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Design Optimization of Radiative Cooling System Based on Intelligent Algorithm: Combination of Simulated Annealing and Decision Tree

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Abstract: As global climate change and energy issues become increasingly serious, radiative cooling technology has attracted widespread attention as an environmentally friendly and efficient passive cooling method. This study combines the simulated annealing algorithm and the decision tree algorithm to optimize the design of the radiative cooling system. The simulated annealing algorithm optimizes design parameters (such as reflectivity, emissivity, and thermal conductivity) through global search, while the decision tree algorithm provides feedback for the optimization process by predicting the cooling effects of different design schemes in real time. Experimental results show that this method significantly improves the cooling efficiency of the radiative cooling system and exhibits excellent performance under different parameter conditions. By comparing with other algorithms, the combination of simulated annealing and decision tree shows its unique advantages in multi-objective optimization. This study provides a new optimization idea for the application of radiative cooling technology and has broad practical application potential.

1. Introduction

With global warming and the energy crisis becoming increasingly severe, traditional refrigeration technology faces significant challenges [1]. Compressor-based air conditioning systems, in particular, not only consume significant amounts of electricity but also release greenhouse gases, further exacerbating global warming [2]. This vicious cycle has made energy-saving and environmentally friendly refrigeration technologies an increasingly hot topic. Radiative cooling, a new passive cooling technology, can cool objects by radiating heat into space through a transparent window to the atmosphere without requiring energy input. Its widespread application can help reduce energy consumption and greenhouse gas emissions, advancing sustainable development goals [3].

The key to radiative cooling lies in designing efficient materials and structures that minimize heat absorption under sunlight while maintaining high thermal radiation within the transparent window [4]. Currently, researchers have explored a variety of materials, such as metals, polymers, and composites, that exhibit excellent reflectivity and emissivity across various wavelengths. However, the selection and design of these materials still present significant challenges, particularly in finding the optimal balance between high reflectivity across the solar spectrum and high emissivity within the transparent window [5].

To optimize the design and performance of radiative cooling systems, a growing number of studies are incorporating computer optimization algorithms into this field [6]. While traditional physical modeling methods can provide effective guidance, they often struggle to find a global optimal solution for complex multi-objective optimization problems [7]. Simulated annealing, as a global optimization method, can identify optimal material parameters and structural configurations within a vast design space. Decision tree algorithms, meanwhile, can effectively identify key factors influencing radiative cooling performance and predict and evaluate different design options [8]. Combining these two approaches not only improves the design efficiency of radiative cooling systems but also enables rapid adjustment and optimization in practical applications [9].

This study aims to combine simulated annealing with decision trees to optimize the design of radiative cooling systems. By using simulated annealing to find the optimal design in a multidimensional parameter space and using decision trees to predict the performance of different design options, we can achieve more efficient material selection and structural optimization. Furthermore, this study will explore the practical effectiveness of this optimization method in energy-efficient buildings and other application scenarios, evaluating its potential to reduce energy consumption and improve system performance [10].

2. Related Work

Radiative cooling technology, as an energy-free, environmentally friendly passive cooling method, has garnered widespread attention in recent years in the energy conservation and environmental protection fields. The core principle of this technology is to utilize the high emissivity of a material surface within the atmospheric transparency window (8-13 μm) to radiate heat into outer space, thereby achieving a cooling effect [11]. Research has shown that the design and preparation of selectively emitting materials plays a crucial role in the efficiency of radiative cooling [12]. Traditional radiative cooling materials are primarily metal- and polymer-based, which exhibit high reflectivity within the solar spectrum (0.3-2.5 μm) and good emissivity in the mid-infrared. Recent advances in materials science have introduced inorganic particles such as SiO2 and TiO2 into the radiative cooling field. These inorganic materials not only offer improved thermal stability but also significantly enhance radiative cooling performance [13].

