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Review

Optimization Design of Internal Cooling Structures for Turbine Blades Based on Machine Learning: A Comprehensive Review

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Abstract

With the steady growth of performance requirements of gas turbines, the optimization design of turbine blade cooling structures has emerged as a critical technical challenge. This paper provides a comprehensive review of the research progress on machine learning methods in the optimization design of turbine blade cooling structures. First, common internal cooling methods for turbine blades are reviewed, including rib turbulated cooling, pin-fin cooling, and impingement cooling. Second, the application and limitations of traditional optimization methods in the optimization design of turbine blade internal cooling structures are analyzed in detail. On this basis, the application of machine learning methods in the optimization design of turbine blade internal cooling structures is comprehensively reviewed, covering mainstream machine learning models such as artificial neural networks, deep learning, generative adversarial networks, and physics-informed neural networks, as well as mainstream optimization algorithms including genetic algorithms, non-dominated sorting genetic algorithms, particle swarm optimization, and simulated annealing. Furthermore, emerging research directions such as data augmentation techniques, temperature field reconstruction, model interpretability, and optimization structure evolution patterns are discussed. The reviewed literature demonstrates that machine learning methods can substantially enhance the efficiency and accuracy of cooling structure optimization, offering robust support for the cooling design of next-generation gas turbines.

Keywords: turbine blade; internal cooling structure; machine learning; performance prediction; optimization design

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1. Introduction

As a high-end power equipment that efficiently and cleanly converts thermal energy into mechanical energy, gas turbines are widely used in aviation propulsion, marine power, land-based power generation, and various industrial fields [1]. As shown in Figure 1, improving thermal efficiency and power output has always been the core goal of gas turbine technology development, and achieving this goal highly depends on increasing the rotor inlet temperature (RIT) [1,2]. Currently, the turbine inlet temperature of advanced gas turbines has reached 1850–1950 K, far exceeding the temperature limit of nickel-based alloys. With further improvements in gas turbine performance, the turbine inlet temperature is expected to exceed 2200 K [2]. To ensure safe and reliable operation of the turbine, 3–5% of the compressed air from the high-pressure compressor is extracted to cool the first-stage stator and rotor blades. Several studies [2,3] have identified two major trends in future

gas turbine development: one is the 2000 K-level high RIT for aviation gas turbines with strictly limited coolant supply; the other is the 300–400 MW class high-power, 60% class high-efficiency land-based gas turbines for combined cycle power generation. In the development of next-generation high-efficiency gas turbines, advanced cooling technologies [3–6] and thermal barrier coatings are critical to breaking the temperature bottleneck. Therefore, in-depth research and development of turbine blade cooling technologies are of great theoretical and engineering significance.

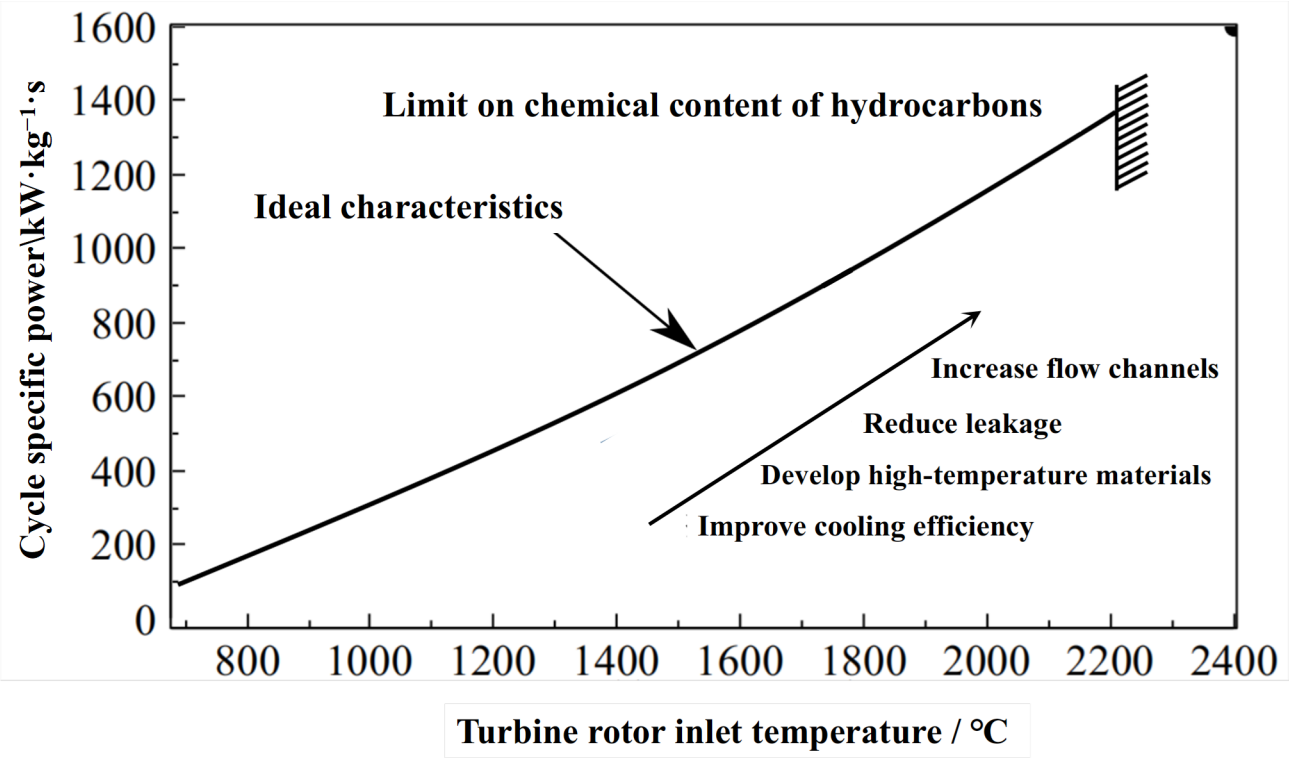


Figure 1. Variation in cycle specific power with inlet temperature for gas turbines.

Turbine blade cooling technology has evolved from empirical induction and model derivation to numerical simulation, and is now gradually entering a new stage of data-intensive science [3]. Modern turbine blades adopt complex composite cooling structures, including internal cooling and external cooling. Internal cooling typically employs enhanced heat transfer methods such as rib turbulated cooling, pin-fin cooling, and impingement cooling, while external cooling mainly relies on film cooling [2]. As cooling structures become increasingly complex, traditional optimization design methods—such as response surface methodology, Kriging, and genetic algorithms—face limitations such as high computational cost, limited surrogate model accuracy, and susceptibility to local optima when dealing with high-dimensional, strongly nonlinear design spaces, making it difficult to meet the demands of rapid iterative design for modern gas turbines [1].

In recent years, machine learning techniques, with their powerful nonlinear fitting capabilities and efficient optimization search strategies, have brought revolutionary solutions to the design of turbine blade cooling structures [1]. Researchers have combined various machine learning methods such as artificial neural networks, deep neural networks, generative adversarial networks, and physics-informed neural networks with optimization algorithms including genetic algorithms, particle swarm optimization, and non-dominated sorting genetic algorithms, widely applying them to performance prediction and geometric parameter optimization of internal cooling structures. For example, Tan et al. [4] used a back-propagation neural network to achieve rapid prediction of the surface temperature

field of a dual-layer wall turbine blade. Wang et al. [5] combined a conditional generative adversarial network with a sparrow search algorithm, significantly improving the film cooling efficiency of a high-pressure turbine blade. Nagesha [6] revealed the heat transfer mechanism of micro-roughness-enhanced jet impingement cooling through a data-driven method. The above studies demonstrate that machine learning methods exhibit great potential in cooling performance prediction and structural optimization.

Nevertheless, current research still faces challenges such as data scarcity, insufficient simulation accuracy, and poor model interpretability. To address these issues, emerging research directions including data augmentation techniques, physics-informed neural networks, efficient temperature field reconstruction, model interpretability analysis, and extraction of optimization structure evolution patterns are gradually becoming research hotspots. This review comprehensively summarizes the research progress of machine learning in the optimization design of internal cooling structures for turbine blades. First, common internal cooling methods for turbine blades and the limitations of traditional optimization methods are introduced. Second, the application of machine learning methods in the optimization of rib cooling, pin-fin cooling, impingement cooling, and other novel cooling structures is comprehensively reviewed. Then, five frontier directions—data augmentation techniques, physics-informed neural networks, temperature field reconstruction, model interpretability, and optimization structure evolution patterns—are discussed. Finally, the existing research is summarized, and future development trends are prospected.

The literature search for this review was conducted in the following manner. Three major academic databases, namely Web of Science, Scopus, and Google Scholar, were searched using combinations of the following keywords: “turbine blade cooling”, “internal cooling”, “rib turbulator”, “pin-fin”, “impingement cooling”, “machine learning”, “artificial neural network”, “deep learning”, “surrogate model”, “optimization”, “genetic algorithm”, and “NSGA-II”. The main search was completed in August 2025, covering the period from January 2014 to August 2025, with a focus on recent advances while including seminal earlier works. During the revision stage, a supplementary search was performed (up to March 2026) to include recently published or early-access studies, ensuring that the most up-to-date developments were incorporated. The inclusion criteria were: (1) peer-reviewed journal articles or conference papers; (2) application of machine learning methods to performance prediction or geometric optimization of turbine blade internal cooling structures; (3) availability of sufficient methodological details for comparative analysis. The exclusion criteria were: (1) studies focusing solely on external film cooling without internal cooling components; (2) review papers (used only for positioning and cross-referencing); (3) studies without quantitative performance metrics. After removing duplicates and screening titles and abstracts, 70 studies were finally included in this review.

