

Appearance Optimization of Environmental Conditioning Equipment: Multi-Physical Field Coupling & Optimization Algorithm Solution

Wen Xinyi¹, Qing Haotian¹ & Wu Zechan¹

¹ Geely University of China, China

Correspondence: Wen Xinyi, Geely University of China, Chengdu, Sichuan, 641400, China.

Received: March 2, 2025; Accepted: March 19, 2025; Published: March 21, 2025

Abstract

For indoor air quality control equipment optimization, data on **ACs**, **humidifiers**, and purifiers is collected. **Shape optimization models** are built for each to analyze shape factor impacts on functions and obtain optimal shapes and sizes[1]. Then a 3-in-1 device **appearance optimization model** is established to maximize energy efficiency, human comfort, purification, and humidification effects.

First, air conditioning temperature field optimization analyzes unit placement, inlet/outlet, and wind speed/volume. With **heat conduction**, **Navier-Stokes**, **and energy equations**, a model of indoor airflow and temperature is built. Particle swarm optimizer, finite difference discretizes, **SIMPLE solves**, and **adaptive mesh improves accuracy** for **uniform temperature**.

Secondly, for air purifier shape optimization, a model linking purification effect and shape is set up, with a multiphysical coupling model of particle motion, airflow, pollutant diffusion, and filtration efficiency for efficient purification. The finite difference method discretizes relevant equations and turns partial differential equations into algebraic ones for solving, and the gradient descent method[2] is employed to obtain optimal shape parameters, ultimately finding the best shape and size to maximize purification.

Thirdly, for humidifier performance optimization, consider its role in vapor processes. Build a math model integrating evaporation rate, diffusion, and shape geometry for **multi-quantity coupling**. Use **simulated annealing**[3] to iteratively find the optimal, achieving precise humidification control and optimal shape/size.

Finally, integrate models of the previous three problems for the three-in-one environmental regulator. Build a **hierarchical optimization model** with **multi-physical field coupling**[4]. Use multi-objective particle swarm genetic algorithm for **overall performance optimization**[5]. Explore field-volume coupling-based hierarchical nested optimization algorithm to handle **multifunctional integration**.

This study constructs a full optimization design system. Despite physical model simplification limitations, it's improvable. The results are extendable to other environmental conditioning equipment optimization.

Keywords: environmental regulator, multi-physical field coupling, multi-objective optimization, particle swarm algorithm, hierarchical optimization, multi-objective genetic algorithm, annealing algorithm

1. Problem Analysis

1.1 Restatement of the Problem

The improvement in people's quality of life has prompted the need for air-conditioning products to have multifaceted functions to meet people's needs. This is a complex engineering problem of multi-objective optimization of a device that combines the functions of an air conditioner, humidifier, and air purifier in a limited space. The core lies in optimizing the shape of the equipment based on aerodynamics to achieve the best temperature regulation, air purification, and humidification under specific room size and equipment constraints. The problem can be split into two single-function optimizations and one multi-function integrated optimization problem, each of which takes into account airflow characteristics, efficiency targets, and physical constraints. Solving this problem requires a combination of computational fluid dynamics (CFD) modeling, multi-objective optimization algorithms, etc.while taking into account equipment performance, energy efficiency, and user experience.

1.2 Analysis of Question 1

The air conditioning profile optimization problem requires a comprehensive consideration of various factors to achieve efficient performance. Firstly, a three-dimensional temperature field model integrating heat conduction,

convection, and radiation is established, and the indoor space cells are divided based on the law of energy conservation, and the distribution of temperature and velocity fields under different operating conditions is simulated using computational fluid dynamics methods. The finite difference method is applied to discretize the model, and the mesh is divided spatially to approximate the partial derivatives by difference, and temporally to advance the computation in a suitable format.

1.3 Analysis of Question 2

The key to optimizing the shape of an air purifier is to establish a multi-physical quantity coupling model covering particle movement, airflow field, pollutant diffusion, and filtration efficiency, discretize the relevant equations by using the finite difference method, and convert the partial differential equations into algebraic equations for solving, to obtain the data of the airflow field, etc., and then optimize the shape parameters iteratively with the purification effect as the objective function by using the gradient descent method to finally determine the optimum shape and size for achieving the maximization of the purification effect. Finally, the optimal shape and size are determined to maximize the purification effect and achieve the purpose of high-efficiency purification.

1.4 Analysis of Question 3

Using the theory of wet air thermodynamics and mass and heat transfer combined with computational fluid dynamics, the water vapor diffusion and mass transfer model is constructed to simulate the spatial diffusion of water vapor and analyze the influence of the shape on the humidification effect and range. Taking humidification uniformity, response speed, and efficiency as the objectives, multivariate optimization algorithms, such as the simulated annealing algorithm, are used to solve the problem with the shape parameter as the decision variable. At the same time, considering the water tank capacity and other practical factors, a constrained optimization model is established to prevent over-humidification and condensation. Through numerical simulation, the performance of different shapes under various humidity conditions is examined to ensure that the design can be reliably adapted to the environment, and the optimal shape is determined to enhance the humidification performance.

1.5 Analysis of Question 4

Comprehensive optimization of three-in-one equipment is a multi-objective optimization problem, aiming to realize the optimal combination of three functions under a unified shape. Hierarchical analysis can be used to clarify the function weights, construct a comprehensive performance evaluation index system, and use multi-objective optimization algorithms such as NSGA-II to find the Pareto optimal solution set. It is necessary to consider the mutual influence of multiple factors, described by a coupling model, such as temperature and humidity, airflow, and the purification effect associated. The optimization should take into account multiple objectives such as energy efficiency, comfort, and practical factors such as structural layout, manufacturing cost, and maintenance convenience. Numerical simulation and sensitivity analysis are used to assess the stability of the design scheme, to ensure that the equipment performs well under all kinds of working conditions, to realize multi-functional synergistic operation, to satisfy diversified needs, and to enhance the overall efficiency and practicability of the equipment.

2. Assumptions

Space and environment assumptions: room $5 \times 8 \times 3$ m regular rectangle, no barriers, unpressurized air and physical stability, temperature diffusion exponentially attenuated, water vapor diffusion according to Fick's law and ignoring the relevant effects, no pollutant response, wall insulation, the air outlet is ideally homogeneous, the initial uniform distribution.

Motion and role-related assumptions: particles are subject to airflow, gravity, Brownian force, and no interaction, airflow with a potential flow model superimposed on the impact of components, power and volume, flow rate related, response time, and the standard deviation of the field quantity, the role of the components is only considered to be superimposed on the airflow, the purification is in line with the first-order decay law.

Optimization and size-related assumptions: linear weighting of the objective function index, the equipment size is continuous and then discrete according to the process, and the strength of the physical field coupling is unchanged.

