

Article

An Attention-Augmented CNN–LSTM Framework for Reconstructing Transient Temperature Fields of Turbine Blades from Sparse Measurements

Yingtao Chen, Langlang Liu *, Dan Sun, Haida Liu and Junjie Yang

School of Aero Engine, Shenyang Aerospace University, Shenyang 110136, China;
19982118@email.sau.edu.cn (Y.C.); phd_sundan@163.com (D.S.); yangjunjie@stu.sau.edu.cn (J.Y.)

* Correspondence: liulanglang2024@163.com

Abstract

Accurately predicting the temperature field of turbine blades is of great significance for evaluating the thermal reliability and service life of high-temperature components in aero-engines. However, due to the high computational cost of numerical simulations and the limitations imposed by complex geometric structures and harsh operating environments, experimental measurements can usually only obtain sparse sensor data, making the acquisition of complete temperature distributions still challenging. Therefore, reconstructing the complete temperature field under sparse measurement conditions has become a key research issue in turbine thermal analysis. To address this problem, this paper proposes an attention-enhanced CNN–LSTM framework for reconstructing transient turbine blade temperature fields from sparse data. The model combines the spatial feature extraction capability of Convolutional Neural Networks (CNNs) with the time-series modeling capability of Long Short-Term Memory networks (LSTM). An SE channel attention module is introduced in the CNN feature extraction stage to achieve adaptive recalibration of channel features, and a temporal attention mechanism is incorporated after the LSTM layer to highlight key transient thermal features. A multi-condition temperature field dataset was constructed by conducting Computational Fluid Dynamics (CFD) simulations on low-pressure turbine guide vanes, and the model was experimentally validated through thermal shock tests. The results show that the proposed model can accurately reconstruct the spatial distribution and transient evolution of the turbine blade temperature field under sparse measurement conditions. Under different operating conditions, the predicted temperature fields are highly consistent with the CFD results, with the maximum Reconstruction error remaining below 19 °C. Error distribution analysis indicates that the model has stable Reconstruction performance and good generalization ability.



Academic Editor: Angel Velazquez

Received: 15 March 2026

Revised: 3 April 2026

Accepted: 13 April 2026

Published: 17 April 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: turbine blade; thermal shock test; physical field reproduction; deep learning; small sample data

1. Introduction

As a key component of aero-engines, turbine blades serve for a long time in environments with complex coupled loads such as high temperature and high pressure. Their extreme working conditions pose severe challenges to material performance, structural reliability, and service life [1]. During actual operation, turbine blades often fail prematurely before reaching the expected equivalent service time [2–4], thereby posing a serious threat

to the safe and stable operation of the engine. However, the causes of turbine blade failure are extremely complex, and the influencing factors cover multiple aspects such as structural design, material performance, and unit operating conditions [5]. A large number of engineering practices and studies have shown that the uneven temperature distribution formed during the service of turbine blades and the local thermal stress induced by it are one of the important reasons for blade damage and failure [6–8]. Therefore, accurately predicting the blade temperature field is of great significance for turbine blade life Reconstruction.

Currently, the acquisition of turbine blade temperature fields mainly relies on two approaches: numerical simulation and experimental measurement. Among them, numerical simulation methods (such as CFD and conjugate heat transfer analysis) can obtain relatively complete temperature distribution information, so they are widely used in blade characteristic research. Gorgulu, YF et al. [9] systematically analyzed the cooling performance of gas turbine blades through the CFD method. Under different incoming flow velocity conditions, a comparative study was conducted on the k – ω SST, k – ε , and Reynolds stress model (RSM). The results showed that the k – ω SST model exhibited good comprehensive performance between Reconstruction accuracy and computational efficiency, with the temperature Reconstruction deviation controlled within 3%. Zacharko, Bartosz et al. [10] performed a steady-state thermal analysis on the uncooled rotor blades of the low-pressure turbine of a dual-rotor turbofan engine using a three-dimensional CFD method based on the Reynolds-averaged Navier–Stokes (RANS) equations, and obtained the distribution laws of the heat transfer coefficient and adiabatic wall temperature on the blade surface. The research results indicated that the heat transfer coefficient in the leading edge region of the blade reached the maximum value under takeoff conditions, and the temperature showed obvious non-uniform distribution characteristics along the radial and axial directions. Tuncil, Ismail et al. [11] studied the influence of parameters such as hole shape, hole diameter, spanwise angle, coolant flow rate, temperature, and turbulence intensity on film cooling efficiency. They used the k – ω SST turbulence model and conducted CFD numerical analysis on C3X turbine blades with the help of ANSYS Fluent. The results showed that the parameter combination of triangular holes, -45° spanwise angle, and 2 mm hole diameter achieved the optimal cooling effect. Triangular holes have outstanding potential in improving cooling performance, which can provide a basis for the optimization of high-temperature turbine film cooling.

Although numerical simulation methods can provide high-precision temperature field information, their calculation process is complex and the computational cost is high, making it difficult to meet the needs of rapid Reconstruction and online evaluation in engineering applications. At the same time, limited by the complex geometric structure of turbine blades and the high-temperature gas environment, experimental measurements can usually only arrange sensors at limited positions. The obtained temperature data show obvious sparsity and non-uniform distribution characteristics, making it difficult to directly reflect the complete evolution law of the temperature field. To improve the temperature measurement capability of high-temperature components, Zhonglin Ji et al. [12] developed a thin-film thermocouple array based on MEMS technology, realizing high-precision and low-intrusive measurement of the transient temperature field of high-temperature components in aero-engines, which provides an important experimental basis for obtaining temperature data in real service environments. In addition, Lavagnoli et al. [13] studied the estimation method of flow parameters related to heat transfer through transient turbine experiments, systematically analyzed the uncertainties of adiabatic wall temperature and convective heat transfer coefficient, and proposed an error quantification method based on multiple test strategies, which can effectively reduce the uncertainty of temperature measurement under complex turbine operating conditions. Although the above studies have achieved

certain results, they still cannot realize the high-precision reconstruction of the complete temperature field under sparse measurement conditions.