Several review papers have been published on machine learning applications in turbine cooling. For example, Zhang et al. [7] provided a broad overview of optimization methods for gas turbine cooling structures, covering both traditional and machine learning approaches, but did not organize the discussion by internal cooling structure type. Xu et al. [8] systematically reviewed machine learning methods in turbine cooling optimization, with a focus on film cooling and overall cooling performance prediction, but gave limited attention to internal cooling structures such as ribbed channels, pin-fin arrays, and impingement cooling. Tian et al. [9] focused specifically on laminated cooling structure optimization. Compared with these existing reviews, the present paper makes the following distinct contributions: (1) it organizes the literature by internal cooling structure type (ribbed cooling, pin-fin cooling, impingement cooling, and other novel structures), enabling structure-specific insights; (2) it provides a comprehensive comparison table that quantifies the ML models, datasets, optimization algorithms, prediction errors, and performance

improvements across studies; (3) it comprehensively identifies and discusses five emerging frontier directions—data augmentation, physics-informed neural networks, temperature field reconstruction, model interpretability, and optimization structure evolution patterns—that have not been collectively reviewed in the context of turbine blade internal cooling; and (4) it extends the future research agenda to include uncertainty quantification, active learning, multi-fidelity modeling, transfer learning, and experimental validation.

2. Common Internal Cooling Methods for Turbine Blades

The traditional cooling methods for gas turbine blades mainly include film cooling, impingement cooling, rib turbulated cooling, and pin-fin cooling [10], with typical structures shown in Figure 2. Film cooling belongs to external cooling, while the other three methods are classified as internal cooling, among which rib turbulated cooling and pin-fin cooling are both turbulent cooling methods, differing only in the type of turbulators used [11]. With the continuous development of blade cooling technology and the pursuit of high cooling efficiency, modern gas turbine blades adopt composite cooling structures combining multiple cooling methods [10]. Internally, such structures include rib turbulated cooling in the mid-chord region, pin-fin cooling in the trailing edge, and array impingement cooling, while externally they include film cooling and slot cooling, resulting in extremely complex configurations.

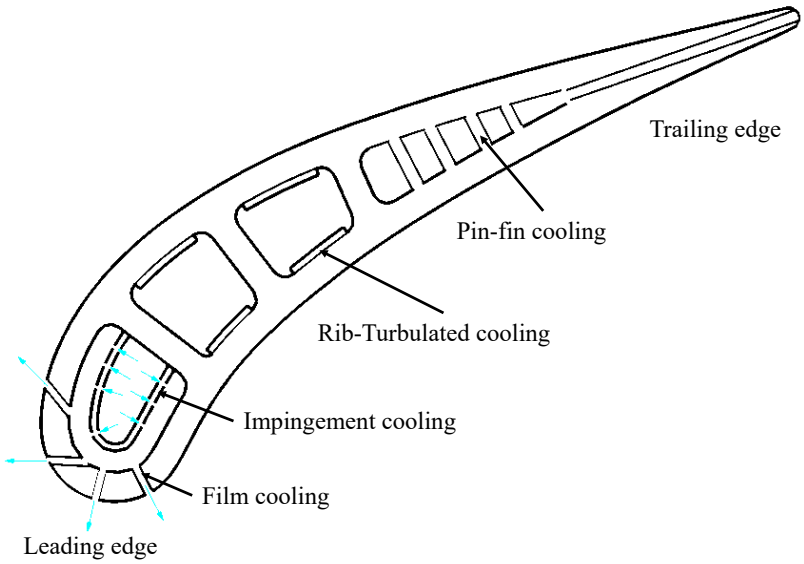
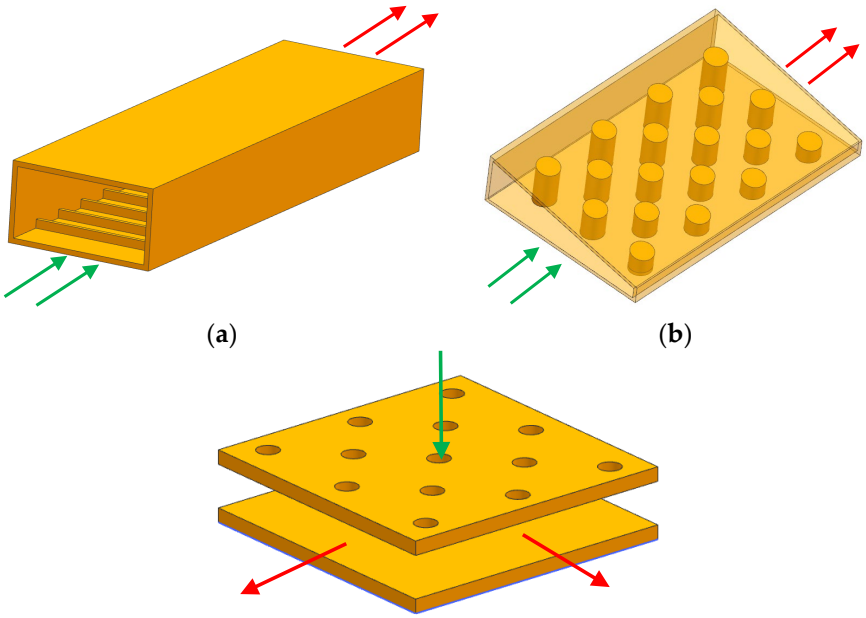


Figure 2. Typical cooling structure of a turbine blade.

Figure 3 presents schematic diagrams of the aforementioned traditional internal cooling methods: (a) rib turbulated cooling, (b) pin-fin cooling, and (c) impingement cooling. Rib turbulated cooling is one of the most widely used cooling methods in the mid-chord region of gas turbine blades. It involves arranging distributed rib turbulators on the pressure side and suction side of the blade periodically. The disturbance effect of the ribs enhances heat exchange between the coolant and the heated wall, thereby improving the heat transfer performance of the internal cooling channel [11,12]. Due to its structural characteristics, pin-fin cooling is typically used to cool the narrow trailing edge region of turbine blades [13]. Pin fins are generally straight cylinders of varying heights, arranged in in-line or staggered arrays within the trailing edge cooling channel. Owing to the relatively large diameter of pin fins, the cooling effect of the pin-fin channel relies not only on convective heat transfer between the coolant sweeping over the cylindrical surfaces and channel walls but also on the conduction heat transfer through the pin fins themselves [13]. Impingement cooling is

one of the most effective methods for enhancing the local heat transfer coefficient on the inner wall of turbine blades [14]. To achieve impingement cooling, an impingement plate with an array of small holes is typically arranged inside the blade. Therefore, impingement cooling is commonly applied in relatively spacious regions such as the leading edge and mid-chord region, rather than in the narrow trailing edge area.



(**a**) (**b**)

(**c**) Impingement cooling

Figure 3. Schematic diagrams of traditional internal cooling methods for turbine blades: (**a**) Rib turbulated cooling; (**b**) Pin-fin cooling; (**c**) Impingement cooling.

3. Traditional Optimization Design Methods for Turbine Blade Cooling Structures

The optimization design of turbine blade cooling structures is a typical multi-objective optimization problem, which requires minimizing flow resistance and coolant consumption while enhancing cooling effectiveness. As shown in Figure 4, traditional optimization methods generally adopt a "surrogate model + optimization algorithm" framework: first, a limited number of sample points are obtained through numerical simulation to construct an approximate model that replaces high-fidelity CFD calculations; then, an optimization algorithm is used to search for the optimum on the surrogate model. Commonly used surrogate models include response surface methodology (RSM), Kriging, radial basis function (RBF), and artificial neural networks (ANN) [11]. Frequently employed optimization algorithms encompass genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), and non-dominated sorting genetic algorithm (NSGA-II) [1]. Although these methods have played an important role in optimizing turbine blade cooling structures, they also have inherent limitations.

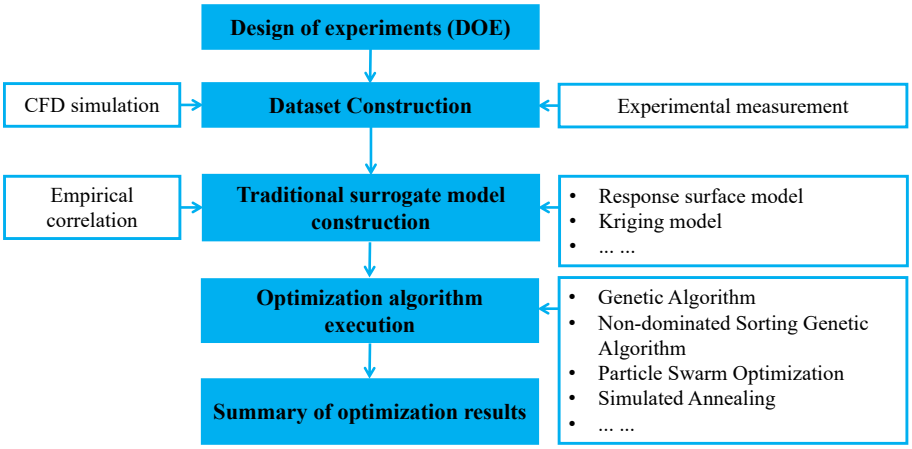


Figure 4. Common traditional optimization methods for turbine blade cooling structures.

Response surface methodology is one of the most widely used surrogate models. It constructs a low-order polynomial to approximate the relationship between design variables and objective functions, offering the advantages of simple modeling and high computational efficiency. Yu et al. [15] combined RSM with NSGA-II to perform multi-objective optimization of a hybrid-rib air cooling channel, obtaining a design scheme with optimal comprehensive performance. Seo et al. [16] also employed RSM for multi-objective optimization of a boot-shaped rib in a cooling channel, analyzing the influence of rib geometry on heat transfer and flow characteristics, thereby providing a reference for cooling structure design.