3. Notations

| symbol | Definitions | unit |
|-----------|----------------------------|------|
| \vec{v} | velocity vector | m/s |
| au | viscous stress tensor | Pa |
| \vec{g} | gravitational acceleration | m/s² |

52

| β | coefficient of thermal expansion | 1/ K | | | |
|---------------------------------|--|-----------------|--|--|--|
| eta_c | Concentration Expansion Coefficient | m³/kg | | | |
| eta_h | Humidity Expansion Coefficient | 1/% | | | |
| T | temperature field | K or °C | | | |
| H | relative humidity field | % | | | |
| С | Pollutant concentration field | $\mu g/m^3$ | | | |
| D_Y | Water vapor diffusion coefficient | m²/s | | | |
| D_C | Pollutant dispersion coefficient | m²/s | | | |
| k | thermal conductivity | $W/(m \cdot K)$ | | | |
| c_{v} | constant-pressure specific heat capacity | J/(kg·K) | | | |
| L_v | Latent heat of vaporization of water | J/kg | | | |
| K_m | mass transfer coefficient | m/s | | | |
| A_s | contact area | m² | | | |
| Y_{s} | Saturated water vapor mass fraction | kg/kg | | | |
| η_{filter} | Filter efficiency | - | | | |
| V_{total} | Total volume of equipment | m^3 | | | |
| Q_{total} | total flow | m³/h | | | |
| P_{total} | total power | W | | | |
| | Time to reach 95% of target | S | | | |
| \overrightarrow{X} | Design Variables Vector | - | | | |
| f_i | The ith objective function | - | | | |
| w_i | Objective function weight coefficients | - | | | |
| Δp | pressure loss | Pa | | | |
| η_{fan} | Fan efficiency | - | | | |
| ϕ | UCSV | - | | | |
| Γ | Generalized diffusion coefficient | m²/s | | | |
| $\mathcal{S}_{oldsymbol{\phi}}$ | Common source items | - | | | |
| Ř | Distance to equipment | m | | | |
| α | thermal diffusion coefficient | m²/s | | | |
| μ | aerodynamic viscosity | Pa·s | | | |
| σ | standard deviation | - | | | |
| ϵ | Convergence criterion threshold | - | | | |
| heta | Horizontal air supply angle | 0 | | | |
| ϕ | Vertical air supply angle | 0 | | | |
| d_{in} | Air inlet size | m | | | |
| d_{out} | Air outlet size | m | | | |

4. Modeling and Solving

4.1 Establishment and Solution of Temperature Field Optimization Model for Problem 1

4.1.1 Analysis of Ideas for Question One

To optimize the temperature field of air conditioning and refrigeration systems, it is necessary to establish a three-dimensional temperature field model that integrates heat conduction, convection, and radiation, divides the indoor space into multiple tiny units based on the law of energy conservation, then discretize the temperature field model by using the finite-difference method, select the particle swarm optimization algorithm to determine the optimal parameters of the air conditioner, and combine it with adaptive mesh optimization to improve the calculation accuracy.

4.1.2 Three-Dimensional Temperature Field Modeling

To accurately present the indoor temperature field distribution, a three-dimensional temperature field model is established. The indoor space is gridded and each cell contains key parameters such as temperature, velocity, and pressure.

Describe the heat transfer motion in terms of Fourier's law:

$$\rho c \frac{\partial T}{\partial t} = \frac{\partial}{\partial x} (k \frac{\partial T}{\partial x}) + \frac{\partial}{\partial y} (k \frac{\partial T}{\partial y}) + \frac{\partial}{\partial z} (k \frac{\partial T}{\partial z}) + Q$$
 (1)

Represent convective motion by the N - S equation:

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} = 0 \tag{2}$$

$$\rho(\frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} + w\frac{\partial u}{\partial z}) = -\frac{\partial p}{\partial x} + \mu(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} + \frac{\partial^2 u}{\partial z^2})$$
(3)

$$\rho(\frac{\partial w}{\partial t} + u\frac{\partial w}{\partial x} + v\frac{\partial w}{\partial y} + w\frac{\partial w}{\partial z}) = -\frac{\partial p}{\partial z} + \mu(\frac{\partial^2 w}{\partial x^2} + \frac{\partial^2 w}{\partial y^2} + \frac{\partial^2 w}{\partial z^2}) + \rho g\beta(T - T_0)$$
 (4)

Radiative heat transfer is described by the Stefan-Boltzmann law:

$$q = \sigma \epsilon (T_1^4 - T_2^4) \tag{5}$$

4.1.3 Multi-Objective Particle Swarm Optimization Algorithm Steps

To find the three-dimensional temperature field model, a particle swarm optimization algorithm is used to determine the optimal parameters of the air conditioner, combined with adaptive characteristics to cope with the complex environment. The steps of the algorithm are as follows: first build the optimization objective function, including temperature uniformity, energy consumption, and comfort index:

$$F_1 = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (T_i - T_{avg})^2}$$
 (6)

$$F_2 = \int_0^t P(t)dt \tag{7}$$

At this point, the submersible is only influenced by ocean currents.

$$F_3 = \sum_{i=1}^{N} w_i \left| V_i - V_{comfort} \right| \tag{8}$$

Where F1denotes the temperature field uniformity, N is the number of grids, Ti is the temperature of the ith grid point, and Tavg is the average temperature;F2denotes the energy consumption, P(t) is the instantaneous power, and F3 denotes the comfort metrics, Vi is the actual speed, Vcomfortis the range of comfortable speeds, and wiis the weighting coefficient.

The comprehensive optimization objective function is:

$$F = \alpha_1 F_1 + \alpha_2 F_2 + \alpha_3 F_3 \tag{9}$$

Where $\alpha 1, \alpha 2$, and $\alpha 3$ are weighting coefficients that need to be adjusted according to specific needs.

4.1.4 Integrated Modeling

To improve the optimization efficiency and accuracy, a comprehensive model is established. This model combines computational fluid dynamics analysis with genetic algorithm optimization, and the optimal solution is foraged through iterative calculations. The finite difference method is used to discretize the control equations:

$$\frac{\partial^2 u}{\partial x^2} \approx \frac{u(x + \Delta x) - 2u(x) + u(x - \Delta x)}{\Delta x^2} \tag{10}$$

Boundary conditions include:

- Wall no-slip boundary conditions: u = v = w = 0
- Air inlet: $u = u_{in}$, $T = T_{in}$
- Air vents: $\partial \varphi / \partial n = 0$

Initial conditions are:

- t = 0 when the room temperature is T_0
- t = 0 when the room temperature is 0

The constraints of the model include:

- 1. Air conditioning volume constraints: $V \le 0.1 \text{ m}^3$
- 2. Power constraints: $P \le 1800W$
- 3. Outgoing air velocity constraints: $v_{out} \le 8.0 \text{ m/s}$
- 4. Flow constraints: $Q_{in} = Q_{out} \le 600 \text{ m}^3/\text{h}$
- 4.1.5 Adaptive Mesh Optimization Solution Strategy

To improve computational efficiency and precision, an adaptive grid optimization policy is adopted:

$$\Delta x_i = \Delta x_{min} + (\Delta x_{max} - \Delta x_{min}) \exp(-\gamma |\nabla T|)$$
 (11)

where Δxi is the grid size, Δx min and Δx max are the minimum and maximum grid sizes, respectively, γ is the adjustment factor, and $|\nabla T|$ is the mode of the temperature gradient.

The SIMPLE algorithm is used to solve the flow field, with second-order windward format air separation and first-order implicit format time separation. To ensure the stability of the calculation, the CFL condition should be fulfilled:

$$CFL = \frac{u\Delta t}{\Delta x} \le 1 \tag{12}$$

Where objfun is the objective function, nvars is the number of design variables, lb and ub are the upper and lower bounds of variables, and nonloon is the nonlinear constraint function.

The three-dimensional temperature field model and optimization algorithm can obtain the optimal installation position of the air conditioner, the optimal layout of the air inlet and outlet, and the operation parameters, and achieve the optimal control of the indoor temperature field, which is the key theoretical guide for the installation and operation of the air conditioner. The model has excellent adaptability and scalability, and the optimization objectives and constraints can be adjusted according to the needs.