In recent years, data-driven deep learning methods have made significant progress in the Reconstruction and inversion of complex physical fields. Compared with traditional numerical methods, such methods can realize fast approximate Reconstruction of high-dimensional nonlinear systems by learning potential mapping relationships from existing data, showing good application prospects in fields such as flow analysis, heat transfer calculation, and structural response evaluation. To meet the high timeliness requirements for thermal protection evaluation of double-wall cooled turbine blades, Xiaoming Tan [14] proposed a performance Reconstruction model based on deep learning. In this study, a dataset was constructed through Latin hypercube sampling and validated CFD simulations, and a BP neural network was used to establish the mapping relationship between thermodynamic parameters, spatial coordinates, and blade surface temperature distribution. The experimental results show that the model exhibits extremely high Reconstruction accuracy in key areas such as the pressure surface and blade tip, with a mean absolute percentage error (MAPE) of less than 2%. Mingyang Hao [15] et al. proposed a physically encoded neural network deep learning method, which can invert the transient temperature field of metals during the entire steady flow cycle through limited surface temperature time series data. The study was verified by multi-dimensional tests, and the results are in good agreement with the real values, which greatly reduces the experimental cost and provides an accurate and economical solution for predicting the transient temperature distribution in the solid domain. For turbine blades with complex cooling channels, Jinxing Li et al. [16] proposed a network (ASP-GNN) to predict aerodynamic strength characteristics and temperature fields under different boundary conditions. The study verified the advantages of the model in Reconstruction accuracy and time consumption, and limited training samples can ensure good generalization. It also quantified the influence of boundary conditions and obtained unsteady characteristics, which can provide a fast method for turbomachinery design and analysis and reduce the workload of complex engineering numerical simulations. Zuobiao Li et al. [17] constructed a super-resolution model based on deep learning to reconstruct the complete pressure and temperature fields on the blade surface from limited observation data. The study proposed a pyramid model with four optional input ports to adapt to data with different numbers of spanwise sections. After evaluating three training strategies, it was confirmed that distributed training is more time-efficient and flexible while maintaining high accuracy. Jin Mi et al. [18] decomposed (SPOD) algorithm and proposed a multi-condition SPOD framework. By decomposing multiple typical transient scenarios, a frequency-domain aware and condition-robust modal basis was constructed, and the reconstruction task was transformed into a compressed sensing inverse problem, using least squares projection to estimate modal coefficients. The study also explored the criteria for dataset construction and verified the model through two sets of sparse measurement data. The results show that compared with the traditional gappy POD algorithm (1.04%), the average reconstruction error of this algorithm is only 0.12%, which significantly improves the accuracy and has a good application prospect in the actual reconstruction of turbine blade temperature fields under variable working conditions. However, existing data-driven models are still prone to problems such as overfitting or insufficient Reconstruction accuracy in local areas when facing highly sparse inputs and strong non-uniform gradient distributions, which limits their popularization and application in actual engineering.

To solve the above problems, a CNN-LSTM transient temperature field reconstruction model fused with an attention mechanism is constructed to reconstruct the temperature field from sparse measurement data. This model combines the advantages of convolutional

neural networks (CNNs) in extracting spatial features with the ability of long short-term memory networks (LSTM) to capture time series [19,20], which can not only effectively extract the spatial distribution law of the blade temperature field but also capture the dynamic evolution characteristics of the temperature field over time. On this basis, the SE module is introduced in the convolution feature extraction stage. This module obtains the channel statistical information of the feature map through global average pooling and uses a fully connected network to model the nonlinear relationship between channels, thereby performing adaptive weight allocation for different channel features. In addition, to further enhance the model's ability to model transient time information, a temporal attention mechanism is introduced after the LSTM layer to capture the gradient change characteristics during the evolution of the temperature field, improving the accuracy and reliability of the overall temperature field reconstruction.

2. Methodology

2.1. Reconstruction Model of CNN-LSTM Framework Based on Attention Mechanism

This section will detail the attention mechanism-based CNN-LSTM framework for turbine blade temperature field reconstruction. This framework aims to reconstruct the global temperature field of turbine blades using limited boundary conditions or sensor measurement data.

2.1.1. Data Preprocessing

To improve computational efficiency and mitigate the impact of feature dimensions on Reconstruction results, normalization is applied to the input data. Let the input feature matrix be $X = [x_1, x_2, \dots, x_T]$, where $x_t \in R^K$ denotes the K known measured point input features (coordinates and temperature) at time t , and the output is the three-dimensional temperature field $Y_t \in R^{M \times N}$ over the entire blade domain. Z-score standardization is performed on the input features and temperature field labels:

$$x'_{t,k} = \frac{x_{t,k} - \mu_k}{\sigma_k} \quad (1)$$

In the formula, $x'_{t,k}$ and $x_{t,k}$ represent the k -th input feature before and after standardization, respectively, while μ_k and σ_k denote the mean and standard deviation of the measured point over the entire training set.

2.1.2. Temperature Field Reconstruction Model

Directly reconstructing the three-dimensional temperature field of turbine blades under sparse measurement conditions is a typical underdetermined inverse problem [21]. To improve the accuracy of temperature field reconstruction, this paper constructs an Attention-enhanced CNN-LSTM framework that integrates the capabilities of spatial feature extraction and time series modeling. The overall network framework is shown in Figure 1.

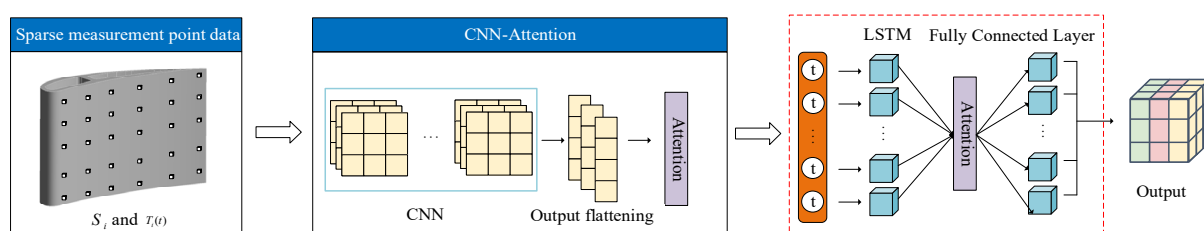


Figure 1. Network Structure.

First, the preprocessed sparse sensor data is input into the network in the form of a time series, and sequentially passes through the input layer and the sequence folding layer. After converting the sequence data into a structure suitable for convolution operations, it is sent to the CNN module. Subsequently, CNN is used to extract the spatial distribution features of the temperature field. Through the mechanisms of local receptive fields and weight sharing, convolution operations effectively capture local correlation patterns in the data, thereby enhancing the model's expressive ability in the feature space. After completing the convolutional feature extraction, the SE attention mechanism is introduced into the network to perform adaptive weighting on the feature channels, so as to enhance the model's ability to focus on key feature channels and make up for the deficiency of CNN in feature recalibration at the channel dimension. Finally, a Long Short-Term Memory network (LSTM) is introduced to model the temporal evolution process of the transient temperature field, and a temporal attention mechanism is added after the LSTM to strengthen the ability to capture key dynamic information, thus achieving high-precision reconstruction of the transient temperature field of turbine blades.

The specific network parameters of the CNN-LSTM model based on the fused attention mechanism are detailed in Table 1, where M represents the total number of training samples.

Table 1. Network parameter table.

No.	Layer Type	Parameters	Output Size	Activation
1	Sequence Input	Input dimension: $3 \times 1 \times 1$	$3 \times 1 \times 1$	–
2	Sequence Folding	Convert sequence to feature map	$3 \times 1 \times 1 \times M$	–
3	Conv2D-1	Kernel: 1×1 , Channels: 32	$3 \times 1 \times 32 \times M$	–
4	ReLU-1	–	$3 \times 1 \times 32 \times M$	ReLU
5	Conv2D-2	Kernel: 1×1 , Channels: 64	$3 \times 1 \times 64 \times M$	–
6	ReLU-2	–	$3 \times 1 \times 64 \times M$	ReLU
7	Global Average Pooling	Channel-wise pooling	$1 \times 1 \times 64$	–
8	SE Attention Block	FC layers: $64 \rightarrow 16 \rightarrow 64$	$1 \times 1 \times 64$	ReLU + Sigmoid
9	Feature Recalibration	Channel-wise multiplication	$3 \times 1 \times 64 \times M$	–
10	Sequence Unfolding	Restore temporal sequence	$3 \times 64 \times M$	–
11	Flatten	Feature vectorization	$64 \times M$	–
12	LSTM	Hidden units = best_hd	best_hd $\times$ M	Tanh
13	Temporal Attention	Attention weights over time	best_hd	Softmax
14	Context Vector	Weighted sum of hidden states	best_hd	–

The specific implementation method of this network structure is detailed as follows:

Since the input measurement point or boundary condition data may contain local spatial correlations, a two-dimensional convolution layer is used to extract deep spatial features [22]. For the feature map of the input layer, the output feature of the i -th layer convolution is calculated as follows:

$$H_i^l = \sigma \left(\sum_j W_{ij}^l * H_j^{l-1} + b_i^l \right) \quad (2)$$

where $*$ denotes the convolution operation, W_{ij}^l is the weight vector of the convolution kernel, b_i^l is the bias term, and $\sigma(\cdot)$ is the nonlinear activation function (the ReLU function is adopted in this paper to alleviate the vanishing gradient problem). After multi-layer convolution and pooling operations, the high-dimensional sparse raw data is mapped into a low-dimensional dense feature vector H_{CNN} that contains rich spatial topological relationships, which serves as the input for the subsequent time-series module. The structure of the designed CNN is illustrated in Figure 2.