Genetic algorithm is favored in multi-objective optimization due to its global search capability. Debnath et al. [17] applied GA and the weighted sum method to multi-objective optimization of impinging jets, investigating the effects of parameters such as Reynolds number and jet spacing on Nusselt number and pressure coefficient, and achieving a balanced trade-off between heat transfer and flow loss. Chen et al. [18] focused on internal cooling strategies for the turbine blade leading edge, aiming to maximize heat transfer rate and minimize friction loss. They optimized geometric parameters including the impingement cavity deformation length, nozzle position, and inclination angle using GA. After optimization, at a Reynolds number of 18,500, heat transfer was enhanced by 7.5–15.5%, friction loss was reduced by 6.7–0.5%, and the overall aerodynamic-thermal efficiency was improved by at least 15.8%. Sa et al. [19] analyzed and optimized the performance of detached pin-fins in a cooling channel, using Latin hypercube design to generate sample points, constructing a response surface model, and obtaining a Pareto optimal set through GA. Chen et al. [20] employed a Kriging surrogate model combined with GA to optimize the flow and heat transfer of pin-fins in a wedge-shaped trailing edge cooling channel, significantly enhancing the cooling performance in the trailing edge region.

Although the above traditional methods have achieved certain results, their limitations are also prominent. First, the accuracy of surrogate models highly depends on the number and distribution of sample points; low-order polynomials such as RSM have limited capability to fit strongly nonlinear problems, which can lead to substantial prediction errors. Second, high-fidelity CFD calculations are computationally expensive, restricting the expansion of sample size and making it difficult to handle high-dimensional design spaces. Moreover, although optimization algorithms possess global search ability, they may still fall into local optima when the surrogate model is inaccurate [1]. These shortcomings have driven researchers to explore more efficient and intelligent optimization methods. In recent years, machine learning techniques, with their powerful nonlinear mapping capabilities

and efficient data-driven search strategies, have provided new breakthroughs for turbine blade cooling structure design and have become a research hotspot.

4. Machine Learning-Based Optimization Design Methods for Turbine Blade Cooling Structures

As the performance requirements of gas turbines continue to increase, the limitations of traditional optimization methods in dealing with complex, high-dimensional design spaces have become increasingly prominent, making it difficult to meet the practical demands for efficient and accurate design of turbine blade internal cooling structures [1]. In recent years, machine learning techniques, with their powerful nonlinear mapping capabilities and data-driven intelligent search strategies, have provided a new technological pathway to overcome this bottleneck [7]. Zhang et al. [7] pointed out that machine learning methods can effectively address complex optimization problems that are difficult for traditional methods to handle, enabling efficient design of cooling structures. Xu et al. [8] comprehensively reviewed the progress in the application of machine learning to turbine cooling optimization, indicating that data-driven optimization strategies have become the mainstream direction of current research. Further complementing the above reviews, Yao et al. [21] summarized secondary air system cooling efficiency prediction methods, and Tian et al. [9] reviewed laminated cooling structure optimization, both laying important methodological foundations for the present work. This section will comprehensively review the research progress and typical applications of machine learning methods in the optimization of rib cooling, pin-fin cooling, impingement cooling, and other novel internal cooling structures. Table 1 systematically summarizes representative studies on machine learning-based optimization of turbine blade internal cooling structures.

Table 1. Comprehensive comparison of machine learning applications in turbine blade cooling optimization and supporting techniques.

Ref.	Cooling Structure	ML Model	Dataset Size	Data Source	Optimization Algorithm	Prediction Error	Computational Savings	Objective Functions	Validation	Improvement over Baseline
[22]	V-shaped rib	ANN	Not specified	CFD	GA	Not specified	Not specified	Nu, ΔP	CFD	Pareto optimal
[23]	Steam-cooled rib	BPNN	90 groups	CFD	GA	Max error 1.9%	Not specified	Nu	CFD	Optimal rib angle and AR
[24]	Crossed rib	RBNN	Not specified	CFD	PSO	Not specified	Not specified	Nu, f	CFD	Enhanced thermal performance
[25]	Extended rib	RSM + ANN	Not specified	CFD	—	Not specified	Not specified	Nu	CFD	Rib length and width optimized
[26]	S-shaped rib	NN	Not specified	CFD	—	Not specified	Not specified	Uniformity	CFD	Improved uniformity
[27]	Ribbed channel	NN	Not specified	CFD	GA	Not specified	Not specified	Nu, f	CFD	Comprehensive optimization

Table 1. *Cont.*

Ref.	Cooling Structure	ML Model	Dataset Size	Data Source	Optimization Algorithm	Prediction Error	Computational Savings	Objective Functions	Validation	Improvement over Baseline
[28]	Rib profile	DeepONet	Not specified	CFD	—	With UQ	Not specified	Nu	CFD	Uncertainty-aware
[29]	Internal channel	Adjoint + ML	Not specified	CFD	Multi-step	Not specified	Not specified	Cooling performance	CFD	Significant improvement
[30]	Ribbed channel	Supervised learning	Not specified	CFD	—	Not specified	Not specified	Cooling performance	CFD	Sensitivity analysis
[31]	Fan-shaped pin-fin	RBFNN	Not specified	LHS/CFD	NSGA-II	Not specified	Not specified	Nu, f	CFD	22.8% (Nu obj.); 11.4% (f obj.)
[32]	Pin-fin array	NN (LM)	Not specified	Exp. + CFD	NSGA-II	Not specified	Not specified	Rth, ΔP	Exp. + CFD	Pareto optimal
[33]	Irregular pin-fin	DNN	Not specified	CFD	GA	Not specified	Not specified	Cooling performance	CFD	High-temperature improvement
[34]	Pin-fin array	ML	Not specified	CFD	GA	Not specified	Not specified	HTC	CFD	Enhanced efficiency
[35]	Pin-fin (trailing edge)	Ensemble (GP + RBF + SVR)	Not specified	CFD	Multi-objective	Not specified	Not specified	Nu, ΔP	CFD	Self-organized geometry
[36]	Lantern pin-fin	pix2pix (DL)	Not specified	CFD	NSGA-II	Not specified	Not specified	Nu, f	CFD	Efficient multi-objective optimization
[37]	Pin-fin array	Bayesian + GP	Not specified	CFD	—	Confidence interval	Not specified	Thermal performance	CFD	Nu increases 17–86%
[38]	Pin-fin array	Multi-fidelity GP	Not specified	CFD	Bayesian	Not specified	6% higher objective; 8 fewer HF points; 2% lower cost	Shape optimization	CFD	Better than traditional
[39]	Non-uniform pin-fin	FCNN	Not specified	CFD	—	Not specified	Not specified	Flow and heat transfer	CFD + Exp.	Small-inlet/large-outlet rule
[40]	Heterogeneous pin-fin	Transfer learning + Bayesian	Not specified	CFD	—	Not specified	60% computation saved	Thermo-hydraulic performance	CFD	Nu increases 6.8%, ΔP decreases 76.7%

Table 1. *Cont.*

Ref.	Cooling Structure	ML Model	Dataset Size	Data Source	Optimization Algorithm	Prediction Error	Computational Savings	Objective Functions	Validation	Improvement over Baseline
[41]	Jet array impingement	ANN	Not specified	CFD	MOGA	Not specified	Not specified	Uniformity, Power	CFD	Uniform cooling
[42]	Corrugated impingement	UNet (DL)	Not specified	CFD	—	Not specified	Not specified	PEC	CFD	PEC increase 11%
[43]	Rotor-stator cavity	ANN	Not specified	CFD	—	Improved accuracy	Not specified	HTC	CFD	Higher accuracy
[44]	Jet impingement	MLP-ANN	Not specified	Experimental	—	$R^2 > 0.98$; MAPE < 1%	Not specified	Local Nu	Experimental	Parameter optimization
[45]	Leading edge impingement	BPNN	Not specified	LHS/CFD	NSGA-II	Not specified	Not specified	ΔP, Nu, Uniformity	CFD	ΔP reduction ~20%; Nu increase 1.48–17.14%; uniformity increase 5.46–8.17%
[46]	Orthogonal rib impingement	ANN	Not specified	CFD	GA	Not specified	Not specified	Thermal performance	CFD	Superior comprehensive performance
[47]	Double swirl impingement	GPR	Not specified	CFD	NSGA-II	Not specified	Not specified	Uniformity, Efficiency	CFD	Uniform and efficient
[48]	X-type truss	ANN	Not specified	CFD	GA	Not specified	Not specified	Nu, ΔP	CFD	Excellent heat transfer and flow performance
[49]	Wedge latticework	GA-BPNN	Not specified	CFD	GA (weights)	Improved accuracy	Not specified	HTC	CFD	Higher prediction accuracy
[50]	Coolant plenum	LS-SVM	Not specified	CFD	Chaotic optimization	Not specified	Not specified	Cd, Non-uniformity	CFD	Cd increase 26%; non-uniformity reduction 79%
[51]	Dimples/protrusions	ANN	Not specified	CFD	GA	Extremely high	Not specified	Cooling performance	CFD	Optimal layout

Table 1. *Cont.*

Ref.	Cooling Structure	ML Model	Dataset Size	Data Source	Optimization Algorithm	Prediction Error	Computational Savings	Objective Functions	Validation	Improvement over Baseline
[52]	Trench vortex generator (film cooling) *	GAN	Not specified	Experimental	—	High accuracy	Not specified	Film cooling effectiveness	Experimental	High accuracy and speed
[53]	Endwall film cooling *	GAN	Not specified	Experimental	—	Good agreement	Not specified	Film cooling effectiveness	Experimental	Good agreement with experiments
[54]	Endwall film cooling *	GAN	Not specified	CFD	GA	Not specified	Not specified	Cooling performance, pressure loss	CFD	Cooling performance increase 119.73–158.26%; pressure loss reduction 12.23–13.59%
[55]	Blade tip (film cooling) *	GAN	Not specified	CFD	—	Not specified	Not specified	Film cooling, aerodynamic	CFD	Excellent performance
[56]	Internal cooling RANS closure	Gene expression programming	Not specified	CFD + Exp.	—	Improved turbulence prediction	Not specified	Heat transfer	CFD + Exp.	Improved RANS accuracy
[57]	Turbine blade flow	PINN	Not specified	CFD	—	High accuracy	Not specified	Flow	CFD	Accurate wake and boundary layer
[58]	Turbine blade temperature field	PINN	Not specified	Sparse data	—	High accuracy	Not specified	Temperature field inversion	CFD + Exp.	Accurate 2D temperature field
[59]	Channel with rotating obstacles	PINN + deep GP	Not specified	CFD	—	Temp. MAPE 2.24%	Not specified	Heat transfer	CFD	Optimized HTPC η = 1.1509
[60]	Turbine vane internal cooling	PINN-LSTM	Not specified	CFD	—	High accuracy	Not specified	Flow and heat transfer	CFD	Efficient coupled solution
[61]	Jet impingement cooling	PINN	Not specified	Sparse temperature data	—	High accuracy	Not specified	Convective HTC	Experimental	Accurate boundary condition inference

