.

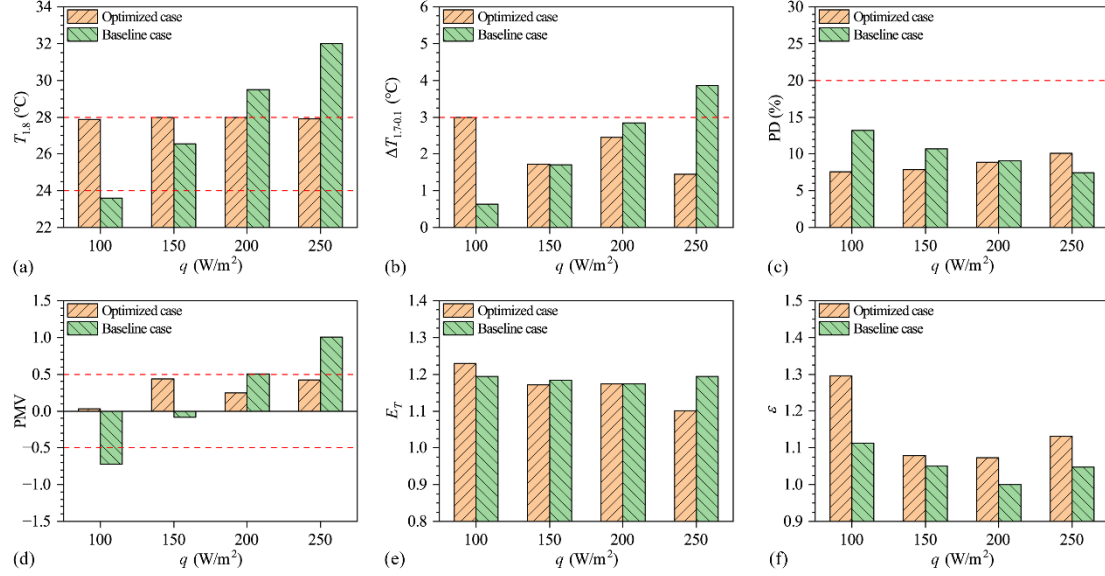


Fig. 15. Comparison of six performance indicators before and after optimization.

4. Conclusions

The thermo-physical characteristics and optimal operating strategies of the impinging jet ventilation and passive chilled beam combined (IPC) systems are investigated through CFD simulations, Sobol global sensitivity analysis, and the BPNN-NSGA-III optimization framework. The main conclusions are summarized as follows:

(1) The airflow organization of the IPC system is significantly regulated by the threshold effect of cooling load intensity. With an increase in the cooling load q from 100 to 250 W/m², the airflow pattern is transformed from a stable downward cold jet-dominated flow to a strong buoyancy-driven turbulent flow. Under high cooling load conditions, the momentum interaction between the upward thermal plume and the downward airflow induced by the PCB units results in heat and contaminant accumulation near the ceiling, indicating that cooling load intensity is a critical factor governing the stability of airflow organization in IPC systems.

(2) The feasible design parameter domains exhibit nonlinear variation characteristics. The feasible solution space initially expands and subsequently contracts with increasing cooling load, reaching the highest adjustment redundancy at 150 W/m². As the cooling load continues to increase, the centroid of the feasible domain is significantly shifted within the multi-dimensional design space, toward higher supply velocity, lower supply temperature, and higher PCB cooling ratio (η). This indicates that the tolerance of the IPC system to parameter fluctuations is substantially reduced under extreme operating conditions, where precise coupling of multiple design parameters is required to maintain acceptable performance.

(3) The PCB cooling ratio (η) is a key factor in the coupled regulation of the IPC system. Sensitivity analysis demonstrates that the total-order effect of η is significantly higher than its first-order effect, indicating strong nonlinear interactions between η and other parameters in improving the energy utilization coefficient (E_T) and ventilation efficiency (ϵ). Enhancing the induced heat transfer of PCB

units serves as the fundamental mechanism for compensating the reduction in forced ventilation efficiency and improving airflow uniformity.

(4) The data-driven optimization framework exhibits excellent robustness. The BPNN surrogate model achieves high prediction accuracy ($R^2 > 0.98$), and the combination with the NSGA-III algorithm effectively resolves the trade-off between thermal comfort and energy efficiency. Across the entire cooling load range, the optimized solutions correct the overcooling issue under low-load conditions and overheating issue under high-load conditions. Meanwhile, the indoor air quality is significantly improved while maintaining PD < 20%, providing theoretical support for the refined regulation of IPC systems.

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Nomenclature

IPC	Impinging jet ventilation and passive chilled beam combined system
IJV	Impinging jet ventilation
PCB	Passive chilled beam
v_s	Supply velocity (m/s)
T_s	Supply temperature (°C)
η	PCB cooling ratio (–)
q	Cooling loads (W/m ²)
$T_{1.8}$	Air temperature at 1.8 m (°C)
T_e	Exhaust temperature (°C)
T_{oz}	Occupied zone temperature (°C)
E_T	Energy utilization coefficient (–)
$\Delta T_{1.7-0.1}$	Vertical temperature difference between 1.7 m and 0.1 m (°C)
ε	Ventilation effectiveness (–)
PMV	Predicted mean vote (–)
PD	Percentage of dissatisfied (%)
S_i	First-order sensitivity index (–)
S_{Ti}	Total-order sensitivity index (–)

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