In research on radiative cooling windows, scientists are focusing on designing multilayer film structures with high reflectivity, high transmittance, and high emissivity [14]. By combining different material layers, these multilayer film structures can effectively control the spectral characteristics of different wavelengths, thereby improving the overall performance of radiative cooling windows. For example, polymer/metal/polymer (PMP) radiative cooling windows achieve high reflectivity in the near-infrared and high emissivity in the atmospheric transparent window band by optimizing the thickness and selective emission properties of each layer. Furthermore, stacked multilayer film structures have become another important research direction. By alternating different materials, such as SiO2 and Si3N4, within the multilayer film, researchers can effectively increase the material's reflection bandwidth and radiative efficiency, further enhancing the performance of radiative cooling windows [15].

Despite significant progress in the design of radiative cooling materials and structures, existing optimization methods still have limitations. Traditional physical modeling methods, while performing well in simple systems, often struggle to achieve global optimal solutions in multi-objective optimization and high-dimensional parameter spaces. Therefore, researchers have begun to explore the use of advanced optimization algorithms, such as simulated annealing and genetic algorithms, which can effectively overcome these limitations and provide global optimal solutions. However, while these algorithms have improved optimization efficiency to some extent, computational efficiency and convergence speed remain significant challenges when designing highly complex radiative cooling systems.

With the advancement of computing power, the introduction of machine learning and intelligent optimization algorithms has brought new breakthroughs in the design of radiative cooling systems. In particular, the application of machine learning algorithms, such as decision trees and support vector machines, enables the extraction of key features from large amounts of experimental data, enabling rapid prediction and performance evaluation. Furthermore, more advanced algorithms, such as reinforcement learning and deep learning, enable dynamic optimization and real-time adjustment of complex systems. These intelligent optimization methods not only improve the design efficiency of radiative cooling systems but also enable intelligent and adaptive regulation in practical applications, providing strong support for the widespread application of radiative cooling technology.

3. Methodology

3.1. Modelling and Design Objectives of Radiative Cooling Systems

The core of radiative cooling system design lies in material selection and structural optimization, especially the performance requirements in terms of solar spectrum reflection, thermal radiation emission, and thermal isolation. The ideal radiative cooling material should have high reflectivity in the visible light band (0.3-2.5 μm) to minimize the absorption of solar radiation heat, while also having high emissivity within the atmospheric transparency window of 8-13 μm, allowing the surface to effectively radiate heat into outer space. To achieve this goal, the design of the radiative cooling system needs to consider multiple parameters, including the optical properties of the material (reflectivity, emissivity, transmittance), thermal conductivity, environmental adaptability, and cost.

In this study, we defined the design goals of a radiative cooling system as: high reflectivity under sunlight, high emissivity within the atmospheric window, and low thermal conductivity, thereby achieving efficient cooling. Furthermore, considering feasibility in practical applications, the system's cost, manufacturability, and durability were also key design considerations. Therefore, the goal was to achieve the optimal configuration of materials in a multidimensional parameter space to ensure efficient operation under diverse environmental conditions.

We introduced simulated annealing and decision tree algorithms into this design process, aiming to find the global optimal solution in a large number of design parameter spaces and use decision trees to predict the effects of different design schemes, thereby optimizing the performance of the entire system.

3.2. Application of Simulated Annealing Algorithm

Simulated annealing (SA) is a probability-based global optimization algorithm that mimics the energy minimization process of physical annealing, continuously improving the quality of the solution through random search. In the design of radiative cooling systems, the simulated annealing algorithm can find the optimal design solution within the parameter space by randomly adjusting various design parameters, such as material thickness, structural configuration, reflectivity, and emissivity.