Table 1. *Cont.*

Ref.	Cooling Structure	ML Model	Dataset Size	Data Source	Optimization Algorithm	Prediction Error	Computational Savings	Objective Functions	Validation	Improvement over Baseline
[62]	Turbine blade temperature field	FERC-PINN	Not specified	Sparse data	—	Max temp. MAPE 4.51%	Not specified	Transient temperature reconstruction	CFD + Exp.	Efficient and accurate reconstruction
[63]	Blade surface temperature	Data fusion	Not specified	Sparse data	—	High accuracy	Not specified	Temperature reconstruction	Experimental	Reduced data acquisition cost
[64]	Turbine blade	ASP-GNN	Not specified	CFD	—	High accuracy	Not specified	Temperature, aerodynamic	CFD	Rapid and accurate prediction
[65]	Turbine blade	POD + ANN	Not specified	CFD	—	Max error 2.61%	793,223× speedup	Temperature field	CFD	793,223× speedup; max error 2.61%
[66]	Turbine vane	Deep learning	Not specified	CFD	—	High accuracy	Not specified	Temperature field	CFD	Fast prediction
[67]	Turbine vane	Two-stage DL	Not specified	CFD	—	High accuracy	Not specified	Temperature field	CFD	Improved reconstruction accuracy
[68]	Fluid/heat transfer (XAI review)	XAI review	Not specified	—	—	—	Not specified	Interpretability	—	—
[69]	Film cooling *	MS-DeCNN	Not specified	Experimental	—	High accuracy	Not specified	Cooling effectiveness	Experimental	Improved accuracy and interpretability
[70]	Turbine blade	DNN	Not specified	CFD	—	High accuracy	Not specified	Temperature, coolant flow	CFD	Optimal trade-off obtained

Note: "—" indicates that the corresponding information was not explicitly reported in the original study. * References [52–55,69] concern film cooling, and [56–62] concern PINN and data-augmentation methodology; they are included as supporting techniques whose methods are transferable to internal cooling optimization. References [63–70] concern temperature field reconstruction and model interpretability. Nu: Nusselt number; ΔP: pressure drop; f: friction factor; HTC: heat transfer coefficient; PEC: performance evaluation criterion; Rth: thermal resistance; Cd: discharge coefficient; UQ: uncertainty quantification; Exp.: experimental; LHS: Latin hypercube sampling; XAI: explainable AI. In total, multiple entries contain source-verified quantitative data covering prediction errors, computational savings, and performance improvements.

4.1. Common Intelligent Optimization Methods for Internal Cooling Structures of Turbine Blades

The application of machine learning methods in turbine blade cooling structure optimization mainly relies on two core components: data-driven prediction models and intelligent optimization algorithms [19]. As shown in Figure 5, unlike low-order surrogate

models such as response surface methodology or Kriging commonly used in traditional optimization methods, machine learning can automatically learn complex nonlinear mapping relationships from large amounts of data, approximate CFD results with higher prediction accuracy, and work synergistically with intelligent optimization algorithms to achieve efficient and high-precision design space exploration [1].

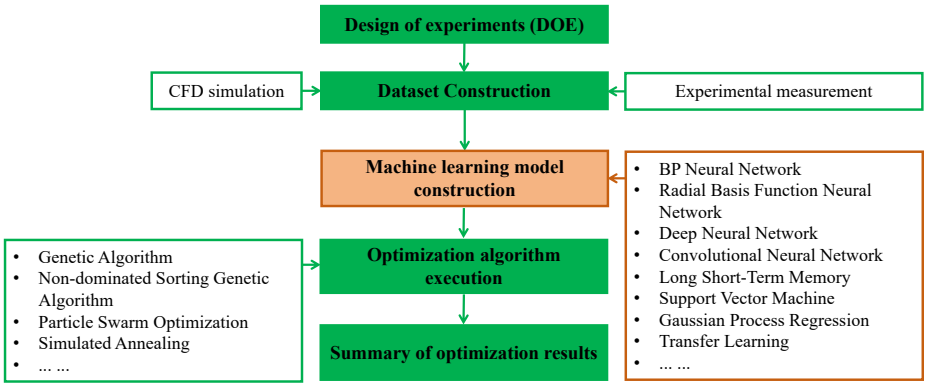


Figure 5. Intelligent optimization design methods for turbine blade cooling structures.

The mainstream machine learning prediction models used in turbine blade cooling optimization can be characterized as follows. Back-propagation neural networks (BPNN) are feedforward networks trained with gradient descent, typically consisting of an input layer (geometric parameters and operating conditions), one or more hidden layers, and an output layer (cooling performance metrics such as Nu and f). BPNN requires sufficient training samples (typically 50–500 CFD cases) and is suitable for low-to-moderate dimensional problems. Deep neural networks (DNN) with multiple hidden layers can capture more complex nonlinear mappings but require larger datasets and are prone to overfitting without regularization. Convolutional neural networks (CNN) are specialized for grid-structured data such as temperature fields, taking 2D/3D field data as input and outputting predicted fields or scalar metrics. Long short-term memory networks (LSTM) are designed for sequential data and are suitable for transient cooling problems. Radial basis function neural networks (RBFNN) use localized basis functions and offer good interpolation properties with smaller sample requirements. Gaussian process regression (GPR) provides nonparametric prediction with built-in uncertainty quantification but has $O(n^3)$ computational complexity, limiting its application to small datasets (typically <500 samples). Support vector machines (SVM) find optimal separating hyperplanes in kernel-induced feature space and perform well with small-to-medium datasets. Generative adversarial networks (GAN) consist of a generator and discriminator trained adversarially, and are used for data augmentation and field reconstruction. Physics-informed neural networks (PINN) embed PDE residuals into the loss function, reducing the need for labeled data but facing training challenges for complex turbulent flows (see Section 5.2 for limitations). The typical prediction errors reported in the literature range from 1% to 15% relative error, depending on the model type, dataset size, and problem complexity, with DNN and ensemble models generally achieving lower errors for sufficiently large datasets. These models, combined with intelligent optimization algorithms such as genetic algorithm (GA), non-dominated sorting genetic algorithm (NSGA-II), and particle swarm optimization (PSO), constitute the core methodological framework for intelligent optimization of internal cooling structures of turbine blades.

In practical applications, deep learning and other machine learning models are used as high-accuracy surrogate models. It should be noted that the relative performance of ML models versus traditional surrogate models (such as RSM, Kriging, and RBF) depends on

the problem dimensionality, sample size, and nonlinearity. For low-dimensional problems with sufficient training samples, Kriging models can achieve comparable or even superior accuracy due to their inherent uncertainty quantification capability and well-understood interpolation properties. However, under the strongly nonlinear and computationally expensive scenarios typical of turbine blade cooling optimization, machine learning models exhibit evident advantages in both prediction accuracy and computational efficiency, which can be quantitatively verified across multiple published studies. For example, in a comparative study on lantern-shaped pin-fin channel heat transfer prediction, when the training sample size was gradually reduced, deep learning surrogate models maintained more stable prediction performance, while RSM, RBF, and ensemble models exhibited larger prediction distortion with limited samples [36]. Xi et al. [23] reported that a BPNN model for steam-cooled ribbed channels achieved a maximum prediction error of only 1.9%. Ghosh et al. [38] demonstrated that a multi-fidelity Bayesian optimization framework improved the objective value by 6% while reducing computational cost by 2% and using 8 fewer high-fidelity simulations. Chen et al. [65] reported that a POD-ANN method for turbine blade temperature field reconstruction increased computational speed by more than 793,223 times compared with traditional CFD, with a maximum relative error of only 2.61%. Liu et al. [45] achieved approximately 20% pressure drop reduction and 1.48–17.14% Nusselt number improvement via BPNN-based leading edge impingement optimization. Fouda et al. [44] demonstrated that an MLP-ANN model for jet impingement heat transfer achieved R^2 values above 0.98 and MAPE below 1% against experimental measurements. Therefore, in the context of turbine blade internal cooling optimization—where high-fidelity CFD samples are expensive and the design space is typically high-dimensional and strongly nonlinear—ML surrogate models generally provide more reliable performance evaluation for optimization. At the same time, their computational cost per evaluation is much lower than that of CFD simulations, enabling large-scale optimization iterations [4–6]. It should be emphasized that these advantages are scenario-specific and do not apply universally across all problem settings.

It is important to note that the majority of ML models reviewed in this paper are trained on CFD-generated data, which introduces a critical consideration regarding uncertainty propagation. CFD simulations themselves contain uncertainties arising from turbulence model selection (e.g., RANS models typically underpredict or overpredict heat transfer in certain flow regimes), mesh resolution and quality, and boundary condition specification. These uncertainties are inherently transferred to the ML surrogate models trained on CFD data, meaning that the ML model's prediction accuracy is bounded by the accuracy of the underlying CFD data. On this basis, it is important to distinguish three levels of validation in this body of research. The first level is CFD-based validation, in which the ML model is trained on a subset of CFD simulations and tested on a held-out subset; this verifies the model's ability to reproduce CFD results but does not guarantee accuracy against real-world measurements. The second level is experimental validation of ML predictions, in which the model outputs are compared directly with physical experimental data; this is more rigorous but remains rare, with only a few studies [32,39,44,61,63] reporting such validation. The third level is validation of optimized designs, in which the geometry or operating conditions identified by the ML-based optimization are confirmed by high-fidelity CFD or experiments to deliver the predicted performance improvements. Most current studies stop at the first level, and future research should prioritize higher-level validation to ensure the reliability of ML-based optimization results in practical engineering applications.