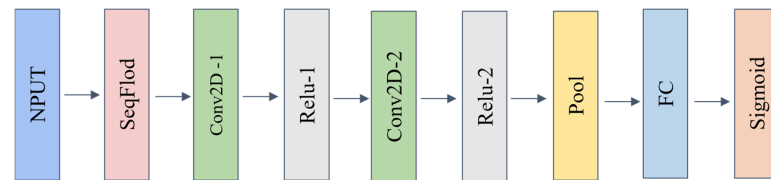


Figure 2. CNN Network Structure.

To further enhance the model's ability to express key feature channels, the Squeeze-and-Excitation (SE) attention mechanism is introduced after the CNN feature extraction module. This module achieves adaptive recalibration of channel features by explicitly modeling the dependencies between feature channels.

Perform global average pooling on the spatial dimensions through the Squeeze operation:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W F_c(i, j) \quad (3)$$

where z_c denotes the global feature descriptor of the c -th channel.

Subsequently, two fully connected layers are used to construct the Excitation operation, generating channel weights:

$$s = \sigma(W_2 \delta(W_1 z)) \quad (4)$$

where W_1 and W_2 are learnable parameters; $\delta(\cdot)$ represents the ReLU activation function; $\sigma(\cdot)$ represents the Sigmoid function.

Finally, the obtained weight vector is multiplied with the original feature map in a channel-wise manner:

$$\tilde{F}_c = s_c \cdot F_c \quad (5)$$

Through this process, the model can automatically enhance the response to important feature channels while suppressing redundant information, thereby improving the feature representation ability.

The heat transfer process of turbine blades is a typical transient process. Standard RNNs are prone to gradient vanishing/explosion when processing long sequences [23]. In contrast, LSTM introduces a unique gating mechanism [24,25] with the collaborative action of input gates, forget gates, and output gates. Combined with convolution and pooling operations for feature extraction, this mechanism effectively solves the aforementioned problem [26].

At time step t , the LSTM unit receives the feature vector $H_{CNN,t}$ extracted by the CNN, as well as the hidden state $H_{CNN,t}$ and cell state C_{t-1} from the previous time step. The LSTM architecture is illustrated in Figure 3.

The forget gate is mainly used to eliminate redundant historical thermal state information and regulate the threshold for retaining or discarding historical thermal features. Its mathematical expression is:

$$f_t = \sigma(W_f \cdot [h_{t-1}, H_{CNN,t}] + b_f) \quad (6)$$

where σ denotes the Sigmoid function, $\odot$ denotes the Hadamard product (element-wise multiplication), and W and b are the weight matrix and bias term of each gate, respectively.

The input gate (determines the retention degree of newly incoming aerothermal boundary information):

$$i_t = \sigma(W_i \cdot [h_{t-1}, H_{CNN,t}] + b_i) \quad (7)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, H_{CNN,t}] + b_C) \quad (8)$$

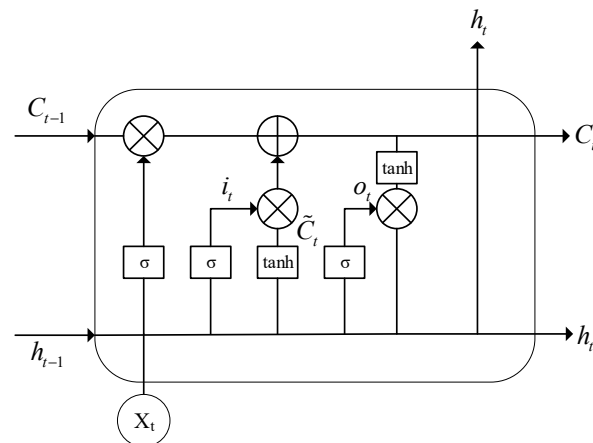


Figure 3. LSTM layers.

The cell state update module fuses the historical thermal state and the current aerothermal input information to realize the iterative update of the cell state. The operation formula is:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (9)$$

The output gate is used to screen the effective thermal features to be output and determine the dimension and core content of the final output features. Its mathematical expression is as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, H_{CNN,t}] + b_o) \quad (10)$$

$$h_t = o_t \odot \tanh(C_t) \quad (11)$$

where σ denotes the Sigmoid function, $\odot$ denotes the Hadamard product (element-wise multiplication), and W and b are the weight matrix and bias term of each gate, respectively.

When the blade experiences abrupt aerodynamic conditions (such as flutter or rapid acceleration), the historical states in certain specific time periods have a decisive influence on the current temperature field distribution; meanwhile, high-temperature gradient regions such as the leading edge and trailing edge of the blade require the model to allocate more attention. Therefore, an attention mechanism is introduced after the LSTM layers:

First, calculate the matching score e_t between the hidden state h_t at time step t and the target state (or learnable context vector u_w):

$$e_t = \tanh(W_a h_t + b_a) \quad (12)$$

The Softmax function is used to normalize the scores, yielding the attention weight e_t :

$$\alpha_t = \frac{\exp(e_t^T u_w)}{\sum_{k=1}^L \exp(e_k^T u_w)} \quad (13)$$

Finally, the outputs of the LSTM are linearly weighted and summed according to the attention weights to obtain the context vector C_{att} that contains key spatio-temporal features:

$$C_{att} = \sum_{t=1}^L \alpha_t h_t \quad (14)$$

This mechanism ensures that the model can adaptively amplify the feature signals in regions with drastic temperature changes and moments of abrupt operating conditions, thereby significantly improving the reconstruction accuracy of hot spots in the temperature field.

The feature vector C_{att} weighted by the attention mechanism is fed into a decoder composed of fully connected layers, which finally maps it to the high-dimensional Reconstruction value $\hat{Y}_t$ of the full-domain blade temperature field:

$$\hat{Y}_t = W_c c + b \quad (15)$$

2.1.3. Training Strategy

All numerical calculations, model training, and inference processes in this study were conducted on a fixed desktop workstation. The operating system of this workstation is Microsoft Windows 10 Professional Edition, the central processing unit is the 13th Generation Intel Core i7-13700KF processor, and the graphics processing unit is the NVIDIA Geforce-3060 GPU processor.