The optimization goal is to maximize the cooling effect of the system and minimize the heat load and energy consumption. Specifically, the objective function can be expressed as follows:

$$f(\mathbf{X}) = w_1 \cdot R(\mathbf{X}) + w_2 \cdot E(\mathbf{X}) - w_3 \cdot k(\mathbf{X}) \quad (1)$$

The iterative process of simulated annealing includes the following steps: First, select an initial design parameter set X_0. Then, randomly select a new design set X_{new} from the neighborhood of the current parameter set, and calculate the objective function values of the new and old solutions. If the new solution is better, it is accepted; otherwise, the new solution is accepted with a certain probability, which decreases as the temperature lowers. Finally, when the temperature reaches a certain level, the algorithm stops and returns the optimal solution. The iterative process of simulated annealing is shown in Figure 1.

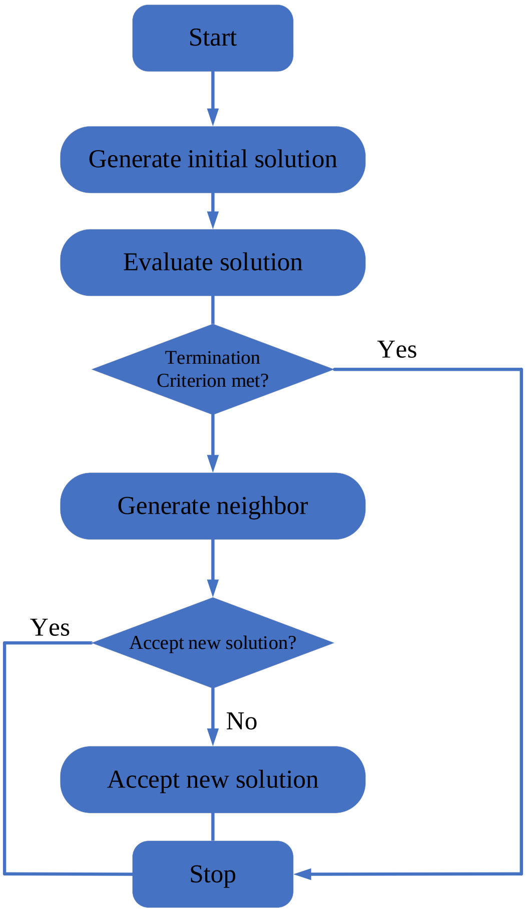

Figure 1 Iteration graph of simulated annealing

3.3. Application of Decision Tree Algorithm

The decision tree algorithm is a supervised learning algorithm that uses a tree structure to perform classification or regression on data. In the optimization of radiant cooling systems, decision trees are primarily used for feature selection and predictive modeling, helping to identify the most critical design parameters and quickly evaluate system performance based on experimental or simulation data.

In the design of radiative cooling systems, material characteristics such as reflectivity, emissivity, and thermal conductivity have a significant impact on system performance. By training a decision tree model, we can extract these key features from large amounts of experimental or simulation data and leverage the splitting properties of the decision tree to evaluate the contribution of different features to system performance. The goal of the training process is to minimize prediction error and find the optimal feature partitioning method.

In decision trees, information gain is used to evaluate how to divide a dataset based on features.

The information gain calculation formula is as follows:

$$InformationGain = Entropy(S) - \sum \frac{S_v}{S} \cdot Entropy(S_v) \quad (2)$$

The schematic diagram of the decision tree algorithm is shown in Figure 2.