4.2. Machine Learning-Based Optimization of Ribbed Cooling Structures

As the most commonly used internal cooling method in the mid-chord region of turbine blades, the optimization design of ribbed cooling structures is of great significance for improving cooling efficiency. In recent years, machine learning methods have achieved remarkable progress in the optimization of ribbed cooling structures, providing new ideas and tools for the design of complex cooling channels [19].

Damavandi et al. [22] combined computational fluid dynamics (CFD) simulations, artificial neural networks (ANN), and genetic algorithm (GA) to perform multi-objective optimization of asymmetric V-shaped ribs in a cooling channel. The results demonstrated that this method can effectively balance heat transfer performance and flow resistance, obtaining a design scheme with optimal comprehensive performance. Lei Xi et al. [23] employed neural networks and genetic algorithm to optimize the heat transfer performance of steam-cooled ribbed channels, establishing a mapping relationship between heat transfer characteristics and structural parameters, thereby providing a theoretical basis for the optimization design of steam-cooled ribbed channels. Afzal et al. [24] proposed a neural network-assisted optimization method to enhance the heat transfer performance of a rectangular channel with crossed ribs, demonstrating the effectiveness of the RBNN-PSO strategy in complex thermo-fluid systems. Kwon et al. [25] combined response surface methodology and artificial neural networks to optimize the heat transfer performance of an internal passage with extended ribs, analyzing the effects of rib length and rib width on cooling effectiveness. Liu et al. [26] investigated the influence of different geometric parameters on the flow and heat transfer characteristics of a bionic S-shaped rib-wall coupled cooling channel, and performed scheme optimization based on neural networks, achieving significant improvement in uniformity while maintaining high heat transfer. Zheng et al. [27] studied the cooling performance of ribbed channels using a combination of neural networks and genetic algorithm, clarifying the influence mechanisms of various structural parameters on cooling performance and achieving comprehensive optimization of heat transfer efficiency and flow resistance. Sahin et al. [28] proposed a deep operator network-based surrogate modeling approach to optimize rib profiles in internal cooling channels, incorporating uncertainty quantification. Nastasi [29] took a square channel with transverse ribs as the research object and adopted a combination of adjoint method and machine learning to perform multi-step optimization of internal cooling channels for gas turbine blades, significantly improving cooling performance. Wang et al. [30] used supervised learning methods for rapid prediction of the performance of ribbed internal cooling channels in gas turbine blades, providing efficient and high-accuracy prediction models for the optimization design of cooling structures.

In summary, the surrogate models constructed by machine learning in ribbed cooling optimization exhibit higher prediction accuracy than traditional response surface methods, accurately capturing the nonlinear effects of parameters such as rib angle and aspect ratio on heat transfer and flow resistance. A comparison across studies reveals several trends: (1) ANN-GA is the most commonly used framework for ribbed channel optimization [22,23,27], while more recent studies have explored deep operator networks [28] and adjoint-ML hybrid methods [29] for higher-dimensional problems; (2) the choice of objective function varies—some studies focus on maximizing heat transfer alone [23], while others adopt multi-objective optimization balancing Nu and pressure loss [22,27]; (3) steam-cooled ribbed channels [23] exhibit different optimal parameter trends compared with air-cooled channels due to the different Prandtl number and thermophysical properties; and (4) the incorporation of uncertainty quantification [28] and sensitivity analysis [30] represents an emerging trend toward more reliable and interpretable optimization. Moreover, the above studies demonstrate that machine learning methods are applicable to various rib

configurations (e.g., V-shaped ribs, steam-cooled ribs, crossed ribs) and different operating conditions, providing high-accuracy evaluation tools for the efficient design of turbine blade ribbed cooling channels.

4.3. Machine Learning-Based Optimization of Pin-Fin Cooling Structures

As the primary cooling method for the trailing edge region of turbine blades, the optimization design of pin-fin cooling structures plays a critical role in improving the overall cooling efficiency of blades. In recent years, machine learning methods have achieved remarkable progress in the optimization of pin-fin cooling structures, offering new ideas and tools for the efficient design of complex pin-fin arrays [19].

Moon et al. [31] employed Latin hypercube experimental design, radial basis function neural networks, and the NSGA-II algorithm to perform multi-objective optimization of the geometric parameters of fan-shaped pin-fins in a rectangular cooling channel, effectively enhancing the heat transfer capacity of the channel while reducing pressure loss. Jadhav et al. [32] investigated the flow and heat transfer characteristics in a straight channel with staggered pin-fin arrays through experimental and numerical methods. Based on the parametric study, they trained a neural network model using the Levenberg–Marquardt algorithm and minimized thermal resistance and pressure loss using NSGA-II, obtaining a Pareto optimal solution set. Yang et al. [33] employed deep neural networks to establish a high-accuracy mapping relationship between pin-fin geometry and heat transfer performance, and then used a genetic algorithm to optimize the pin-fin shape, significantly improving cooling performance under high-temperature conditions. Nguyen et al. [34] combined genetic algorithm and machine learning to perform shape optimization of pin-fin arrays in a cooling channel, effectively enhancing heat transfer efficiency. Hu et al. [35] constructed an ensemble surrogate model comprising Gaussian process (GP), radial basis function (RBF), and support vector regression (SVR), and used self-organizing geometry and multi-objective methods to optimize the pin-fin cooling of a turbine blade trailing edge. Gao et al. [36] investigated the flow and heat transfer characteristics in a lantern-shaped pin-fin channel using deep learning methods. They adopted an improved pix2pix framework (integrating residual network units and stochastic gradient Hamiltonian Monte Carlo) to build a surrogate model, and achieved efficient multi-objective optimization based on NSGA-II with the objectives of maximizing Nusselt number and minimizing friction factor. Mihalko et al. [37] used Bayesian methods combined with a Gaussian process surrogate model to optimize the flow and heat transfer performance of pin-fin arrays, and indirectly evaluated prediction uncertainty through the confidence intervals of the surrogate model. Ghosh et al. [38] proposed a Bayesian optimization framework based on a multi-fidelity Gaussian process and successfully applied it to the shape optimization of pin-fin arrays in turbine blade cooling channels. The results demonstrated that this framework significantly saves computational resources while obtaining better design results than traditional optimization methods. Sarosi et al. [39] established a machine learning framework based on a fully connected neural network (FCNN) to predict the flow and heat transfer characteristics of non-uniform pin-fin arrays with different sizes, and used this framework to optimize the shape of the pin-fin array. Mihalko et al. [40] further proposed a transfer learning framework combining Bayesian optimization and computational fluid dynamics, which significantly improved the comprehensive thermo-hydraulic performance of pin-fin channels.

Similarly, the surrogate models constructed by machine learning methods in pin-fin cooling optimization exhibit high prediction accuracy, accurately capturing the complex mapping relationship between pin-fin geometric parameters and thermo-hydraulic performance. A comparison across studies reveals that: (1) RBFNN-NSGA-II [31] and NN-NSGA-II [32] are the dominant frameworks for pin-fin optimization, while more recent

studies have explored DNN-GA [33], ensemble models [35], and deep learning [36] for higher-dimensional problems; (2) Bayesian and multi-fidelity approaches [37,38] offer uncertainty quantification and reduced computational cost, representing an emerging trend; (3) transfer learning [40] has shown promise for heterogeneous pin-fin arrays, reducing the need for extensive new training data; and (4) experimental validation has been conducted in a few studies [32,39], while most rely on CFD validation. Therefore, machine learning methods are applicable to pin-fin arrays with different arrangements and geometric features, effectively supporting the optimization design of turbine blade trailing edge cooling structures.

4.4. Machine Learning-Based Optimization of Impingement Cooling Structures

Impingement cooling is one of the most effective methods for enhancing the local heat transfer coefficient on the inner wall of turbine blades, and is particularly suitable for regions with high thermal loads such as the leading edge and the mid-chord region [11]. In recent years, machine learning methods have achieved significant progress in the optimization of impingement cooling structures, providing new ideas and tools for the efficient design of complex impingement cooling systems [19].

Jahromi et al. [41] constructed a high-accuracy surrogate model based on artificial neural networks (ANN) to map the relationship between the heat transfer performance of turbulent jet array impingement on a turbine blade surface and geometric parameters, and then performed multi-objective optimization of the jet array using a multi-objective genetic algorithm, aiming to achieve uniform cooling of the turbine blade while minimizing compression power. Özel et al. [42] combined computational fluid dynamics (CFD) with a deep learning model based on the UNet architecture to optimize an extended jet impingement cooling system on a corrugated surface, achieving an approximately 11% improvement in the comprehensive thermal performance (PEC). Boutarfa [43] adopted a combined CFD and ANN approach to construct a mapping between heat transfer characteristics and geometric parameters for a rotor-stator cavity cooled by multiple jets, significantly improving prediction accuracy and providing an optimization basis for cooling system design. Fouda et al. [44] performed experimental analysis and used a multilayer perceptron artificial neural network (MLP-ANN) to predict the local Nusselt number of a turbulent air jet impinging on a flat surface with high accuracy, and optimized the heat transfer performance by adjusting parameters such as Reynolds number and jet spacing. Liu et al. [45] employed Latin hypercube sampling (LHS) experimental design, a back-propagation neural network (BPNN) surrogate model, and the NSGA-II algorithm to conduct multi-objective optimization of the jet impingement cooling structure in the leading edge cavity of a first-stage turbine stator vane. The obtained Pareto optimal solutions achieved approximately 20% reduction in pressure drop, while increasing the area-averaged Nusselt number by 1.48–17.14% and the heat transfer uniformity index by 5.46–8.17% compared with the original design. Zhou et al. [46] carried out thermal performance analysis and multi-objective optimization of orthogonal rib-enhanced jet array impingement cooling at the blade leading edge, constructing a multi-objective optimization framework by combining ANN and GA, and obtained a design scheme with superior comprehensive performance. Yan et al. [47] proposed a double-swirl structure optimization method for blade leading edge impingement cooling, using Gaussian process regression (GPR) to build a surrogate model and combining it with the NSGA-II algorithm to achieve multi-objective optimization. By optimizing the swirl structure, they obtained uniform and efficient cooling performance.