Given the limited sample size in this study, further adopting a fixed and independent partitioning method for the training set, validation set and test set will reduce the amount of data available for model training, which is unfavorable for the model to fully learn the spatiotemporal evolution characteristics of the temperature field. Therefore, this paper adopts the leave-one-out cross-validation framework for model training and evaluation. In the outer cross-validation, one sample is reserved from all samples as the test set in each round, and the remaining $N-1$ samples are used for model development. On this basis, one sample is further divided from these $N-1$ samples as the validation set for hyperparameter selection, training process monitoring and early stopping judgment, while the remaining samples serve as the training set for model parameter updating. The above process is repeated until each sample is independently evaluated as a test sample once, and the average value of the test results from each round is finally taken as the overall performance index of the model. After completing cross-validation and determining the optimal model configuration, all samples are further utilized to retrain the final model, so as to realize the reconstruction and Reconstruction of the full-domain temperature field of the blade.

The model training process uses the Adaptive Moment Estimation (Adam) optimizer to complete the iterative update of network parameters. The optimizer is set with a first-order moment exponential decay rate β_1 of 0.9 and a numerical stability constant ϵ of 1×10^{-8} to balance the stability and convergence speed of parameter updates. The initial learning rate for training is set to 0.01, and a step decay strategy is adopted to dynamically adjust the learning rate. When the loss does not decrease for 180 consecutive training epochs, the learning rate is reduced by 90%, and a lower limit of 1×10^{-6} is set for the learning rate to avoid convergence stagnation caused by an excessively low learning rate. The total number of training epochs is set to 2000.

The backpropagation algorithm is adopted for model training. To ensure full-domain reconstruction accuracy while preventing model overfitting, the loss function is defined as a combination of the mean squared error L_{MSE} and the regularization term L_{grad}

$$L_{MSE} = \frac{1}{N} \sum (T_{pred} - T_{true})^2 \quad (16)$$

$$L_{grad} = \left\| \nabla T_{pred} - \nabla T_{true} \right\|^2 \quad (17)$$

$$L = L_{MSE} + \lambda L_{grad} \quad (18)$$

2.2. CFD Model and Methodology

The numerical model used in this study is a certain type of aero-engine low-pressure turbine guide vane, whose geometric structure is shown in Figure 4. To simplify the calculation, the geometric model only includes the three-dimensional surface structure of the stacked blade profiles. There are two independent cooling air cavities inside the

blade. The cooling gas enters the cavities through the blade root area, is distributed through the internal channels, then flows along the flow direction, and conducts convective heat transfer with the inner wall of the blade.

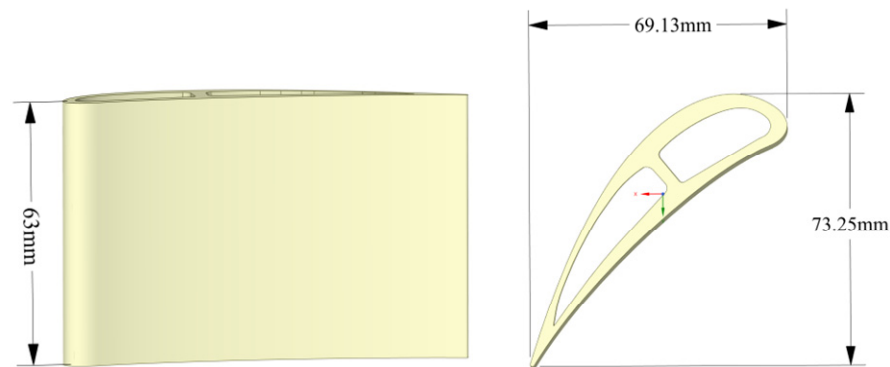


Figure 4. Simplified blade model.

It is assumed that the distribution of flow variables at the inlet and outlet is uniform. Rotational periodic constraints are set on both circumferential sides. Other boundaries are adiabatic and no-slip walls. To better approximate the real flow state, rotational periodic boundaries are set on both circumferential sides, and the fluid–structure interaction model is shown in Figure 5.

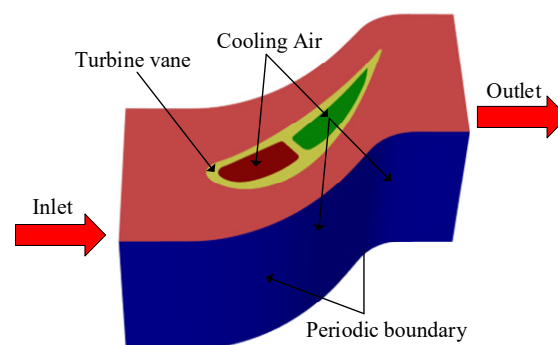


Figure 5. Fluid solid coupling model.

In this model, in the model adopted in this study, the blade is made of 0Cr25Ni20 high-chromium-nickel austenitic stainless steel, whose typical chemical composition (mass fraction) is as follows: carbon 0.05%, silicon 0.70%, manganese 0.95%, phosphorus 0.025%, sulfur 0.006%, chromium 24.5%, and nickel 19.3%. This material exhibits excellent corrosion resistance in oxidizing media, and its mechanical properties meet the requirements: tensile strength ≥ 515 MPa, elongation $\geq 35\%$, making it suitable for corrosion-resistant components and high-temperature working condition components below 1000 °C. Air is simulated as an ideal gas for calculation and analysis. The relevant thermophysical properties of these two materials are summarized in Table 2. Since this study mainly focuses on the impact of high temperature on the blade, the factor of aerodynamic pressure is not considered for the time being.

In this paper, the Fluent Meshing 2024 is used to divide the computational domain model into grids, constructing a poly-hexahedral hybrid grid structure. This grid type combines the core advantages of hexahedral grids and polyhedral grids: hexahedral grids have the characteristic of high computational accuracy and can effectively reduce numerical dissipation in the boundary layer and mainstream regions; polyhedral grids, on the other hand, exhibit excellent adaptability in complex geometric regions such as the leading edge

and trailing edge of the blade. Therefore, they can significantly reduce the total number of grids while ensuring computational accuracy. To verify the comprehensive performance of this hybrid grid, this paper designed three sets of comparative experiments, using tetrahedral grids, pure hexahedral grids, and poly-hexahedral hybrid grids for numerical simulation respectively. The comparison results show that: under the condition that the computational accuracy is of the same order of magnitude, the number of tetrahedral grids reaches 2.1 million, and its computation time is 2.7 times that of the hybrid grid; the pure hexahedral grid has severe grid distortion in complex regions such as the leading edge and trailing edge of the blade, with grid orthogonality lower than 0.3, which cannot meet the computational convergence requirements of the turbulence model [27]; in summary, the poly-hexahedral hybrid grid shows significant advantages in balancing accuracy and computational efficiency.

Table 2. Material parameters related to temperature.

Properties	Air	Steel	Units
Density	Ideal Gas	8030	[kg/m ³]
Mass specific heat	1006.43	502	[J/(kg/K)]
Dynamic Viscosity	1.78×10^{-5}	–	[kg/(m × s)]
Thermal conductivity	0.0242	0.0115T + 9.9105	[W/(m × K)]

To improve the ability to analyze key flow characteristics, this paper performs local grid refinement on core regions such as the leading edge and trailing edge of the blade to accurately capture the flow separation phenomenon that may occur near the blade tip. By increasing the grid resolution in key areas of the blade surface, the accuracy of numerical calculations is effectively improved. At the fluid–structure interaction interface, this paper constructs a three-layer boundary layer grid and further refines the near-wall region. It should be noted that the core of this study is the influence of high-temperature environments on the thermal response characteristics of the blade, so the effect of aerodynamic pressure factors is not considered in the numerical calculation. Figure 6 shows a detailed schematic diagram of the overall grid layout and local refined regions.