4.1.6 Visualization and Analysis of Problem 1 Model Solution Results

According to Matlab programming solution, the code structure and function are as follows:

- 1. Initialize graphic display and Chinese font parameters.
- 2. Define the problem parameters such as room dimensions air conditioning constraints, and grid division.
- 3. Solve the problem with MATLAB Particle Swarm Algorithm Toolbox with variables covering air conditioning location and wind parameters.
- 4. Weight the objective function to synthesize the temperature, airflow uniformity, and comfort.
- 5. Set constraints such as air conditioning air velocity.
- 6. Calculate the temperature and velocity field with a simplified model, actually need to solve the complete N S and energy equations.
- 7. Visualize the three-dimensional distribution of the temperature and velocity field and store high-resolution maps.

Analysis of the Solution Results:

Temperature field distributions illustrate the spatial variation of indoor temperature:

The local vortex zone facilitates the mixing of indoor air, and the optimized solution ensures cooling, reduces the temperature difference, and allows the wind speed in the personnel activity zone to be appropriate and the power to be qualified in terms of energy efficiency and comfort. Although the model is simple, it presents the key features of air conditioning, which can be used as a reference for engineering design. If there is enough time, we can use a more detailed model and incorporate more actual situations to improve the model and enhance the guiding value.

Optimization results show that:

Air velocity at the outlet maximum, with distance from the outlet increases and decreases, its flow direction by the air conditioning installation angle, and there is a local vortex area to help indoor air mixing.

Energy efficiency and comfort analysis:

The optimization scheme preserves cooling and moderates the local temperature difference so that the airflow velocity in the personnel activity area is appropriate and the system operating power is up to standard.

Although this model adopts some simplistic settings, it can still show the key features of the air-conditioning system very well and provide very useful references for actual engineering design. If there is enough time, the model can be made even better in the future by adopting a more detailed and complex physical model, and then taking into account more situations that will be encountered in practice.

Table 1. Results of the solution

| X | Y | Z | horizontal | Vertical | Wind | Outlet air |
|----------|----------|----------|------------|----------|---------|-------------|
| Location | Location | Location | angle | angle | speed | temperature |
| 4.007 | 2.5 | 1.5 | -33.2647 | -30.114 | 1.00008 | 17.00005 |

Temperature field 3D cut-away map: three orthogonal cut-aways are used to show the temperature distribution and the location of the air conditioner is labeled.

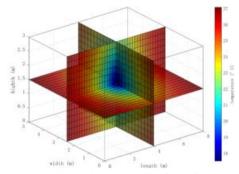


Figure 1. Three-dimensional distribution of indoor temperature field

Temperature isothermal surface maps: characterize the spatial distribution of temperature.

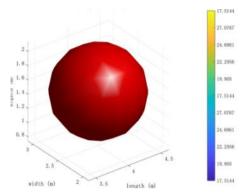


Figure 2. Isothermal surface distribution in indoor temperature

Airflow Field Streamline Diagram: Showing air flow paths through streamlines.

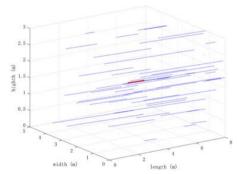


Figure 3. Indoor airflow field streamline distribution

Heat Map of Temperature Distribution at Different Altitudes: Shows the temperature distribution at different altitudes.

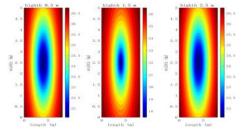


Figure 4. Uniformity temperature distribution map

Airflow Field Dynamic Animation: Create particle motion animations to visualize airflow movement.

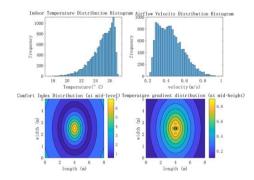


Figure 5. Comprehensive Analysis of Air Conditioner Performance

Comprehensive analysis plot: Contains temperature distribution histogram, speed distribution histogram, comfort index distribution, and temperature gradient distribution.

4.2 Problem 2 Establishment and Solution of Multi-Objective Particle Dispersion Optimization Model for Air Purifier

4.2.1 Analysis of Ideas for Question Two

Air purifier efficiency is affected by many factors, and the shape design is extremely critical to airflow organization and purification efficiency. Therefore, it is necessary to consider the correlation between airflow path, pollutant diffusion, and internal structure layout. A mathematical model integrating particle motion, airflow field, and filtration efficiency is constructed, which should incorporate the shape of the purifier as well as key geometric parameters such as air inlets and outlets. The multi-objective particle swarm algorithm is used to solve the problem with purification efficiency as the core optimization objective, taking into account the energy consumption and noise factors. In the process of solving, the model calculation results under different shape parameters are analyzed to obtain the optimal shape design with comprehensive performance, including the determination of specific shapes and precise dimensional parameters. The optimal shape is further drawn and its parameters are clearly labeled. Finally, a sensitivity analysis is performed to verify the stability and reliability of the design under different environmental conditions and parameter fluctuations, to achieve a good balance between purification efficiency, energy consumption, and noise.

4.2.2 Comprehensive Particle Motion Modeling

To analyze the air purification process, the Eulerian - Lagrangianmethod was used to construct a comprehensive particle motion model, which contains the airflow field and particle motion equations, which are interrelated to explain the complex physical phenomena during purification:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \, \vec{v}) = 0 \tag{13}$$

$$\frac{\partial(\rho\vec{v})}{\partial t} + \nabla \cdot (\rho \vec{v} \vec{v}) = -\nabla p + \nabla \cdot \tau + \rho \vec{g} + \vec{F}_{p}$$
 (14)

Where ρ is the air density, \vec{v} is the velocity vector, p is the pressure, τ is the viscous stress tensor, \vec{g} is the gravitational acceleration, and \vec{F}_p is the reaction of the particulate matter on the airflow.

For the movement of particles, the Lagrangian method was used to track the trajectory of each particle:

$$m_{p} \frac{d\overrightarrow{v_{p}}}{dt} = \overrightarrow{F_{D}} + \overrightarrow{F_{g}} + \overrightarrow{F_{B}} + \overrightarrow{F_{L}}$$
 (15)

Where m_p is the particle mass, $\overrightarrow{v_p}$ is the particle velocity, and the right-hand terms are drag, gravity, Brownian force, and lift, respectively:

$$\overrightarrow{F_{D}} = \frac{18\mu}{\rho_{p}d_{p}^{2}C_{c}}(\overrightarrow{v} - \overrightarrow{V_{p}}) \tag{16}$$

$$\overrightarrow{F_g} = m_p \, \overrightarrow{g} \, (1 - \frac{\rho}{\rho_p}) \tag{17}$$

$$\overrightarrow{F_B} = \zeta \sqrt{\frac{216\mu k_B T}{\pi^2 \rho_p d_p^5 \Delta t}} \tag{18}$$

$$\overrightarrow{F_L} = \frac{1}{8}\pi\rho d_p^2 C_L (\overrightarrow{v} - \overrightarrow{v_p})^2 \tag{19}$$

Where μ is the aerodynamic viscosity, ρ_p is the particle density, d_p is the particle diameter, C_c is the Cunninghamslip modifier, k_B is the Boltzmann constant, Tis the temperature, ζ is a normally distributed random number, C_L is the lift coefficient.

Capture efficiency modeling of filters considers multiple capture mechanisms:

$$\eta_{\text{total}} = 1 - \prod_{i=1}^{n} (1 - \eta_i) \tag{20}$$

Where η_i includes the trapping efficiency of mechanisms such as inertial collisions, interception, and Brownian diffusion:

$$\eta_{inertial} = \frac{Stk^2}{(Stk + 0.25)^2} \tag{21}$$

$$\eta_{interception} = \frac{1 - \alpha}{K_u} \frac{R^2}{1 + R} \tag{22}$$

$$\eta_{diffusion} = 2.9K_u^{-1/3}Pe^{-2/3} \tag{23}$$

Where Stk is the Stokes number, R is the retention parameter, Pe is the Peckley number, α is the filtration media fill rate, and K_u is the Kuwabara hydrodynamic factor.