In impingement cooling optimization, machine learning methods similarly greatly improve the prediction accuracy of surrogate models, accurately approximating the heat transfer and pressure drop distributions under complex jet impingement conditions. A

comparison across studies reveals that: (1) ANN-MOGA [41] and BPNN-NSGA-II [45] are the most commonly used frameworks, while UNet-based deep learning [42] has emerged for full-field prediction; (2) the optimization objectives range from single-objective (maximize uniformity or minimize power) [41] to multi-objective (Nu, pressure drop, uniformity) [45,47]; (3) GPR-based surrogate models [47] offer built-in uncertainty quantification for double swirl structures; and (4) experimental validation has been conducted by Fouda et al. [44], while most studies rely on CFD validation. It is evident that machine learning methods are applicable to various impingement cooling configurations (e.g., jet arrays, swirl structures, corrugated target surfaces), providing reliable tools for the design of impingement cooling at the leading edge and mid-chord region of turbine blades.

4.5. Machine Learning-Based Optimization of Other Internal or Hybrid Cooling Structures

In addition to ribbed, pin-fin, and impingement cooling structures, researchers have also applied machine learning methods to the optimization of other complex cooling structures such as lattice structures, wedge-shaped latticework, coolant collection/distribution plenums, and dimples/protrusions, achieving significant progress [19].

Lei Xi et al. [48] employed artificial neural networks and genetic algorithm to analyze the cooling performance and optimize the structural parameters of X-type truss array channels. In their study, ANN was used to establish a high-accuracy mapping relationship between the geometric parameters of the truss structure and its cooling performance, and a multi-objective optimization was achieved by combining with GA. The optimized X-type truss array channel exhibited excellent performance in both heat transfer and flow resistance. Yu et al. [49] used a GA-optimized back-propagation neural network (GA-BPNN) to predict the heat transfer characteristics of a wedge-shaped latticework cooling structure under high thermal load. By optimizing the initial weights and thresholds of the BPNN through GA, the prediction accuracy was significantly improved, providing a reliable tool for the optimization design of complex cooling structures. Chai et al. [50] performed multi-objective optimization design of a turbine coolant collection/distribution plenum based on a surrogate model approach. They employed a least squares support vector machine (LS-SVM) surrogate model to establish a quantitative mapping relationship between the plenum geometric parameters and flow performance, and combined it with a chaotic optimization algorithm, achieving an approximately 26% increase in discharge coefficient and an approximately 79% reduction in outlet non-uniformity. Singh [51] numerically investigated the effects of geometric parameters of protrusions and dimples on cooling performance during slot jet impingement on a concave surface, and optimized the layout of the protrusions and dimples using artificial neural networks and genetic algorithm. The results indicated that the ANN-GA hybrid method can efficiently predict the optimal layout with extremely high prediction accuracy.

In summary, for other cooling structures of turbine blades such as lattice structures, wedge-shaped latticework, plenums, and dimples/protrusions, machine learning methods exhibit high-accuracy nonlinear mapping capabilities, effectively handling the heat transfer and flow characteristics of these complex structures. A comparison across studies reveals that: (1) ANN-GA [48] and GA-BPNN [49] are the dominant frameworks for lattice and truss structures; (2) LS-SVM with chaotic optimization [50] achieved a 26% increase in discharge coefficient and 79% reduction in outlet non-uniformity for coolant plenums; (3) the optimization objectives vary across structure types, from thermal performance [48,49] to flow uniformity and discharge coefficient [50]; and (4) these novel structures represent an emerging area where ML optimization can provide significant design insights. It is evident that machine learning methods have good applicability across the above-mentioned various

internal cooling structures, providing technical references for the engineering design of novel turbine blade cooling schemes.

5. Future Perspectives on Machine Learning in Optimization Design of Turbine Blade Cooling

Although significant progress has been made in the application of machine learning to the optimization design of turbine blade cooling structures, challenges such as data scarcity, insufficient simulation accuracy, and poor model interpretability remain key bottlenecks that constrain further development. To address these challenges, future research should focus on the following five directions: data augmentation techniques, physics-informed neural networks (PINNs), efficient temperature field reconstruction, model interpretability analysis, and extraction of optimization structure evolution patterns. Breakthroughs in these directions are expected to significantly improve data quality and simulation accuracy, enhance model transparency, and reveal the underlying mechanisms of design optimization, thereby providing more reliable and efficient technical support for the design of next-generation gas turbine blade cooling systems.

5.1. Data Augmentation Techniques: A New Direction for Driving Intelligent Optimization of Turbine Blade Cooling Structures

Data augmentation techniques offer new breakthrough opportunities for the optimization design of turbine blade cooling structures. Traditional cooling data acquisition relies on expensive experimental measurements and time-consuming numerical simulations, which cannot meet the demand of machine learning models for large-scale training data, severely restricting the application of intelligent optimization methods in blade cooling design [52–55]. Generative adversarial networks (GANs) and their variants (e.g., CGAN/CTGAN, the schematic diagram of which is shown in Figure 6) possess powerful data generation capabilities and can efficiently generate high-quality cooling data, thereby providing sufficient data support for the intelligent optimization of cooling structures [52]. This not only helps to reduce design costs and shorten design cycles, but more importantly, it improves the accuracy and reliability of optimization design, laying a data foundation for the design of high-efficiency cooling structures.

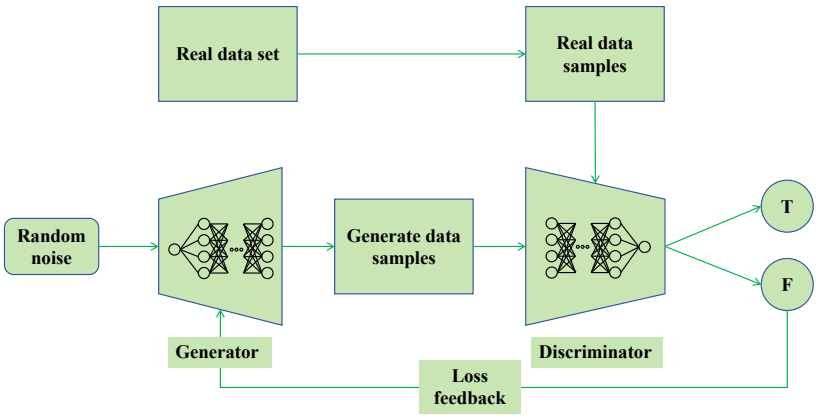


Figure 6. Schematic diagram of the CTGAN principle.

Currently, several preliminary studies have explored the application of GANs to cooling data generation and quality enhancement for turbine blades. Wang et al. [52] employed GANs to optimize the design of a trench vortex generator for film cooling, demonstrating that the data-augmented model could efficiently predict the two-dimensional film cooling effectiveness with high accuracy and computational speed. Zhang et al. [53] applied a

GAN model to predict the film cooling effectiveness on the endwall of a turbine blade; the predictions agreed well with experimental data, demonstrating that GANs are effective tools for cooling data generation. Song et al. [54] further constructed a GAN-based surrogate model and performed global optimization of endwall film cooling using a genetic algorithm. The optimized film hole arrangement increased the endwall cooling performance by 119.73–158.26% and reduced the total pressure loss in the channel by 12.23–13.59%, achieving an optimal balance between cooling effectiveness and pressure loss. Moreover, Tao et al. [55] applied a GAN-based surrogate model to optimize the film cooling and aerodynamic performance of an asymmetric cavity-bottom blade tip, and the optimized tip geometry exhibited excellent performance in both aspects. Although the above studies mainly focus on film cooling and blade tip cooling, the data generation methods and optimization frameworks are also transferable to the intelligent optimization of internal cooling structures (e.g., ribbed channels, pin-fin arrays).

In addition to directly generating cooling data, machine learning can also be used to improve turbulence models, indirectly enhancing the quality of cooling data. Hammond et al. [56] employed gene expression programming to augment the RANS turbulence closure model for internal cooling systems of turbine blades, significantly improving the prediction accuracy of heat transfer by the turbulence model, and demonstrating the great potential of data augmentation methods in improving RANS models under complex three-dimensional geometries.

In summary, data augmentation techniques can not only effectively alleviate the bottleneck of cooling data scarcity but also improve the accuracy of cooling performance prediction, providing more reliable decision-making bases for multi-objective optimization. Although current research is mostly concentrated on film cooling and blade tip cooling, with the continuous development of generative models and turbulence closure augmentation methods, data augmentation techniques are expected to play an even greater role in the intelligent optimization of internal cooling structures for turbine blades, providing strong support for the cooling design of next-generation gas turbines.

5.2. Physics-Informed Neural Networks for Improving CFD Simulation Accuracy of Turbine Blade Cooling

Physics-informed neural networks (PINNs), as an emerging class of machine learning methods, embed physical equations (e.g., Navier–Stokes equations, energy equations) as constraints into the loss function of neural networks, offering a completely new technical pathway for the simulation and optimization of turbine blade cooling structures [57,59–62]. Traditional CFD methods often face challenges such as time-consuming mesh generation, high computational cost, and convergence difficulties when dealing with complex flow and heat transfer problems. By integrating physical prior knowledge with data-driven approaches, PINNs can accurately predict flow and temperature fields with limited or even no labeled data, while significantly improving computational efficiency, thus providing a powerful tool for the efficient design and parameter inversion of turbine blade cooling systems. The basic principle of PINN is illustrated in Figure 7.