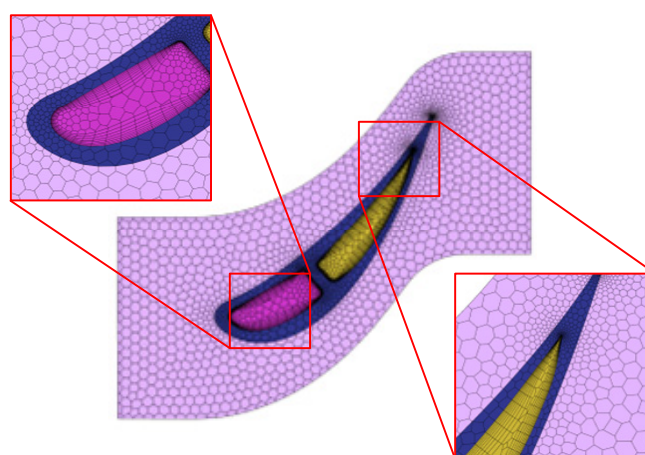


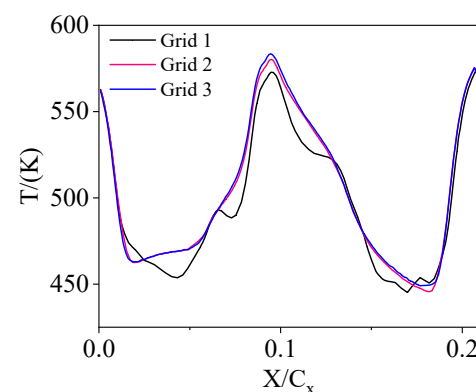
Figure 6. Grid structure.

To ensure high numerical accuracy and computational efficiency, a grid independence study was conducted on this model. Three gradually refined grid schemes were generated and evaluated, as shown in Table 3.

Table 3. Grid schemes.

Scheme	Grid 1	Grid 2	Grid 3
Grid quantity/ten thousand	88	110	120

This paper mainly focuses on the temperature characteristics of turbine blades. Therefore, the temperature distribution on the surface of the middle section of the blade is selected for grid independence verification. The verification results using four different grid configurations are shown in Figure 7. When the number of grids reaches 1.11 million, the temperature distribution law on the blade surface almost coincides with that when the total number of grids is 1.20 million, and the change in calculation results is less than 0.5%. Considering both calculation accuracy and resource efficiency, 1.10 million grids are finally used in the numerical simulation for numerical calculation.

**Figure 7.** Section temperature variation in different grid numbers.

In this study, ANSYS Fluent 2024 is used to perform numerical simulations on a turbine blade model. The flow and heat transfer processes are described by solving the three-dimensional Reynolds-averaged Navier–Stokes equations, and the Realizable k- ϵ turbulence model is employed to simulate turbulent effects. During the numerical solution process, the COUPLED algorithm is used to achieve the coupled calculation of the pressure field and velocity field. The spatial gradients and pressure terms are discretized using the least-squares cell-based method and a second-order scheme. The turbulent dissipation is discretized with the second-order upwind method. All terms except the turbulent dissipation are discretized by the third-order MUSCL scheme. The convergence of the calculation results is determined by monitoring the changes in residuals. In the simulation process, the mainstream gas temperature is selected as a variable. During the thermal cycle test, by adjusting the heating and cooling rates of the mainstream gas temperature while keeping other operating parameters unchanged, the blade temperature distributions under different working conditions are obtained. These three working conditions cover the typical transient processes of an aero-engine from idle to takeoff and then back to idle, with differences in mainstream heating rate, peak total temperature, cooling start time, and cooling air flow rate, which can effectively verify the reconstruction accuracy and generalization ability of the model under different heat loads and transient change rates. The variation law of the mainstream gas temperature under each working condition is shown in Figure 8, and the remaining test parameters are listed in Table 4.

The detailed operating parameters of the three working conditions (Working Condition 1, Working Condition 2, Working Condition 3) are shown in Table 5. The mainstream peak total gas temperature is maintained at 1200 K under all working conditions, and the variable parameters are mainly concentrated on the gas heating rate and the starting time of cooling.

Among them, the heating rate of Working Condition 1 is 20 K/s, and cooling starts at 90 s; the heating rate of Working Condition 2 is 17.14 K/s, with the cooling starting time advanced to 85 s; the heating rate of Working Condition 3 is further reduced to 15 K/s, and the cooling starting time is advanced to 80 s.

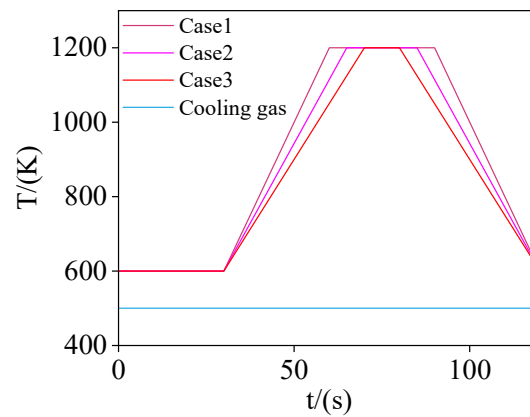


Figure 8. Mainstream gas inlet temperature.

Table 4. Boundary parameters of the fluid domain under experimental conditions.

Boundary Conditions	Value	Units
Total temperature at inlet of main gas flow domain	Figure 8	[K]
Total pressure at inlet of main gas flow domain	0.8	[MPa]
Specific heat capacity of gas	C_{pgas}	[J/kg·K]
Mass flow at outlet of main gas flow domain	6.3631	[kg/s]
Mass flow at inlet of cooling airflow	0.2/0.1	[kg/s]
Total temperature at inlet of cooling gas	500	[K]

Table 5. Core operating parameters of the three working conditions.

Working Condition	Mainstream Peak Total Temperature [K]	Heating Rate [K/s]	Cooling Start Time [s]
Case 1	1200	20	90
Case 2	1200	17.14	85
Case 3	1200	15	80

In this study, a zoned and fixed-point measuring point layout scheme is adopted to obtain sparse temperature data that are more consistent with actual working conditions. Specifically, five typical characteristic cross-sections are selected along the spanwise direction on the outer surface of the blade, and 12 temperature sampling points are evenly arranged along the circumferential direction on the outer surface of each cross-section, resulting in a total of 60 measuring points on the outer surface. Meanwhile, considering that the internal cooling air cavities of the blade exert a significant influence on the overall heat transfer process, 6 temperature sampling points are respectively arranged in the key areas of the internal cooling air cavities corresponding to Cross-Section 1, 4 and 5, with a total of 18 internal measuring points set up. Accordingly, the total number of measuring points inside and outside the blade is 78. The specific locations of each measuring point are shown in Figure 9.

The above measuring point layout fully covers the main heat transfer areas of turbine blades, including key parts such as the leading edge, trailing edge, pressure surface, suction surface and internal cooling air cavities. The measuring points on the outer surface are arranged evenly by sections, which helps characterize the overall distribution law of the

temperature field on the blade surface; the internal measuring points are arranged in the key areas of the cooling air cavities to capture the influence of internal cooling on local temperature distribution. The total number of 78 internal and external measuring points is consistent with the maximum deployable scale of sensors in actual engineering tests, thus possessing favorable engineering implement ability. Based on the above standardized measuring point layout method, representative sparse measured data can be provided for subsequent temperature field reconstruction.