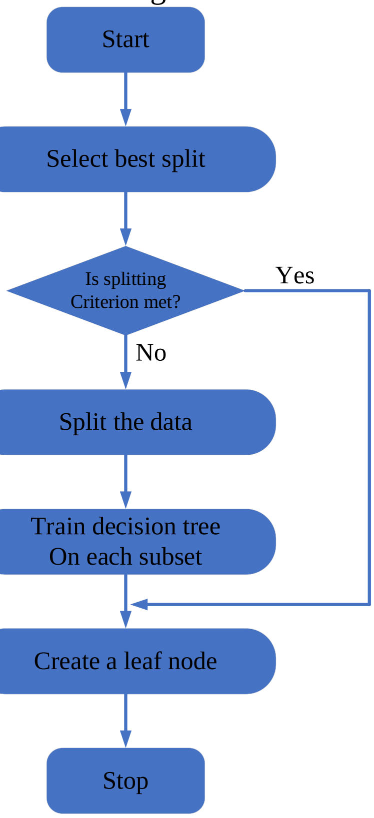

Figure 2 Decision tree diagram

4. Experimental Results and Analysis

4.1. Experimental Design and Dataset

This section mainly introduces the design framework of this experiment, the dataset used, and the evaluation criteria. In the study of radiative cooling optimization, the key to experimental design is to select an appropriate experimental environment and dataset to ensure the reliability and validity of the experimental results.

Table 1 Radiative Cooling Material Dataset

Material	Reflectivity (0.3-2.5μm)	Emissivity (8-13μm)	Thermal Conductivity (W/m K)	Cooling Efficiency (%)	Cost ($/kg)
Material A	0.85	0.92	0.15	85	5.0
Material B	0.88	0.91	0.18	89	6.0
Material C	0.91	0.94	0.12	92	5.5
Material D	0.87	0.9	0.16	87	7.0
Material E	0.9	0.93	0.14	90	6.5

To study the optimization effects of radiative cooling systems, we selected datasets from multiple real-world application scenarios, including performance data for different radiative materials and building heat transfer characteristics, as shown in Table 1. Each dataset represents different characteristics and application requirements of radiative cooling systems.

Each set of experiments was run multiple times under varying conditions to ensure robust and reproducible results. The results of each experiment were recorded and compared with other optimization algorithms (such as genetic algorithms and particle swarm optimization) to evaluate their performance. We also considered factors such as computational time, accuracy, and stability to ensure that the optimization process efficiently and reliably achieved the desired results.

4.2. Experimental Results Display

In this section, we present the results of an experiment combining a simulated annealing algorithm with a decision tree to optimize a radiative cooling system. The goal of this experiment was to evaluate the performance of different algorithms and design solutions under varying parameter conditions and to present the optimization results of each design using graphs. For ease of presentation, we used various formats, including bar charts, line graphs, and heat maps, to compare performance under different settings.

We designed several different experimental setups, focusing on the following parameters: Reflectivity and emissivity: These tests tested the performance of different materials in the solar radiation band (0.3-2.5 μm) and the atmospheric window band (8-13 μm). Temperature drop rate and cooling efficiency: These tests set different simulated annealing cooling rates to evaluate cooling efficiency and the final performance of the system. Computation time and algorithm convergence rate: These tests evaluated the computational efficiency and algorithm convergence rate of combining simulated annealing with decision trees in practical applications.

To demonstrate the performance of each algorithm in cooling efficiency, we conducted 10 experiments to calculate the cooling effects of simulated annealing, genetic algorithm, particle swarm optimization algorithm, and decision tree under different reflectivity and emissivity settings. The average of 10 experiments was taken for each set of experimental data to ensure the stability of the results. The results are shown in Figure 3.