Hanrahan et al. [57] used PINNs to predict the transitional and turbulent flow around a turbine blade. Their study demonstrated that PINNs can accurately simulate the wake loss profile, boundary layer regions, and the separation and transition characteristics on the suction side, as well as capture the delay of the separation point of the trailing edge separation bubble. Roozbahani et al. [59] combined PINNs with deep Gaussian processes to analyze and optimize the heat transfer performance of a two-dimensional channel with rotating cylindrical obstacles, achieving a significant improvement in heat transfer in the optimized channel. Li et al. [60] proposed a physics-informed long short-term memory net-

work (PINN-LSTM) framework that integrates the temporal modeling capability of LSTM with the physical constraints of PINNs, enabling efficient solution of complex fluid flow and heat transfer coupling problems inside turbine blades, thus providing a high-accuracy and high-reliability surrogate model for cooling system optimization. Hazra et al. [61] developed a PINN-based method for estimating the convective heat transfer coefficient in jet impingement cooling. This method does not require explicit modeling of the fluid domain; instead, it accurately infers boundary conditions using only sparse temperature data from the solid domain, offering a significant advantage in practical engineering scenarios where flow conditions are unknown or difficult to model accurately. Qin et al. [62] proposed a Fourier-enhanced residual-connected physics-informed neural network (FERC-PINN) that effectively overcomes the training instability issues of conventional PINNs in reconstructing the transient temperature field of turbine blades, enabling efficient and accurate reconstruction of the blade temperature field from sparse surface measurement data.

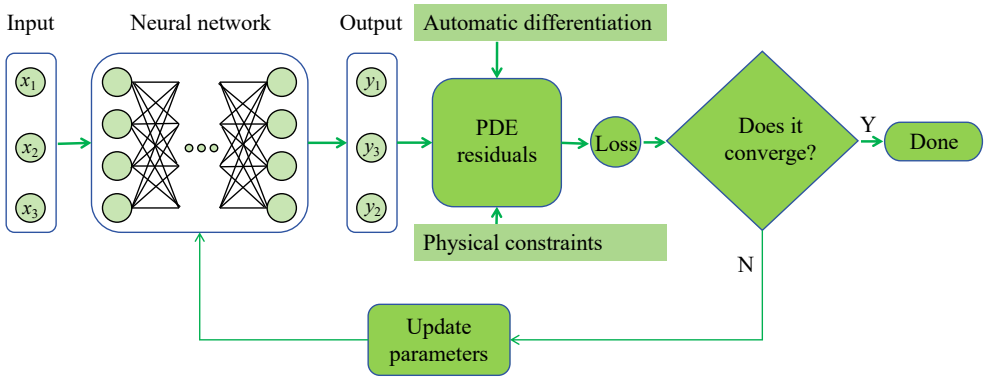


Figure 7. Schematic diagram of PINN.

In summary, PINNs provide an efficient and accurate data-driven approach for the simulation and optimization of turbine blade cooling structures by embedding physical equations into the neural network framework, and are expected to play an increasingly important role in future turbine blade design.

Despite the promising potential of PINNs, several significant limitations must be acknowledged, particularly for turbine blade cooling applications. First, standard PINNs face substantial challenges in handling complex three-dimensional geometries with intricate internal cooling passages, as the weak imposition of boundary conditions on complex boundaries can lead to significant prediction errors. Second, for high-Reynolds-number turbulent flows—typical of turbine blade cooling conditions—PINNs generally remain less accurate and less computationally efficient than high-order CFD methods. The strong nonlinearity, multi-scale dynamics, and sensitivity to initial conditions in turbulent flows create ill-conditioned optimization landscapes that frequently cause training instabilities and convergence failures. In particular, for cavity flows at $Re \geq 1000$, no reliable PINN solution agreeing with accurate numerical simulation has been reported without labeled data. Third, the training process of PINNs is often unstable due to competing loss terms (data loss, PDE residual loss, boundary condition loss), requiring careful loss weighting and hyperparameter tuning. Fourth, while PINNs reduce the need for labeled data, their training computational cost can be substantial, especially for 3D problems, and the additional integration over control volumes in advanced PINN formulations further increases training time. Therefore, PINNs currently serve as complementary tools or surrogate models for filling data gaps rather than full replacements for conventional CFD approaches in turbine blade cooling applications. Ongoing research on multi-scale weak-form PINNs, neural operators, and hybrid CFD-PINN frameworks aims to address these limitations.

5.3. Deep Learning-Based Temperature Field Reconstruction Methods for Turbine Blades

Accurate acquisition of the temperature field of turbine blades is crucial for the optimization design of cooling structures. Traditional experimental measurements and computational fluid dynamics (CFD) methods suffer from high cost, long turnaround time, and sparse data, making it difficult to meet the demands of rapid iterative design for modern gas turbines. Deep learning methods provide an efficient and accurate new approach for temperature field reconstruction [63–67], significantly reducing computation time while maintaining prediction accuracy, thereby offering strong support for the optimization design of turbine blades.

Wen et al. [63] adopted a data fusion strategy to achieve high-accuracy reconstruction of the blade surface temperature by fusing multiple sources of sparse data, effectively reducing the cost of data acquisition and providing reliable thermal boundary information for cooling optimization. Li et al. [64] developed a fast multidisciplinary prediction and reconstruction model for turbine blades based on supervised graph learning, namely the aerodynamic strength prediction graph neural network (ASP-GNN), which can rapidly and accurately predict temperature fields and aerodynamic characteristics under different boundary conditions even with limited training samples. Chen et al. [65] proposed an efficient turbine blade temperature field reconstruction method combining proper orthogonal decomposition (POD) and artificial neural networks (ANN). In this method, POD is first used to extract the dominant spatial modes and their coefficients, greatly reducing data complexity; then, a feedforward neural network predicts the mode coefficients to achieve rapid temperature field reconstruction. Validation results demonstrate that the computational speed of this method is increased by more than 793,223 times compared with traditional CFD, with a maximum relative error of only 2.61%, demonstrating extremely high engineering application value. Long et al. [66] pioneered the use of deep learning methods for rapid prediction and reconstruction of turbine blade temperature fields under active modulation of cooling air flow. Subsequently, Long et al. [67] further proposed a two-stage deep learning method: in the first stage, an n-Net method is used to achieve stable mapping from low-dimensional parameters to a high-dimensional temperature field; in the second stage, an Attention Pix2PixHD method is employed, utilizing a spatial attention mechanism to further improve the prediction and reconstruction accuracy of the temperature field, providing a powerful tool for active cooling control and design optimization of turbine blades.

In summary, deep learning-based temperature field reconstruction methods can increase computational speed by several orders of magnitude while maintaining high accuracy, effectively addressing the high computational cost of traditional CFD methods, and providing important technical support for rapid optimization design of turbine blades and performance evaluation of cooling systems. The temperature field reconstruction process for turbine blade cooling summarized from the above literature is shown in Figure 8.

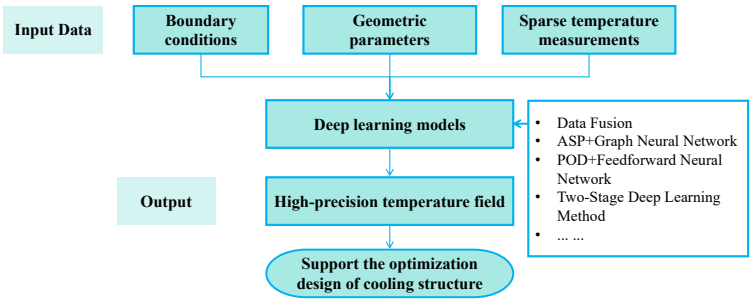


Figure 8. Temperature field reconstruction process for turbine blade cooling.

5.4. Interpretability of Machine Learning Models

Machine learning models are increasingly widely used in the optimization of turbine blade cooling structures; however, their "black box" nature limits their credibility and acceptance in engineering decision-making. Interpretability analysis methods can reveal the internal decision-making mechanisms of the models, helping engineers understand the intrinsic relationships between design parameters and cooling performance, thereby improving the reliability and interpretability of optimization design.

Cremades et al. [68] systematically reviewed explainable artificial intelligence methods in the fields of fluid dynamics and heat transfer, with a focus on the principles, characteristics, and application scenarios of feature attribution techniques. They also provided a detailed elaboration of four common implementations of SHAP (Shapley Additive exPlanations) values, offering a rich theoretical reference for interpretability research on machine learning models in thermo-fluid sciences. Wang et al. [30] performed sensitivity analysis on the cooling performance of gas turbine blades using a supervised learning method based on conditional generative adversarial networks, successfully identifying key parameters affecting cooling performance and providing an interpretable reference for cooling structure design. Jahromi et al. [41] also adopted sensitivity analysis in their study on impingement cooling optimization, systematically analyzing the influence mechanisms of key parameters such as Reynolds number and jet spacing on cooling uniformity, thereby enhancing the interpretability of the constructed machine learning model. Liu et al. [69] developed a prediction model for turbine blade film cooling effectiveness using a multi-scale deconvolution neural network (MS-DeCNN) and quantified the contribution and interactions of each input feature to the predicted output through SHAP values, significantly improving both the prediction accuracy and interpretability of the model. Chen et al. [70] constructed a high-accuracy surrogate model based on deep neural networks to predict the blade temperature and coolant flow rate of turbine blades. Using SHAP-based interpretability analysis, they identified the film hole diameter as the most critical parameter, and subsequently performed bi-objective Pareto optimization to obtain the optimal trade-off between blade temperature and coolant flow rate.

In summary, interpretability analysis methods provide important support for the application of machine learning models in the optimization design of turbine blade cooling structures. Among them, the SHAP method is currently a widely used approach for machine learning model interpretability, the principle of which is illustrated in Figure 9. By revealing the decision-making mechanisms and key influencing factors of the models, engineers can apply machine learning methods with greater confidence, achieving efficient and reliable optimization design of cooling structures.