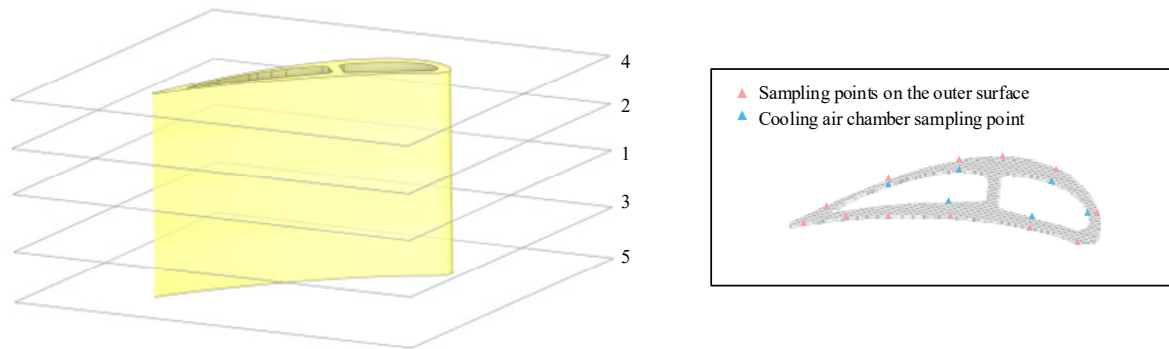


Figure 9. Distribution location of sampling points.

It should be noted that the CFD results are used only to extract sparse temperature samples at selected locations, so as to simulate the sparse temperature measurements that can be obtained in real experiments

2.3. Thermal Shock Test

To verify the accuracy and reliability of the established model, a thermal shock test on turbine blades was conducted to obtain the blade test data under real working conditions. The test was carried out using the thermal shock test bench at Shenyang Aerospace University, Shenyang, China and the test bench is shown in Figure 10.

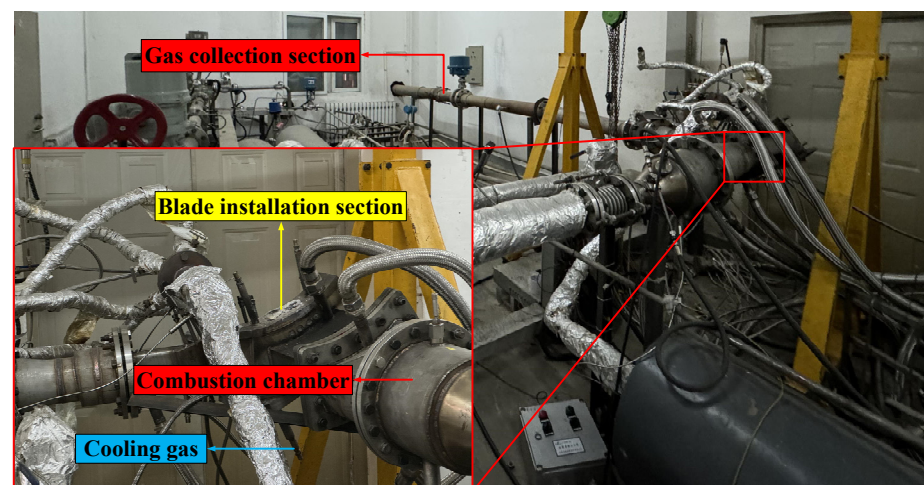


Figure 10. Thermal shock test rig.

The test piece uses a certain type of high-pressure turbine guide vane, adopting a layout form of 2 test blades paired with 2 accompanying test blades to form a 4-blade 3-flow-channel standard test piece. The specific layout is shown in Figure 11 below. This layout method can effectively simulate the real flow field environment of turbine blades, avoid the boundary effect and flow field distortion problems of single-blade tests, ensure

that the temperature measurement data is consistent with the actual working conditions, and improve the authenticity and reliability of the test results.

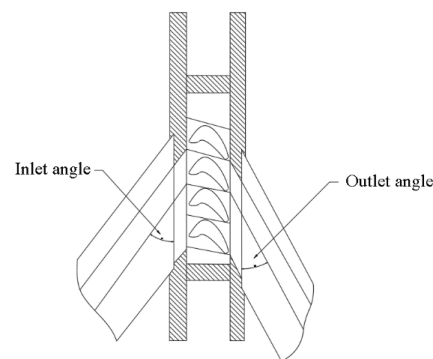


Figure 11. Blade distribution diagram.

To ensure that the numerical simulation results can be effectively compared and validated against the experimental measurements, the boundary conditions of the CFD numerical simulation are strictly set according to the actual operating parameters measured in the thermal shock test. During the test, flow meters, pressure sensors, and temperature-measuring thermocouples were installed at the inlet and outlet of the test section to monitor key parameters in real time. Additionally, precise control is exerted over major operating parameters such as the total temperature of the inlet airflow, total pressure, Mach number, cooling air flow rate, and outlet back pressure. The real-time measured parameters of the test are used as the boundary conditions of the CFD numerical simulation, to ensure that the numerical model can accurately reproduce the flow and heat transfer process in the test, and the simulation results have a reliable comparative basis with the experimental data.

To obtain the measured data of Blade temperature, two temperature-measuring thermocouples were arranged in the leading edge area of the mid-section on the outer surface of the Blade. Each thermocouple was fixedly installed in a buried manner, and their specific positions are shown in Figure 12. The computer data acquisition system collected the temperature of each measuring point in real time with a sampling frequency of not less than 2 Hz, and simultaneously completed data transmission, storage, and preprocessing, providing reliable experimental data for subsequent numerical simulation verification.

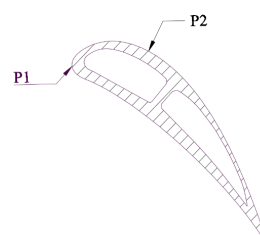


Figure 12. Temperature couple distribution.

3. Results and Discussion

3.1. Numerical Results and Experimental Verification

The temperature field distribution results of turbine blades under different working conditions were obtained through CFD numerical calculations. The temperature data of two sampling points corresponding to the test measuring points were extracted at the leading edge of the blades and compared with the experimental measurement results, as shown in Figure 13. The comparison results show that under the three working conditions, the time-varying trends of the temperatures at the two measuring points on the leading edge of the blade are generally consistent with the experimental results, indicating that

the numerical model can well reflect the transient temperature change characteristics of the blade.