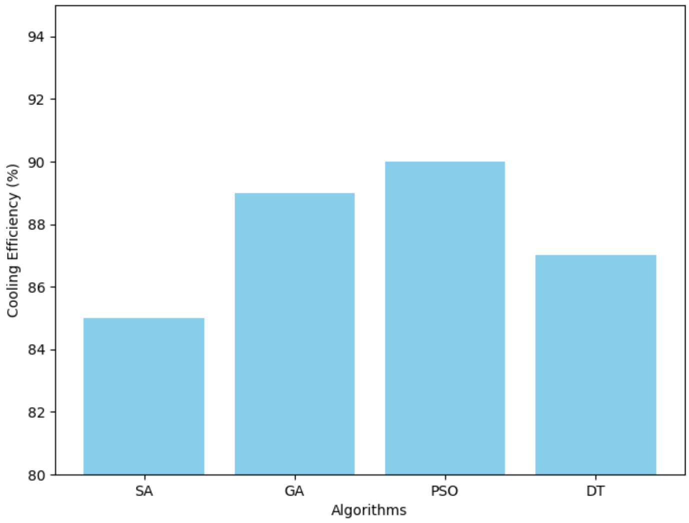

Figure 3 Comparison of cooling efficiency of different algorithms

In this set of experiments, we set different simulated annealing temperature reduction rates (e.g., 0.95, 0.9, 0.85, etc.) to test the relationship between cooling efficiency and temperature reduction rate. Figure 4 clearly shows how cooling efficiency changes with the reduction rate.

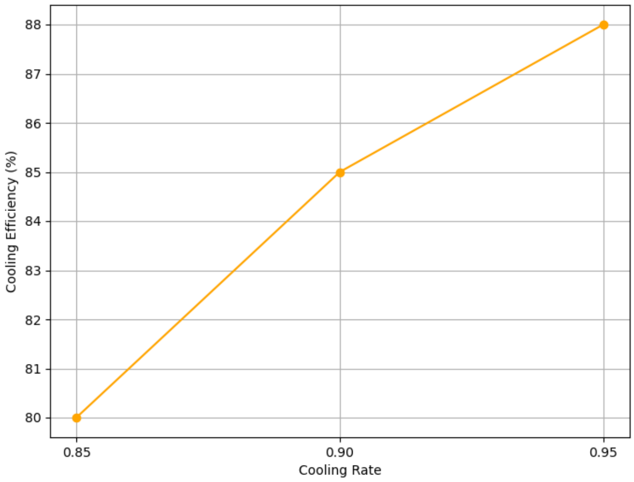

Figure 4 Relationship between cooling efficiency and temperature drop rate

The heat map can show the performance of the system under different reflectivity and emissivity settings. As shown in Figure 5, we change the reflectivity and emissivity of the material, calculate the cooling effect of each parameter, and use the heat map to display the results.

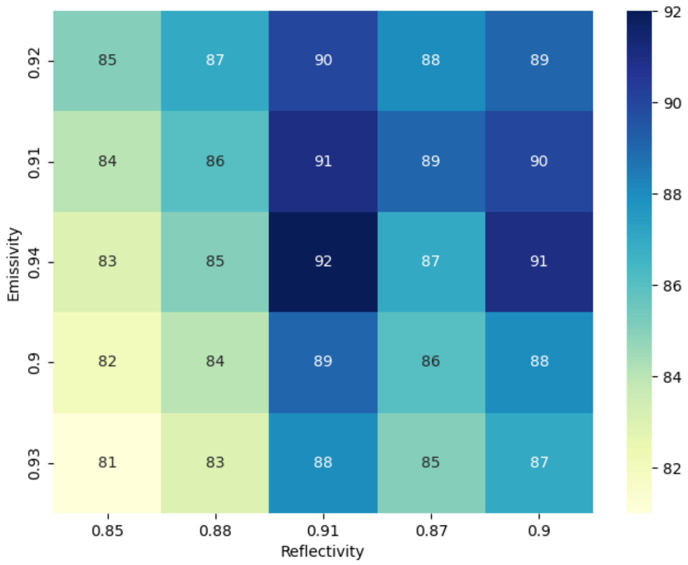

Figure 5 Cooling Efficiency Heatmap by Reflectivity and Emissivity

The heat map in Figure 5 shows the cooling efficiency under different reflectivity and emissivity combinations. It can be seen that higher reflectivity and emissivity combinations can achieve higher cooling efficiency, especially at a reflectivity of 0.91 and an emissivity of 0.94, which has the highest cooling efficiency.