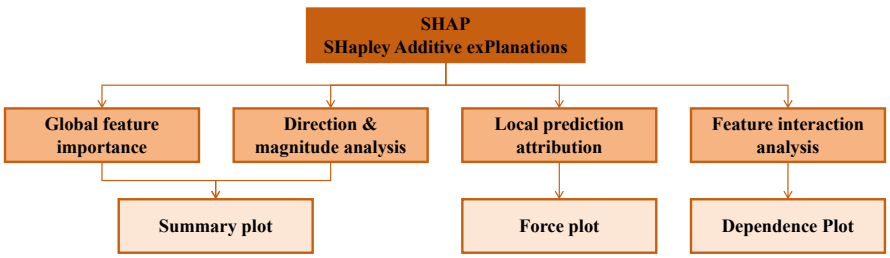


Figure 9. SHAP interpretability method for machine learning models.

5.5. Evolution Pattern Analysis of Optimized Structures

After obtaining the optimal cooling structure parameters under different operating conditions using machine learning methods, researchers can perform post-processing analysis on the variation trends of these optimal parameters as operating conditions such

as Reynolds number, and thereby summarize design rules with engineering guidance or fit empirical correlations convenient for engineering application. It should be emphasized that the extraction of such evolution patterns is not automatically accomplished by the machine learning models themselves, but rather relies on manual induction and analysis based on the optimization results. This combination transforms isolated optimal solutions into generalizable design criteria for variable-condition operation.

Damavandi et al. [22] combined CFD, artificial neural networks, and the NSGA-II algorithm to obtain the Pareto optimal front of V-shaped ribs. The results demonstrate that the smaller the deviation distance of the V-shaped rib apex from the channel centerline, the better the heat transfer and pressure drop performance; meanwhile, as the angle between the two rib legs increases, both heat transfer and pressure drop increase simultaneously. This trade-off relationship provides a key basis for cooling design targeting different performance objectives. Xi et al. [23] found that the optimal aspect ratio and optimal rib angle of a steam-cooled ribbed channel both increase monotonically with Reynolds number, and accordingly provided guidelines for selecting the rib angle under different aspect ratios, offering a direct reference for variable-condition design of ribbed channels. Sarosi et al. [39] optimized non-uniform pin-fin arrays using a machine learning framework, and discovered that a non-uniform size distribution strategy with "small diameter at the inlet side and large diameter at the outlet side" can significantly reduce pressure drop with almost no increase in exit temperature. This concise empirical rule has been subsequently verified by experiments. Xi et al. [48] demonstrated that for X-type truss array channels, whether the objective is to maximize the average Nusselt number or to maximize the comprehensive thermal coefficient, the optimal truss rod diameter ratio, transverse spacing ratio, and streamwise spacing ratio all increase with increasing Reynolds number. In that study, the optimal parameters were fitted into empirical correlations, which can be directly used for rapid engineering design without relying on a large number of CFD calculations.

In summary, machine learning methods provide highly efficient means for searching optimal cooling structures. However, the evolution patterns of optimal parameters with varying operating conditions and the corresponding design criteria still need to be summarized and refined through post-processing analysis of the optimization results. By comprehensively generalizing the optimal parameters obtained under a large number of operating conditions, empirical correlations or parameter selection principles can be established, thereby providing directly applicable theoretical bases and methodological tools for the variable-condition engineering design and performance prediction of turbine blade cooling structures.

5.6. Additional Emerging Directions

In addition to the five directions discussed above, several other important topics are emerging as critical enablers for machine learning-based optimization of turbine blade cooling structures.

Uncertainty quantification (UQ): Geometric manufacturing tolerances, operating condition variations, and CFD model uncertainties can significantly affect the performance and lifespan of turbine blades. UQ methods, such as Bayesian neural networks and Gaussian process regression, can provide confidence intervals for ML predictions, enabling robust optimization that accounts for performance dispersion. Recent studies have applied UQ to turbine cooling optimization, demonstrating its value in identifying designs that maintain performance under uncertainty [28,37]. Future research should integrate UQ into the ML-based optimization framework to produce reliability-aware cooling designs.

Active learning: Instead of using a fixed set of pre-computed CFD samples, active learning strategies iteratively select the most informative sample points for CFD simulation based

on the current surrogate model's uncertainty. This approach can significantly reduce the number of CFD simulations needed to achieve a given accuracy, making high-dimensional optimization more tractable. Bayesian optimization and expected improvement criteria are commonly used active learning strategies in thermal-fluid optimization [38].

Multi-fidelity modeling: Multi-fidelity surrogate models combine data from sources of varying accuracy and cost—such as coarse-mesh CFD (low-fidelity) and fine-mesh CFD or experiments (high-fidelity)—to achieve high prediction accuracy at reduced computational cost. Methods such as co-Kriging, multi-fidelity Gaussian processes, and multi-fidelity neural networks have shown promise in turbomachinery applications [38,40]. For turbine blade cooling, multi-fidelity approaches can leverage abundant low-fidelity data to pre-train models and fine-tune with scarce high-fidelity samples.

Transfer learning: Transfer learning enables knowledge learned from one cooling configuration or operating condition to be adapted to another, reducing the need for extensive new training data. This is particularly valuable for turbine blade cooling, where new geometric variants or operating conditions are frequently encountered. Mihalko et al. [40] demonstrated that transfer learning combined with Bayesian optimization can significantly improve the thermo-hydraulic performance of heterogeneous pin-fin arrays. Future research should explore transfer learning across different cooling structure types and operating regimes.

Generalization to unseen operating conditions: A key challenge for ML surrogate models is their ability to generalize to operating conditions outside the training distribution. Most current models are trained and validated within a narrow range of Reynolds numbers and boundary conditions. Physics-informed constraints, domain adaptation, and out-of-distribution detection techniques are needed to ensure reliable predictions across the wide operating envelope of gas turbines.

Experimental validation: As discussed in Section 4.1, the majority of ML-based cooling optimization studies rely solely on CFD validation. Experimental validation is essential to confirm that ML-optimized designs perform as predicted under real conditions. Future research should prioritize experimental campaigns to validate ML-optimized cooling structures, thereby bridging the gap between numerical optimization and engineering application.

5.7. Synthesis and Cross-Cutting Insights

Beyond the categorical review of individual cooling structures and ML methods, several cross-cutting insights emerge from the synthesis of the literature. First, a consistent finding across all cooling structure types is that ML surrogate models coupled with evolutionary optimization algorithms (particularly NSGA-II) have become the dominant framework, suggesting a methodological convergence in the field. Second, the dataset size remains a critical bottleneck: most studies use 50–300 CFD samples, which is sufficient for low-dimensional parameter optimization but inadequate for high-dimensional geometric design or full-field reconstruction. Third, there is a clear gap between the complexity of ML models employed and the validation rigor: while increasingly sophisticated models (DeepONet, GAN, PINN) are being proposed, experimental validation remains rare, with most studies relying solely on CFD hold-out validation. Fourth, the optimization objectives have evolved from single-objective (maximize Nu or minimize ΔP) to multi-objective (Pareto front of Nu vs. f), and more recently to include uniformity and reliability as additional objectives. Fifth, the transferability of ML models across cooling structure types and operating conditions remains largely unexplored, with most models trained and validated for a single specific configuration. These synthesized insights suggest that the field is transitioning from proof-of-concept applications to more rigorous and practically relevant methodologies, with data

scarcity, validation gaps, and generalization capability being the key barriers to broader engineering adoption.

6. Conclusions

This paper has comprehensively reviewed the research progress of machine learning in the optimization design of turbine blade cooling structures. The main conclusions are as follows:

(1) The surrogate models widely adopted in traditional optimization methods include response surface methodology (RSM), Kriging, and radial basis function (RBF). These surrogate models have limited capability to fit complex nonlinear relationships and exhibit limited prediction accuracy, thereby compromising the accuracy and reliability of the optimization results, making it difficult to meet the high-precision design requirements of modern turbine blade cooling structures. However, for low-dimensional problems with sufficient training samples, traditional surrogates such as Kriging can achieve comparable or superior performance relative to ML models.

(2) The machine learning models currently widely used in the optimization of turbine blade cooling structures include artificial neural networks (ANN), deep neural networks (DNN), convolutional neural networks (CNN), long short-term memory networks (LSTM), generative adversarial networks (GAN), and physics-informed neural networks (PINN). These models exhibit strong nonlinear mapping capabilities and high prediction accuracy, substantially enhancing both the design accuracy and optimization efficiency of internal cooling structures for turbine blades. Nevertheless, important limitations remain: most models are trained on CFD data and inherit CFD uncertainties; experimental validation remains rare; PINNs face significant challenges for complex 3D geometries and high-Reynolds-number turbulent flows; and the generalization of ML models across different cooling structures and operating conditions remains largely unexplored.

(3) Future research should focus on the following directions:

Data augmentation techniques: Employ generative models such as GANs to address the issue of data scarcity in turbine blade cooling, providing sufficient training samples for intelligent optimization.

Physics-informed neural networks (PINNs): Incorporate physical equations into neural networks to improve the CFD simulation accuracy of turbine blade cooling and achieve efficient forward problem solving and parameter inversion, while addressing current limitations for complex 3D turbulent flows.

Temperature field reconstruction: Achieve rapid and high-accuracy reconstruction of turbine blade temperature fields based on deep learning methods, significantly reducing the computational cycle.

Model interpretability: Introduce interpretability analysis methods such as SHAP to reveal the decision-making mechanisms of machine learning models, providing interpretability foundations for machine learning models used in turbine blade cooling performance prediction.

Optimization structure evolution patterns: Through post-processing analysis of a large number of optimization results, summarize the variation patterns of optimal structural parameters with operating conditions, and extract empirical correlations and design guidelines to directly guide engineering design and application.

Additional emerging directions: Integrate uncertainty quantification, active learning, multi-fidelity modeling, and transfer learning into the ML-based cooling optimization framework; prioritize experimental validation of ML-optimized designs to bridge the gap between numerical optimization and engineering application.

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