4.2.3 Multi-Objective Particle Swarm Optimization Algorithm Steps

To solve this complex optimization problem, we propose a multi-objective particle swarm algorithm based on adaptive weights. The optimization objective function includes:

$$v_{i,d}^{k+1} = w \times v_{i,d}^{k} + c_1 \times r_1 \times (p_{i,d}^{k} - x_{i,d}^{k}) + c_2 \times r_2 \times (g_d^{k} - x_{i,d}^{k})$$
(24)

Where $v_{i,d}^{k+1}$ is the velocity of the ith particle in the dth dimension in the K+1 iteration

Energy consumption targets:

$$f_2 = \frac{Q\Delta p}{\eta_{fan}} \tag{25}$$

Noise Objectives:

$$f_3 = 10\log_{10}(\frac{Q^3\Delta p}{Q_0^3\Delta p_0}) \tag{26}$$

Integrated objective function:

$$F = w_1 f_1 - w_2 f_2 - w_3 f_3 \tag{27}$$

Where w_i is the adaptive weight coefficient, which is dynamically adjusted according to the current distribution of the population:

$$w_{i} = \frac{1/\sigma_{i}^{2}}{\sum_{j=1}^{3} 1/\sigma_{j}^{2}}$$
 (28)

Where σ_i is the standard deviation of the ith objective function in the current population.

Design variables include:

- Purifier external size parameters: length L, width W, height H
- Air inlet parameters: location, size, quantity
- Parameters of air outlets: location, size, quantity
- Filter parameters: area, thickness, material properties

Constraints include:

Total volume constraints:

$$V_{total} \le V_{max} \tag{29}$$

Flow constraints:

$$Q_{\min} \le Q \le Q_{\max} \tag{30}$$

Pressure drop constraints:

$$\Delta p \le \Delta p_{\text{max}}$$
 (31)

Geometric constraints:

$$L_{min} \le L \le L_{max}$$
$$W_{min} \le W \le W_{max}$$

 $H_{min} \le H \le H_{max}$ The main steps of the algorithm include:

- Initialization population: generates an initial design solution that satisfies the constraints.
- Evaluating individual fitness: calculating flow field distributions, performing particle trajectory simulations, calculating purification efficiencies, evaluating energy consumption and noise, and calculating integrated objective function values.
 - 3. Selection operation: using an elite strategy based on non-dominated sorting.
 - Crossover operation: using the adaptive simulated binary crossover (SBX) operator: 4.

$$\beta = \begin{cases} (2u)^{\frac{1}{\eta_{c+1}}} & \text{if } u \le 0.5\\ \left(\frac{1}{2(1-u)}\right)^{\frac{1}{\eta_{c+1}}} & \text{if } u > 0.5 \end{cases}$$
 (32)

$$x_1^{new} = 0.5[(1+\beta)x_1 + (1-\beta)x_2] x_2^{new} = 0.5[(1-\beta)x_1 + (1+\beta)x_2]$$

Mutation operation: Adaptive polynomial mutation is used: 5.

$$x^{new} = x + (x_u - x_l)\delta (33)$$

$$\delta = \begin{cases} [(2u)^{\frac{1}{\eta_{m+1}}} - 1] & \text{if } u \le 0.5\\ [1 - (2(1-u))^{\frac{1}{\eta_{m+1}}}] & \text{if } u > 0.5 \end{cases}$$
(34)

- Updating populations: merging parent and child populations, selection based on non-dominated ordering and crowding distance.
 - Adaptive adjustment of control parameters:

Crossing probabilities:

$$p_c = p_{c0}(1 + \alpha exp(-\beta g/G)) \tag{35}$$

Mutation probability:

$$p_m = p_{m0}(1 + \gamma exp(-\delta g/G)) \tag{36}$$

 $p_m = p_{m0}(1 + \gamma exp(-\delta g/G))$ Where g is the current generation and G is the maximum generation.

Check convergence conditions: maximum number of generations reached, Pareto front stabilized, objective function value converged.

Multi-objective particle swarm optimization algorithm has significant advantages, it balances the objectives of purification efficiency, energy consumption, and noise by dynamically adjusting the weighting coefficients, ensures the practicality of the solution with full consideration of the physical mechanism, improves the search efficiency by using adaptive operation operator, and accelerates the convergence speed by applying the elitist strategy, which provides a highly efficient and practical solution for the related optimization design.

4.2.4 Visualization and Analysis of the Results of the Model Solution for Problem 2

In the code implementation of air purifier optimization design, a shape optimization model based on a multiobjective particle swarm algorithm is constructed, with geometric dimensions and inlet/outlet parameters as optimization variables, and the objective function matrices of purification efficiency, energy consumption, and noise are borrowed for multi-dimensional evaluation, and the non-dominated sorting multi-objective optimization is realized by using MATLAB's gamultiobj function, and the optimal solution is reasonably set up. In the calculate concentration field function, a simplified physical model is used to simulate the pollutant concentration and velocity fields, the concentration field describes the diffusion characteristics with an exponential decay model, and the velocity field constructs a vector field to simulate the airflow; constraint function imposes constraints on the design variables, such as the volume, flow rate, and geometry, to ensure that the results comply with the actual engineering requirements. Constraints_function constrains the design variables such as volume, flow, and geometry to ensure that the results meet the actual engineering requirements; patch, slice, quiver, and streamline functions and Pareto front diagrams are used to construct a visualization system to display the optimization results; and finally, the optimization results (geometric and performance parameters) are saved in an Excel table and high-definition images, and the key performance indicators are output using the print function to help intuitively understand the results.

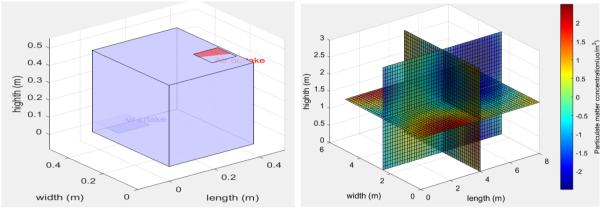


Figure 6. Optimal shape design for air purifiers

Figure 7. Indoor particulate matter concentration distribution

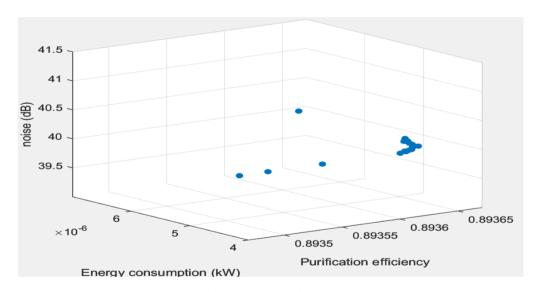


Figure 8. Pareto frontier

Table 2. Optimization results

| length | height | highth | air inlet X | air inlet Y | air Inlet Size | air outlet X | air outlet Y | air outlet Size |
|--------|--------|--------|----------------|----------------|-------------------|--------------|--------------|--------------------|
| 0.201 | 0.207 | 0.309 | 0.001 | 1.000 | 0.084 | 0.406 | 0.805 | 0.112 |
| 0.204 | 0.206 | 0.307 | 0.001 | 1.000 | 0.088 | 0.406 | 0.801 | 0.109 |
| 0.231 | 0.222 | 0.391 | 0.001 | 1.000 | 0.079 | 0.361 | 0.812 | 0.110 |
| 0.212 | 0.207 | 0.309 | 0.001 | 1.000 | 0.077 | 0.406 | 0.807 | 0.114 |
| 0.204 | 0.205 | 0.307 | 0.001 | 1.000 | 0.089 | 0.406 | 0.793 | 0.109 |
| 0.203 | 0.205 | 0.304 | 0.001 | 0.999 | 0.090 | 0.400 | 0.794 | 0.109 |
| 0.206 | 0.207 | 0.310 | 0.001 | 1.000 | 0.073 | 0.406 | 0.804 | 0.112 |
| 0.206 | 0.210 | 0.335 | 0.001 | 1.000 | 0.078 | 0.372 | 0.810 | 0.111 |
| 0.214 | 0.209 | 0.311 | 0.001 | 1.000 | 0.078 | 0.405 | 0.805 | 0.114 |