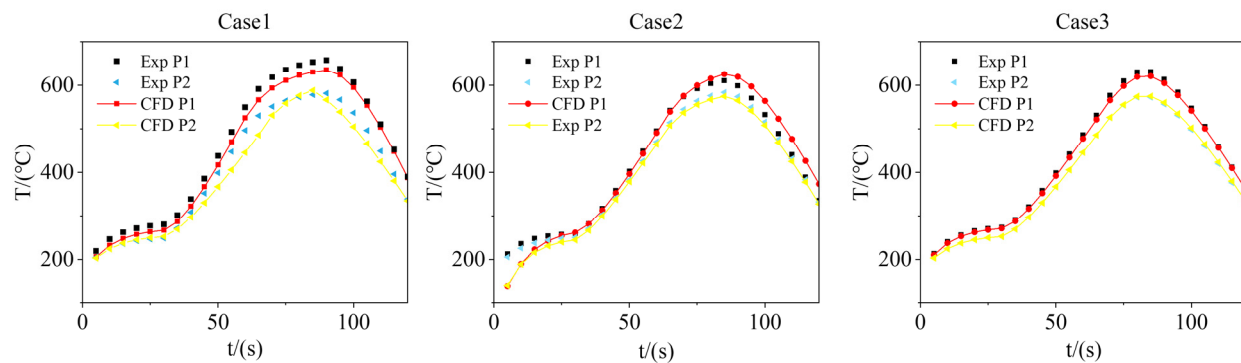


Figure 13. Comparison between Simulation Results and Experimental Data under Different Working Conditions.

Figure 14 shows the variation law of the maximum blade temperature with time under three operating conditions (Case 1–Case 3). Overall, the maximum blade temperature under the three operating conditions all exhibits the typical transient response characteristic of “first increasing and then decreasing”. In the initial stage, as the high-temperature gas continues to act on the blade surface, the intensity of convective heat transfer gradually increases, and the blade wall continues to absorb heat, resulting in a rapid rise in the maximum temperature. When the gas temperature starts to drop, the heat input on the blade surface gradually weakens, and the continuous heat accumulation process on the wall is terminated. Therefore, the maximum blade temperature reaches its peak and then gradually decreases.

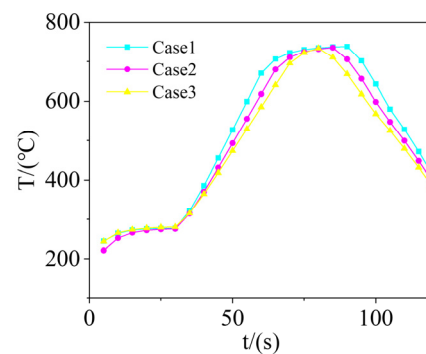


Figure 14. Trend of maximum temperature variation with temperature.

A further comparison of different working conditions reveals that the time when the maximum blade temperature reaches its peak is advanced in sequence under Case 1–Case 3. This phenomenon is mainly related to the differences in the timing of gas temperature changes. Among the three working conditions, the gas temperature starts to drop at approximately 90 s, 85 s, and 80 s respectively, and the maximum temperature reaches its peak around the corresponding times. In addition, there are certain differences in the peak values of the maximum blade temperature under different working conditions, with the peak temperature under Case 1 being the highest. This is mainly because the high-temperature gas acts for a longer duration under this working condition, allowing the blade to absorb heat for a longer time, thereby resulting in a more obvious heat accumulation effect. In contrast, in Case 2 and Case 3, the gas temperature drops earlier, and the heat input to the blade wall weakens in advance, leading to relatively lower peak values of the maximum temperature. The above results indicate that the gas temperature change

process has a significant impact on the transient thermal response of the blade, which not only determines the magnitude of the peak temperature but also affects the time when the peak occurs.

Based on the sensor layout scheme specified in Section 2.2 (a total of 78 measuring points: 5 cross-sections with 12 surface measuring points each plus 3 cross-sections with 6 internal cooling air cavity measuring points each), we extract the temperature time series of these 78 measuring points from the full-domain computational fluid dynamics data. To conform to the data acquisition specifications of practical engineering, the temperature time series with a 1 s time step in the computational fluid dynamics simulation is resampled to 1 s (consistent with the 1 Hz sampling frequency of actual sensors), and ultimately 120 time-step temperature data points are obtained for each measuring point. For each working condition, the final input data volume is 78 measuring points multiplied by 120 time steps, amounting to 9360 temperature values, which forms an input time series matrix with a dimension of 78×120 .

3.2. Reconstruction Performance of Models Under Different Operating Conditions

The sparse transient temperature field data extracted under different working conditions are input into the Reconstruction model for training. After the training is completed, the mean square error loss on the training set and the average value of the mean square error loss of the cross-validation test set in each round are counted respectively, and the results are shown in Table 6. Overall, the mean square error loss of the test set under the three working conditions is slightly higher than that of the training set. This is mainly because during the cross-validation process, some test samples contain measuring points located in areas with large temperature gradient changes, which leads to an increase in the average mean square error loss. Nevertheless, the loss values of the training set and the test set under each working condition are generally maintained at a low level, indicating that the established Reconstruction model has been sufficiently trained under the three working conditions and exhibits excellent temperature field reconstruction capability and Reconstruction stability.

Table 6. Core operating parameters of the three working conditions.

Case	Training Loss	Test Loss
1	7.04×10^{-5}	2.13×10^{-4}
2	7.62×10^{-5}	2.22×10^{-4}
3	7.45×10^{-5}	2.38×10^{-4}

To further verify the accuracy of the proposed Reconstruction model, the predicted results of the turbine blade temperature field under three different operating conditions were compared and analyzed with the CFD numerical simulation results. Figure 15 presents the comparison results of the temperature field on the pressure side of the blade at $t = 75$, while Figure 16 shows the temperature distribution on the suction side at the corresponding moment. Overall, under the three operating conditions of Case 1–Case 3, the model's predicted results and the CFD results have a high degree of consistency in the temperature distribution pattern, and can well reproduce the main spatial characteristics of the temperature field on the blade surface. This indicates that the established Reconstruction model can effectively capture the overall variation law of the temperature field under different operating conditions.

In terms of the overall distribution characteristics, the temperature fields on the blade surface show similar spatial structures under the three operating conditions. This is because only the mainstream gas temperature is changed among different operating conditions,

while the blade geometry, cooling airflow conditions, and other boundary conditions remain unchanged. Therefore, the overall distribution pattern of the temperature fields is basically consistent, with differences only in temperature levels. From the perspective of local heat transfer mechanisms, the leading edge of the blade is directly impacted by the high-temperature mainstream gas, and the high convective heat transfer intensity causes this area to form an obvious high-temperature zone. Meanwhile, due to the restriction of adjacent blade passages in the trailing edge region, strong airflow mixing and heat exchange processes occur in the narrow space, so the temperature near the trailing edge is also relatively high. In addition, since the blade adopts a cooling structure where cooling air is supplied from the lower end and discharged from the upper end, the cooling gas first acts on the lower area of the blade and exchanges heat with the wall surface, significantly reducing the temperature in this area. Therefore, the lowest temperature usually appears at the lower end of the suction surface near the cooling gas inlet.

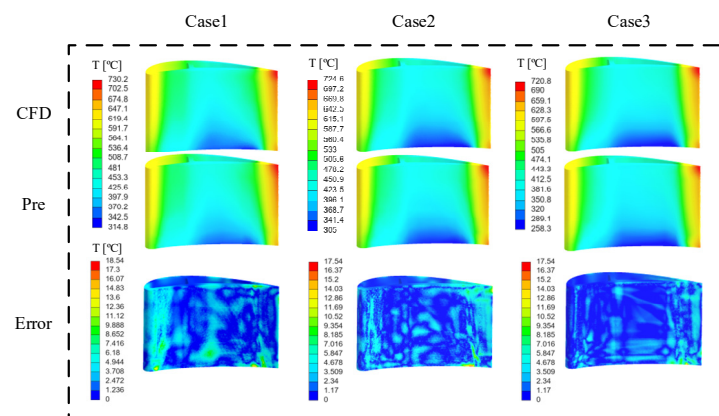


Figure 15. CFD results and Reconstruction results of pressure side temperature field of turbine blades under different operating conditions. Note: Different color bar ranges are used to improve the visibility of local temperature gradients under different operating conditions; absolute values should be interpreted according to the corresponding labeled scales.