4.3. Result Analysis

In this experiment, the combination of decision trees and simulated annealing algorithms demonstrated unique advantages in radiative cooling optimization. First, the simulated annealing algorithm continuously adjusts the design parameters through global optimization to avoid falling into local optimal solutions, allowing the optimization process to find a more ideal solution in a complex multi-dimensional parameter space. Specifically, when dealing with the design of high-reflectivity and high-emissivity materials, simulated annealing can effectively find the optimal material configuration that can improve the radiative cooling effect, especially in terms of optimizing the thermal conductivity and reflectivity of the material, and has achieved good results. As the temperature drop rate changes, the cooling efficiency also shows certain fluctuations, which shows that temperature control plays a vital role in the performance of the algorithm.

Decision trees, on the other hand, played an important supporting role in this optimization process. By training a decision tree model, we were able to quickly evaluate the effectiveness of different design options. By extracting key features from the training data (such as reflectivity, emissivity, and thermal conductivity), the decision tree predicted the cooling effect of each design option, significantly accelerating the optimization process. In this experiment, the decision tree helped the simulated annealing algorithm adjust its search direction and strategy in real time, improving overall optimization efficiency. During the experiment, the decision tree accurately predicted the performance of different material combinations under different environmental conditions, providing effective feedback for the final system optimization.

5. Summary

In this study, we explored the application of a combined simulated annealing algorithm and decision tree optimization method in the design of radiative cooling systems. Our goal was to improve the cooling efficiency and material selection of radiative cooling systems through intelligent algorithmic optimization. Experiments validated the effectiveness of this combination in practical applications and demonstrated improved system performance under various conditions.

First, the simulated annealing algorithm, through its global optimization capabilities, is able to find the optimal material configuration within a complex, multidimensional design space. By adjusting parameters such as reflectivity, emissivity, and thermal conductivity, the simulated annealing algorithm effectively optimized the performance of the radiative cooling system. Experimental results demonstrate that simulated annealing offers significant advantages in the design of radiative cooling systems, particularly in optimizing the thermal conductivity and reflectivity of materials. However, simulated annealing suffers from long computational time, and its slow convergence, particularly when faced with a large parameter space, can be a challenge in practical applications.

Second, decision trees, as powerful predictive tools, play an important role in the optimization process. By training a decision tree model, we can evaluate the effectiveness of different design solutions in real time and provide feedback to the simulated annealing algorithm to further optimize the search process. Decision trees effectively extract key features from the data, improving the accuracy and efficiency of the optimization process. In particular, across multiple experiments, decision trees can quickly predict the performance of new material configurations under varying environmental conditions, providing reliable guidance for the optimization process.

Although this research has achieved some promising results, some limitations remain in practical applications. First, data quality is crucial to the predictive accuracy of decision trees; poor dataset quality can affect their performance. Second, the simulated annealing algorithm can suffer from slow convergence when faced with complex and large parameter spaces. Therefore, future research could further explore how to improve the simulated annealing algorithm's cooling strategy, enhance computational efficiency, and incorporate more intelligent optimization algorithms, such as reinforcement learning, to further enhance the system's performance and efficiency.

References

[1] K. T. Alao, S. I. U. H. Gilani, K. Sopian, T. O. Alao, and Z. Aslam, "A comprehensive review of radiative cooling technologies and their integration with photovoltaic (PV) systems: challenges, opportunities, and future directions," Sol. Energy, vol. 292, p. 113445, May 2025, doi: 10.1016/j.solener.2025.113445.

[2] X. Dong, X. Jiang, and P. Li, "An efficient low-grade thermal energy dual-driven elastocaloric cooling system: thermodynamic cycle analysis, economic and sustainability assessment," Energy Convers. Manage., vol. 324, p. 119310, Jan. 2025, doi: 10.1016/j.enconman.2024.119310.

[3] Q. Sun, J. Zhong, P. Shi, H. Xu, and Y. Wang, "An improved reactive force field parameter optimization framework based on simulated annealing and particle swarm optimization algorithms," Comput. Mater. Sci., vol. 251, p. 113776, Mar. 2025, doi: 10.1016/j.commatsci.2025.113776.