Final optimal external dimensions: 0.37 x 0.44 x 0.47 m

4.3 Problem 3 Establishment and Solution of Shape Optimization Model for Multi-Physics Coupled Humidifier

4.3.1 Analysis of Ideas for Question Three

When designing an air humidifier, a comprehensive mathematical model must be constructed, which should include an indoor humidity and temperature model, a water vapor evaporation model, and a humidifier geometry model. Through this model, the coupling of multiple physical quantities can be realized to accurately reflect the operating characteristics of the humidifier. Then, the simulated annealing algorithm is used to take the shape parameters of the humidifier as the decision variables and the humidification effect as the objective function. Through multiple iterations and accepting inferior solutions with a certain probability to avoid falling into local optimal solutions, the humidifier shape and size combinations that can achieve the best humidification effect are finally determined to realize precise control. Afterward, the simulation results are analyzed and verified to assess the performance under different working conditions and compared with actual data or experimental results. If deviations exist, the model is further optimized and more practical factors are taken into account to improve the reliability of the model and provide an accurate theoretical basis for the optimal design of the humidifier.

4.3.2 Optimization Modeling of Multi-Physics Coupled Transmission

Based on the principles of conservation of mass, conservation of momentum, and conservation of energy, we establish a coupled transport model containing the flow field, temperature field, and humidity field. First, the governing equations of the airflow field include the continuity equation and the momentum equation:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \, \vec{v}) = S_m \tag{37}$$

$$\frac{\partial(\rho\vec{v})}{\partial t} + \nabla \cdot (\rho \,\vec{v}\,\vec{v}) = -\nabla p + \nabla \cdot \tau + \rho \,\vec{g}\,\beta(T - T_0) + \rho \,\vec{g}\,\beta_c(C - C_0) \tag{38}$$

Where ρ is the gas mixture density, \vec{v} is the velocity vector, p is the pressure, τ is the viscous stress tensor, S_m is the mass source term, β is the thermal expansion coefficient, β_c is the concentration expansion coefficient, and T and C are the temperature and water vapor concentration, respectively.

Transport diffusion equation for water vapor:

$$\frac{\partial(\rho Y)}{\partial t} + \nabla \cdot (\rho \, \vec{v} \, Y) = \nabla \cdot (\rho D \nabla Y) + S_Y \tag{39}$$

Where Y is the mass fraction of water vapor, D is the diffusion coefficient, and S_Y is the water vapor source term. The energy transfer equation takes into account the effect of the latent heat of phase transition:

$$\frac{\partial(\rho h)}{\partial t} + \nabla \cdot (\rho \, \vec{v} \, h) = \nabla \cdot (k \nabla T) + S_h \tag{40}$$

Where h is the specific enthalpy, kis the thermal conductivity, and S_h is the energy source term.

Source term calculations for phase transition processes:

$$S_Y = K_m A_s (Y_s - Y) \tag{41}$$

$$S_h = -L_v S_Y \tag{42}$$

Where K_m is the mass transfer coefficient, A_s is the contact area, Y_s is the saturated water vapor mass fraction, and L_v is the latent heat of gasification.

For the optimization of the humidifier shape, we introduce the shape parameterization method:

$$\vec{x} = \vec{x_0} + \sum_{i=1}^{n} \alpha_i \, \vec{\phi_i} \tag{43}$$

Where \vec{x} is the shape coordinate, $\overrightarrow{x_0}$ is the base shape, $\overrightarrow{\varphi_i}$ is the shape basis function, and α_i is the shape parameter to be optimized.

4.3.3 Simulated annealing algorithm steps

To solve this complex optimization problem, we use a simulated annealing algorithm to follow the temperature changes in real time:

Temperature update target:

$$T_{k+1} = \alpha \times T_k \tag{44}$$

Where T_k is the current temperature, T_{k+1} is the temperature of the next iteration, and α is the coefficient of cooling, which usually takes values between (0, 1).

An adaptive Response Surface-based Multifield Coupled Optimization (ARMCO) algorithm is applied:

Humidification efficiency goals:

$$f_1 = 1 - \frac{1}{V} \int_V \left| \frac{RH - RH_{target}}{RH_{target}} \right| dV$$
 (45)

Where RH is the relative humidity and RH_{target} is the target humidity.

Uniformity goals:

$$f_2 = \sqrt{\frac{1}{V} \int_V (RH - \overline{RH})^2 dV}$$
 (46)

Energy consumption targets:

$$f_3 = \frac{Q\Delta p}{\eta_{fan}} + W_{humidifier} \tag{47}$$

Where Q is the air volume, Δp is the pressure drop, η_{fan} is the fan efficiency, $W_{humidifier}$ is the humidification power.

Response time goals:

$$f_4 = t_{95} (48)$$

Where t_{95} is the time required to reach 95% of the target humidity.

The integrated objective function uses an adaptive weighting approach:

$$F = \sum_{i=1}^{4} w_i f_i \tag{49}$$

$$w_i = \frac{\exp(-\lambda f_i/f_i^*)}{\sum_{j=1}^4 \exp(-\lambda f_j/f_j^*)}$$
 (50)

Where f_i^* is the desired value of the ith target and λ is the adaptive parameter.

Design variables include:

- Humidifier shape parameters: length L, width W, height H
- Inlet and outlet parameters: position, size, angle
- Parameters of humidification elements: position, number, operating parameters

Constraints include:

1. Volume constraints:

$$V_{total} \leq V_{max}$$

2. Humidification constraints:

$$Q_{water,min} \leq Q_{water} \leq Q_{water,max}$$

3. Relative humidity constraints:

$$RH_{min} \leq RH \leq RH_{max}$$

4. Power constraints:

$$P_{total} \leq P_{max}$$

Agent model update:

$$\widehat{y}(\vec{x}) = \sum_{i=1}^{m} \beta_i f_i(\vec{x}) + Z(\vec{x})$$
(51)

Where $\hat{y}(\vec{x})$ is the response surface prediction, $f_i(\vec{x})$ is the basis function and $Z(\vec{x})$ is the stochastic process component.

Adaptive sampling strategy:

$$EI(\vec{x}) = (y_{min} - \hat{y}(\vec{x}))\Phi(\frac{y_{min} - \hat{y}(\vec{x})}{\hat{s}(\vec{x})}) + \hat{s}(\vec{x})\Phi(\frac{y_{min} - \hat{y}(\vec{x})}{\hat{s}(\vec{x})})$$
(52)

Where EI is the expected improvement and $\hat{s}(\vec{x})$ is the predicted standard deviation.

Local search optimization:

A sequential quadratic programming (SQP) approach is used for local optimization:

$$\min_{\Delta \vec{x}} \quad \nabla F(\vec{x})^T \Delta \vec{x} + \frac{1}{2} \Delta \vec{x}^T H \Delta \vec{x}$$

$$s. t. \quad g_i(\vec{x}) + \nabla g_i(\vec{x})^T \Delta \vec{x} \le 0, i = 1, ..., m$$
(53)

Global convergence criterion:

- When the maximum number of iterations in the optimization process reaches a predefined value
- When the improvement after each iteration is less than a set threshold value
- Prediction error meets requirements

To improve the computational efficiency of the algorithm, we use the following strategy:

Grid adaptive refinement:

$$\Delta x_i = \Delta x_{min} + (\Delta x_{max} - \Delta x_{min}) exp(-\gamma | \nabla \phi |)$$
 (54)

where φ is the physical quantity of interest.

Parallel computing strategies: sample point parallel evaluation, multi-scale analysis parallelism, field volume solution parallelism

Convergence acceleration techniques: multigrid methods, preprocessing techniques, solution extrapolation

With the help of this optimization model and algorithm, the ideal shape of the humidifier, the optimal layout of the air inlet and outlet, and the optimal settings of the humidification components and operating parameters can be obtained. Although the model is complicated to compute, the appropriate numerical method and parallel computing strategy can get the required optimization results in an acceptable time, and the modular design of the model facilitates the subsequent expansion and improvement as needed.

4.3.4 Visualization and Analysis of Model Solution Results for Problem 3

Present the indoor humidity distribution by drawing the humidity distribution cloud, reflecting the humidity size with color; draw the humidification rate curve to show the humidification speed of different shapes of humidifiers over time; if time permits, it can also produce an animation of the water vapor diffusion path. Evaluate the humidity uniformity from the humidity distribution cloud, and calculate the standard deviation for quantitative analysis. Compare humidification rate curves to analyze humidification efficiency, combined with energy consumption trade-offs. Change the shape parameters to re-run the model, observe its impact on humidity distribution and humidification rate, and determine the sensitive parameters. Comprehensively consider humidity uniformity, humidification efficiency, and other factors, weigh the performance indicators, and select the optimal humidifier shape and size parameters based on the visualization results.

Visualization of results analysis:

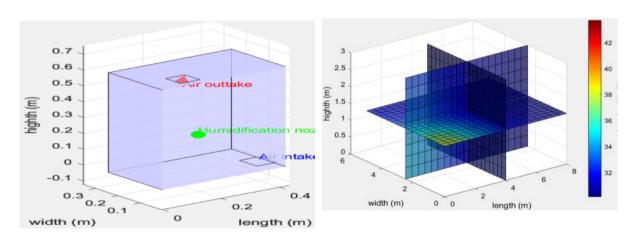


Figure 9. Humidifier optimized shape

Figure 10. Indoor relative humidity distribution

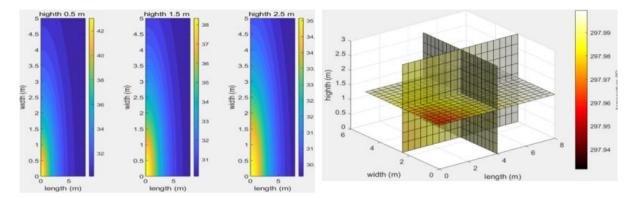


Figure 11. Humidity Uniformity Analysis

Figure 12. Indoor temperature distribution

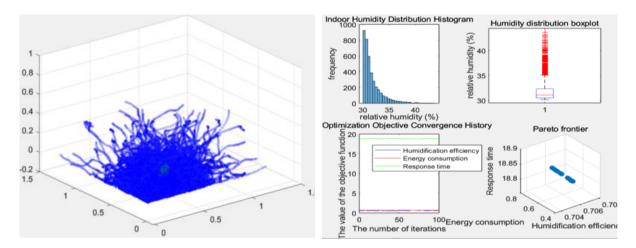


Figure 13. Water vapor diffusion process Time step: 70

Figure 14. Performance Evaluation

Visual display humidifier layout is reasonable, air inlet and outlet and nozzle location is conducive to airflow organization, humidity and temperature field is good, water vapor diffusion animation evidence of its design is effective. In the engineering application, the optimization result has obvious advantages in appearance, energy consumption, humidity distribution and response time, etc. Although the average humidity is not up to the standard, it can be improved by adjusting the parameters of the nozzle, increasing the humidity capacity, optimizing the airflow organization and increasing the self-adaptive strategy, which has a broad application prospect.

The optimization results are shown in Table 1 of the supporting material

The final optimal humidifier size is obtained: 0.42 x 0.25 x 0.63 m

4.4 Problem 4 Establishment and solution of multi-objective coupled optimization model for three-in-one environmental regulator

4.4.1 Analysis of Ideas for Question Four

Based on previous research, the core of designing a 3-in-1 environmental regulator is to consider the interactions and coupling between the subsystems (cooling and heating, humidification, and purification). Airflow organization, the subsystems interfere with each other; in the temperature and humidity field, they interact with each other; purification efficiency is related to airflow characteristics. For example, the air conditioning temperature field affects the humidification water vapor evaporation and diffusion, humidification latent heat and affect the temperature field; airflow organization is related to pollutant transport capture, temperature and humidity field affects the movement of particles. Therefore, to build a multi-physical field coupling model, taking into account the performance of the subsystem and the mutual influence to achieve the overall optimum, optimization of synergistic effects, to avoid one-sided optimization.

4.4.2 Multi-Physical Field Coupling Hierarchical Optimization Modeling

Based on the models of the previous three problems, a coupled transport model covering the temperature field, humidity field, particle concentration field and velocity field is constructed[6]. Its main set of governing equations contains:

(math.) continuity equation:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \, \vec{v}) = 0 \tag{55}$$

momentum equation (math.):

$$\frac{\partial (\rho \vec{v})}{\partial t} + \nabla \cdot (\rho \vec{v} \vec{v}) = -\nabla p + \nabla \cdot \tau + \rho \vec{g} \beta (T - T_0) + \rho \vec{g} \beta_c (C - C_0) + \rho \vec{g} \beta_h (H - H_0)$$
 (56)

Energy equation:

$$\frac{\partial(\rho c_p T)}{\partial t} + \nabla \cdot (\rho c_p \vec{v} T) = \nabla \cdot (k \nabla T) + S_T$$
(57)

Humidity transport equation:

$$\frac{\partial(\rho Y)}{\partial t} + \nabla \cdot (\rho \, \vec{v} \, Y) = \nabla \cdot (\rho D_Y \nabla Y) + S_Y \tag{58}$$

Particulate matter transport equation:

$$\frac{\partial C}{\partial t} + \nabla \cdot (C \vec{v}) = \nabla \cdot (D_C \nabla C) + S_C \tag{59}$$

Where the coupling of the variables is represented by the source term and physical property parameters:

Temperature source term:

$$S_T = -L_v S_V + Q_{ac} \tag{60}$$

Moisture source term:

$$S_{V} = K_{m}A_{s}(Y_{s} - Y) \tag{61}$$

Particulate matter source term:

$$S_C = -\eta_{filter} C v_{filter} \tag{62}$$

Optimized design variables include:

$$\vec{X} = [L, W, H, X_{ac}, Y_{ac}, Z_{ac}, X_{hum}, Y_{hum}, Z_{hum}, X_{pur}, Y_{pur}, Z_{pur}, d_{in}, d_{out}, \theta, \phi]$$
(63)

Where (L,W,H) is the external dimensions of the device, (X,Y,Z) denotes the positional coordinates of the three functional components, respectively, d denotes the size of the air inlet and outlet, and θ and ϕ denote the angle of air supply.