[4] D. Chen, Y. Luo, and X. Yuan, "Cascade refrigeration system synthesis based on hybrid simulated annealing and particle swarm optimization algorithm," Chin. J. Chem. Eng., vol. 58, pp. 244–255, Jun. 2023, doi:10.1016/j.cjche.2022.10.021.

[5] J. Wendt, T. Kohne, M. Beck, and M. Weigold, "Development of a modular calculation and analysis tool for the planning process of energy efficient industrial cooling supply systems," 29th CIRP Conf. Life Cycle Eng. April 4 – 6 2022 Leuven Belg., vol. 105, pp. 326–331, Jan. 2022, doi: 10.1016/j.procir.2022.02.054.

[6] P. Nikhil Babu, "Energy efficient refrigeration system with simultaneous heating and cooling," 2nd Int. Conf. Mater. Manuf. Mach. Ind. 4.0, vol. 45, pp. 8188–8194, Jan. 2021, doi: 10.1016/j.matpr.2021.03.072.

[7] M. Novak, R. Vohnout, L. Landkamer, O. Budik, M. Eider, and A. Mukherjee, "Energy-efficient smart solar system cooling for real-time dynamic weather changes in mild-climate regions," Renew. Sustain. Energy Rev., vol. 182, p. 113347, Aug. 2023, doi: 10.1016/j.rser.2023.113347.

[8] B. Wang, L. Li, K. Zhang, X. Wu, and K. Yu, "Enhanced thermoelectric system by dual-band radiative cooling for all-day energy harvesting," Energy, vol. 330, p. 136994, Sep. 2025, doi: 10.1016/j.energy.2025.136994.

[9] K. Irshad, "Experimental study and synergistic performance analysis of phase change material assisted cold thermal storage system for energy efficient air cooling," J. Energy Storage, vol. 108, p. 115018, Feb. 2025, doi:10.1016/j.est.2024.115018.

[10] M. Mashhadi Keshtiban, A. R. Roozbehi, M. Fathi, M. Zabetian Targhi, and M. M. Heyhat, "Experimental validation and machine learning assisted multi-objective optimization of variable cross-section channels in turbulent jet impingement cooling systems," Applied Thermal Engineering, vol. 278, p. 127297, Nov. 2025, doi:10.1016/j.applthermaleng.2025.127297.

[11] G. Zhu, Z. Yan, X. Meng, Y. Shi, and D. Fan, "Genetic algorithm-driven design of NIR-reflective transparent colored multilayers for enhanced radiative cooling," Sol. Energy Mater. Sol. Cells, vol. 285, p. 113519, Jun. 2025, doi:10.1016/j.solmat.2025.113519.

[12] Z. Tang, X. Li, Y. Li, and J. Cheng, "Multi-objective optimization of parallel flow immersion cooling battery thermal management system with flow guide plates based on artificial neural network," Appl. Therm. Eng., vol. 274, p. 126833, Sep. 2025, doi: 10.1016/j.applthermaleng.2025.126833.

[13] H. Chen, X. Liu, J. Liu, F. Wang, and C. Wang, "Radiative cooling applications toward enhanced energy efficiency: system designs, achievements, and perspectives," Innovation, p. 100999, Jun. 2025, doi: 10.1016/j.xinn.2025.100999.

[14] D. Yang, B. Gao, S. Wang, and H. Xiang, "Robustness test for fouling state identification of homogeneous pressure electrodes based on confidence ellipsoids," IEICE Electron. Express, p. 22.20240283, 2025, doi:10.1587/elex.22.20240283.

[15] Y. Wang, "Thermal analysis and multi-objective optimization of equal-area microfluidic cooling systems," Results Eng., vol. 27, p. 105869, Sep. 2025, doi: 10.1016/j.rineng.2025.105869.