The objective function is designed using a weighted integrated evaluation method:

Temperature regulation performance:

$$f_1 = \sqrt{\frac{1}{V} \int_V \left(\frac{T - T_{target}}{T_{target}}\right)^2 dV}$$
 (64)

Humidification performance:

$$f_2 = \sqrt{\frac{1}{V}} \int_V \left(\frac{H - H_{target}}{H_{target}}\right)^2 dV$$
 (65)

Purification Performance:

$$f_3 = 1 - \frac{\int_V C \, dV}{\int_V C_0 \, dV} \tag{66}$$

Energy efficiency:

$$f_4 = \frac{P_{total}}{P_{rated}} + \frac{Q_{total}}{Q_{rated}} \tag{67}$$

System responsiveness

$$f_5 = \max(t_{95.T}, t_{95.H}, t_{95.C}) \tag{68}$$

Composite objective function:

$$F = \sum_{i=1}^{5} w_i f_i \tag{69}$$

Constraints include:

Volumetric constraint:

$$V_{total} \leq V_{max}$$

Power constraint:

$$P_{total} \le P_{max}$$

Flow rate constraint:

$$Q_{total} \leq Q_{max}$$

Temperature constraint:

$$T_{min} \leq T \leq T_{max}$$

Humidity constraints:

$$H_{min} \le H \le H_{max}$$

Geometric constraint:

$$X_{min} \le X \le X_{max}$$

 $Y_{min} \le Y \le Y_{max}$
 $Z_{min} \le Z \le Z_{max}$

4.4.3 Steps of the Hierarchical Nested Optimization Algorithm

To efficiently handle this complex optimization problem, the Hierarchical Nested Optimization Algorithm (HNOA) of the MATLAB Optimization Toolbox is applied:

The outer layer optimization is performed using the gamultiobj function for multi-objective optimization:

$$\min_{\vec{X}} [f_1(\vec{X}), f_2(\vec{X}), f_3(\vec{X}), f_4(\vec{X}), f_5(\vec{X})]$$

Where the computation of the objective function involves the solution of the inner optimization problem.

The inner layer optimization is localized for each of the three subsystems:

Air conditioning system:

$$min_{X_{ac}}$$
 $f_{ac}(X_{ac}) = w_{t1}f_1 + w_{t2}f_4$ (70)

Humidifying systems:

$$min_{X_{hum}}$$
 $f_{hum}(X_{hum}) = w_{h1}f_2 + w_{h2}f_4$ (71)

Purification system:

$$min_{X_{pur}}$$
 $f_{pur}(X_{pur}) = w_{p1}f_3 + w_{p2}f_4$ (72)

Coupling between subsystems is handled in the following way:

Gas-flow field coupling:

$$\vec{v}_{total} = \vec{v}_{ac} + \vec{v}_{hum} + \vec{v}_{mur} \tag{73}$$

Temperature field coupling:

$$T = T_{ac} + \Delta T_{hum} \tag{74}$$

Humidity field coupling:

$$H = H_{base} + \Delta H_{hum} \tag{75}$$

Algorithm implementation steps: first of all, the inner and outer layer optimization settings should be carried out, and the optimization function should be invoked to calculate the subsystem performance, to calculate the coupling effect and to calculate the comprehensive performance index.

Numerical computation strategy:

Meshing:

$$\Delta x_i = \Delta x_{min} + (\Delta x_{max} - \Delta x_{min}) exp(-\gamma |\nabla \phi|)$$
 (76)

Time step:

$$\Delta t = min(\frac{\Delta x}{|v|_{max}}, \frac{\Delta x^2}{2\alpha})$$
 (80)

Iteration format:

$$\phi^{n+1} = \phi^n + \Delta t (\nabla \cdot (D\nabla \phi^n) - \nabla \cdot (\vec{v} \phi^n) + S) \tag{81}$$

Convergence criterion (math.):

Standard deviation criterion (math.):

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (f_i - \overline{f})^2} \le \epsilon_1 \tag{82}$$

Maximum rate of change criterion:

$$\max \left| \frac{f_i^{n+1} - f_i^n}{f_i^n} \right| \le \epsilon_2 \tag{82}$$

The optimization model has multiple features, including complete coupling of multiple physical fields, hierarchical optimization for structural efficiency, independent subsystems and overall synergy, and easy to be solved in MATLAB environment. The model can be used to obtain the optimal overall shape, the best layout of functional components, the optimal configuration of operating parameters and the quantitative evaluation of system performance.

4.4.4 Visualization and Analysis of Model Solution Results for Problem 4

The code implementation for the optimized design of the 3-in-1 environmental regulator covers several key modules. The global parameter construction and initialization module organizes the parameters in a structure to improve readability, and the random seed setting ensures that the optimization results are repeatable. The optimization problem construction module reasonably defines the optimization variables and boundaries, selects the multi-objective particle swarm algorithm and balances the computational resources. The Physical Field Calculation Module couples multiple physical fields in a discrete way, which does not completely solve the complex equations but reflects the main physical characteristics. The objective function evaluation module comprehensively evaluates multiple optimization objectives to meet the comprehensive performance requirements. The constraints handling module handles multiple constraints to ensure engineering feasibility. The visualization system module utilizes a variety of functions to visualize the shape of the equipment, the distribution of physical fields, and performance evaluation, and stores the graphics in high-definition format. The data post-processing module stores and outputs key data for analysis.

From the visualization point of view, the equipment shape visualization shows the layout of each functional component, the physical field distribution visualization presents the indoor environment changes, and the performance evaluation visualization assists in program selection. In terms of numerical results, the equipment

size makes reasonable use of space, and the performance indicators are excellent. Temperature control is good but there are trade-offs, humidity control is affected by many factors but still has good results, purification efficiency is very high thanks to the synergy of components, low energy consumption reflects the optimization results, and the response time is short to quickly adapt to changes in the environment. Overall, the optimization results reflect good performance both visually and numerically, with a balance struck between all aspects, providing a basis for practical application and improvement of the equipment, and the code implementation strategy ensures that the whole process is efficient, reliable and scalable.

Figure: Optimized form factor for 3-in-1 environmental regulator

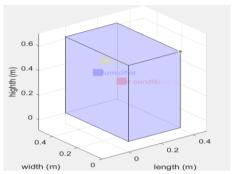


Figure 15. Triple function environmental regulator optimized design

The air inlet and outlet design of the equipment is highly compatible with the needs of airflow organization, which ensures the smooth circulation of airflow and the effective play of various functions when the equipment is in operation.

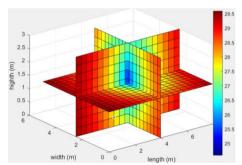


Figure 16. Indoor temperature distribution

Temperature field section map presents the indoor temperature distribution, the color gradient shows that its transition is smooth, no obvious leap region, indicating that the air-conditioning refrigeration is uniform, there is no local cooling and heating inequality, and reflecting the airflow organization is reasonable.

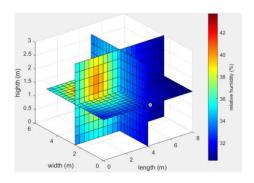


Figure 17. Indoor humidity distribution

The humidity field distribution exhibits spatial diffusion of water vapor, reasonable changes in humidity gradient, and no over-humidified areas.

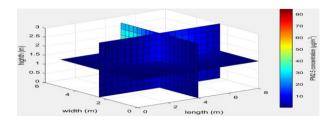


Figure 18. Indoor PM2.5 Concentration Distribution

The purification system captures particulate matter efficiently, and the uniformity of the concentration field shows that the purification effect is spread over the entire space.

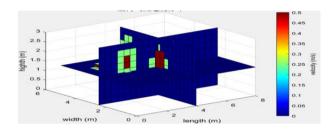


Figure 19. Indoor Airflow Velocity Distribution

Velocity field distribution shows the indoor air flow situation, the airflow organization is reasonable, no dead ends, to help play the functional module performance, the velocity gradient changes gently, to avoid local airflow is too fast to cause discomfort.

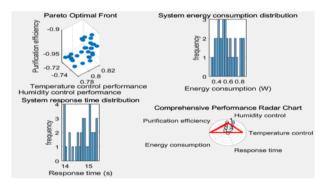


Figure 20. Comprehensive Performance Evaluation

The performance evaluation charts present the comprehensive system performance in a variety of formats. Pareto Frontier plots present target tradeoffs, energy consumption and response time histograms show performance stabilization, and radar plots demonstrate metrics balance.

The optimization results are shown in Table 2 of the supporting material

In summary, the optimal size of the three-in-one environmental regulator is $0.32 \times 0.51 \times 0.62$ m. The optimized design has good performance indicators, especially outstanding purification efficiency and energy efficiency, and the distribution characteristics of each physical field also show good performance.

5. Evaluation and Generalization of the Model

5.1 Problem 1 Evaluation and Extension of Air Conditioning Temperature Field Optimization Models

Vantage:

This model constructs a distance-based temperature field diffusion and airflow organization model, which couples airflow velocity, direction and temperature to accurately reflect the temperature regulation characteristics of air conditioning, and its simplified processing takes into account the computational efficiency and the main

characteristics of the temperature field, which is of great significance for engineering optimization. The MATLAB genetic algorithm toolbox is used to set a reasonable population size and iteration number for optimization, and incorporate constraints such as volume, flow rate and geometry to ensure that the optimization results can be implemented in the project.

Drawbacks:

The simplified model of temperature field diffusion does not solve the energy equation completely, omitting the complex processes such as radiation heat transfer and wall heat transfer, and the calculations under special working conditions may deviate from the reality. Simplified potential flow model for airflow field calculation does not take into account viscous effects and turbulence characteristics, complex geometry or high Reynolds number, the airflow organization prediction is not accurate.

Potential for replication:

Complex heat transfer models can be introduced to consider radiative and wall heat transfer; solve the complete N-S equation and energy equation using computational fluid dynamics; add coupling of temperature and humidity fields; and incorporate the effects of obstacles such as indoor furniture. With this improvement, the model will be more accurate and practical, and the application prospect will be broader.

5.2 Problem 2 Evaluation and Extension of Air Purifier Optimization Models

Vantage:

The model constructs a coupled model of particle movement and airflow field, which integrates multiple performance indicators such as filtration efficiency, airflow organization and energy consumption, effectively describes the physical characteristics of air purification, and makes the optimization results very valuable for practical application. Multi-objective optimization is used to solve the Pareto front for the three objectives of purification efficiency, energy consumption and noise, which provides multiple choices for engineering design and enhances the design flexibility.

Drawbacks:

The particle movement model is simplified without taking into account the interactions between particles and with the wall surface, which may interfere with the accurate prediction of purification efficiency. The filtration efficiency model uses a simplified empirical formula that does not take into account the microstructure of the filtration material and the particle size distribution of the particles, thus weakening the general applicability of the model.

Potential for replication:

It is possible to introduce a fine particle movement model and consider the particle size distribution; to construct a microstructure-based filtration efficiency model; to incorporate the role of temperature and humidity fields on the movement of particles; and to consider the effect of aging of filter materials. Through this expansion, the model will be more accurate and perfect, and the application scope can be further broadened.

5.3 Problem 3 Evaluation and Extension of Humidifier Optimization Models

Vantage:

This model constructs a water vapor diffusion and mass transfer model, which fully considers the process of water vapor generation, diffusion and transport and combines with the influence of airflow organization to accurately describe the physical characteristics of humidification, with a high degree of physical significance. The optimization objectives cover humidification efficiency, uniformity, energy consumption and response time, etc. Multi-objective optimization effectively balances the performance indicators and is highly practical.

Drawbacks:

The water vapor diffusion model is simplified without incorporating the effect of temperature field on diffusion, and ignores the role of latent heat of phase change on the temperature field, which may lead to inaccurate prediction of humidification effect. The model lacks in-depth consideration of the condensation phenomenon and anticondensation design, which may be a potential problem in practical engineering applications.

Potential for replication:

The model can be improved by constructing a complete coupling model of temperature and humidity fields, incorporating condensation phenomenon and anti-condensation design, enriching the types of humidification

methods, and considering the influence of indoor airflow organization. After this optimization, the model will be more accurate and reliable, and more adaptable to engineering applications.

5.4 Evaluation and Extension of the Integrated Optimization Model for the 3-in-1 Environmental Regulator

Vantage:

The model presents the whole picture of the regulator with multi-field coupling, the synergy of functional modules is shown, and the optimization is systematic. Hierarchical optimization solves multi-objective problems with both quality and efficiency, and engineering constraints ensure feasibility.

Drawbacks:

Physical field coupling with multiple assumptions and impaired accuracy. The setting of weight coefficients for the optimization objective is subjective and may affect the universality of the optimization results.

Extension potential:

The integrated model has a large space for promotion and improvement: the integrated model can introduce complex physical models to refine the coupling, construct a physical mechanism weighting method, incorporate more engineering factors, and be extended to other devices. The optimized application value will be more reflected.

Overall, the four models evolve gradually from single-function to multi-function comprehensive optimization to build a relatively complete optimization system for environmental regulation equipment. Although containing simplified assumptions, reasonable mathematical expressions and optimization algorithms can still provide useful references for engineering design.

References

- [1] Wang, W. (2024). Evaluation of ambient air quality and analysis of influencing factors[J]. *Leather Making and Environmental Protection Technology*, *5*(11). https://doi.org/10.20025/j.cnki.CN10-1679.2024-11-57
- [2] Wang, J. C., Liu, Y. L., Zhang, P., Liu, M. H., & Zhao, X. H. (2024). Privacy-preserving scheme for SVM training based on small batch stochastic gradient descent method[J]. *Information Security Research*, 10(10).
- [3] Qiu, Y., Zhu, P., Su, Y., Mollal, A., & Ren, Y. (2024). Optimization of NO₂ air monitoring stations based on spatial simulated annealing algorithm: a case study of southwestern Fujian urban agglomeration[J]. *Journal of Ecology*. (Published online: 2024-11-21 16:20:54).
- [4] Zeng, B. (2024). *Urban Construction Theory Research (Electronic Edition*), 29. https://doi.org/10.19569/j.cnki.cn119313/tu.202429038
- [5] Yuan, H., Ke, Y., Xiang, K., Fan, L., Ma, H., Wang, C., & Xilei. (2024). Hierarchical optimal scheduling of wind-gas-fire-storage multi-source systems for peak shifting[J]. *Hydroelectric Power Generation*. (First published online: 2024-11-01 10:48:24).
- [6] Li, X., Gui, Y., Jia, H., Li, X., Hao, M., Zhong, Y., & Zhang, L. (2024). Thermal-fluid coupling simulation model of flat slab slurry grouting in cracks with polymer slurry[J]. *Engineering Mechanics*. (Web debut: 2024-11-08 14:52:53).

Copyrights

Copyright for this article is retained by the author(s), with first publication rights granted to the journal.

This is an open-access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/).