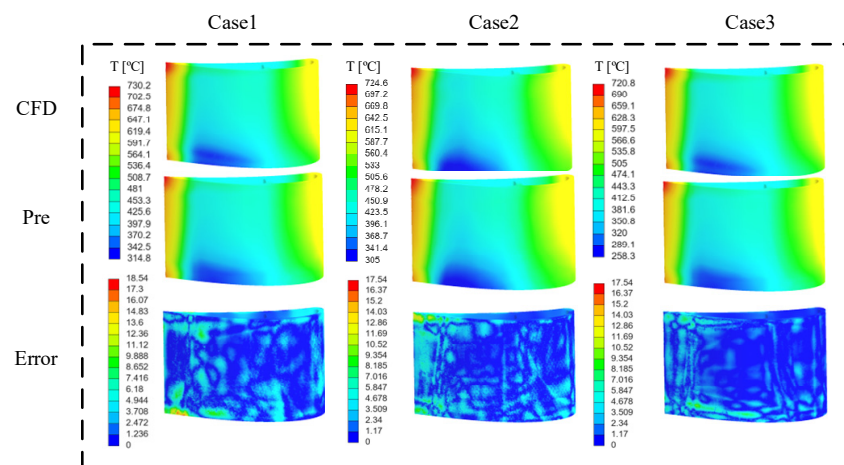


Figure 16. CFD results and Reconstruction results of suction side temperature field of turbine blades under different operating conditions.

Analysis of the error distribution reveals that the overall Reconstruction errors of the model are relatively small, and they are mainly concentrated in regions with large temperature gradients, such as near the leading edge and trailing edge. This is primarily because the flow structures in these regions are complex, and the local heat transfer processes exhibit strong nonlinear characteristics, causing more drastic changes in the temperature field and

thus increasing the difficulty of model Reconstruction. Nevertheless, the Reconstruction errors in most regions remain at a low level, indicating that the proposed model still has good predictive ability under complex flow and heat transfer conditions. Under three different operating conditions, the Reconstruction accuracy of the model remains stable overall, with the maximum temperature error not exceeding 19 °C. Among them, the Reconstruction error under Case 3 is the smallest, only 14 °C, indicating that the model has good generalization ability under different operating conditions.

To further evaluate the Reconstruction stability and error characteristics of the proposed model under different operating conditions, a statistical analysis was conducted on the RMSE between the predicted temperature field and the CFD calculation results, as shown in Figure 17. The error distributions under the three different operating conditions all conform to the normal distribution, and are generally centered around zero. Among them, under the Case 3 operating condition, the RMSE distribution is relatively concentrated, with most error values distributed within a small range, and the probability density curve has an obvious peak and good symmetry, indicating that the model has high Reconstruction accuracy and stability under this operating condition. In contrast, the error distributions under Case 1 and Case 2 operating conditions are slightly expanded, with the peaks of the RMSE probability density curves being slightly lower and the distribution ranges relatively larger. This is mainly because under higher heat load conditions, the temperature gradient on the blade surface is more intense, and more complex transient heat transfer characteristics may appear in local areas, thereby increasing the difficulty of model Reconstruction. In summary, this method has good Reconstruction accuracy and stability under different operating conditions.

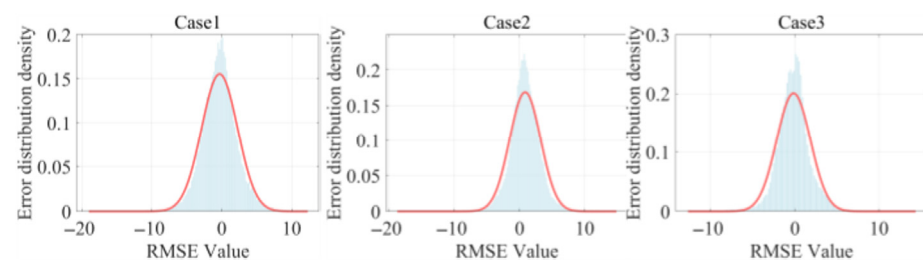


Figure 17. Error distribution density.

3.3. Unsteady Characteristic Reconstruction

Case 1 is selected as the representative working condition to analyze the unsteady temperature evolution of turbine blades. The CFD calculation results, model Reconstruction results, and corresponding error distributions of the blade surface temperature field at multiple time nodes ($t = 30$ s, 60 s, 90 s, and 120 s) are presented respectively.

As shown in Figures 18 and 19, in the initial stage of the transient process ($t = 30$ s), the overall temperature on the blade surface is at a relatively low level, with a relatively gentle temperature distribution, mainly showing a temperature gradient that gradually increases along the chord direction. It can be observed from the figure that the model Reconstruction results are highly consistent with the CFD results in terms of the overall distribution structure, and the positions of the high-temperature regions and low-temperature regions basically coincide. The error distribution map shows that the error in most regions is small, and larger errors only occur in local positions where the temperature gradient changes rapidly.

As time progresses to $t = 60$ s and $t = 90$ s, the temperature on the blade surface gradually increases, and the temperature gradient significantly strengthens, especially near the leading edge of the blade and local flow separation regions, where the high-temperature

regions gradually expand. It can be seen from the figure that the predicted temperature field can still well track the changing trend of the temperature distribution and accurately reproduce the spatial position of the high-temperature regions. Although there is a certain degree of error diffusion in local high-gradient regions, the overall error remains at a low level, with a maximum error of 20.46 °C. This indicates that the model can not only learn the characteristics of the spatial temperature distribution with limited data but also effectively capture the dynamic evolution process of temperature changes over time.

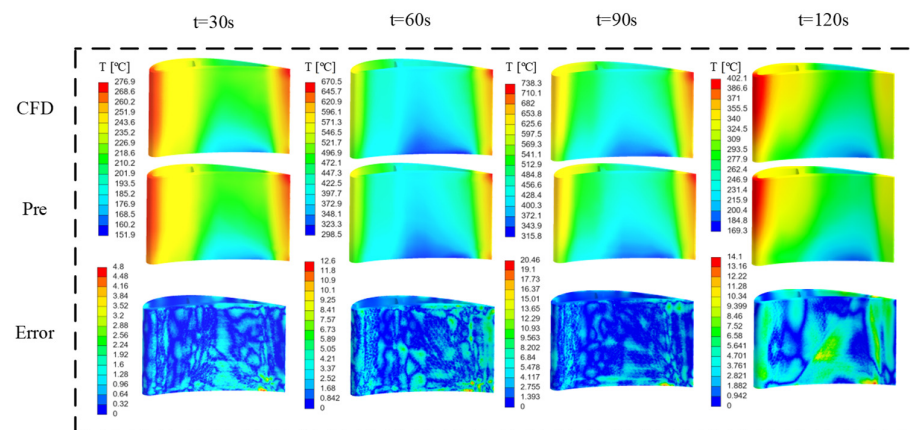


Figure 18. The temperature field of the pressure side of the blade over time under operating condition Case 1.

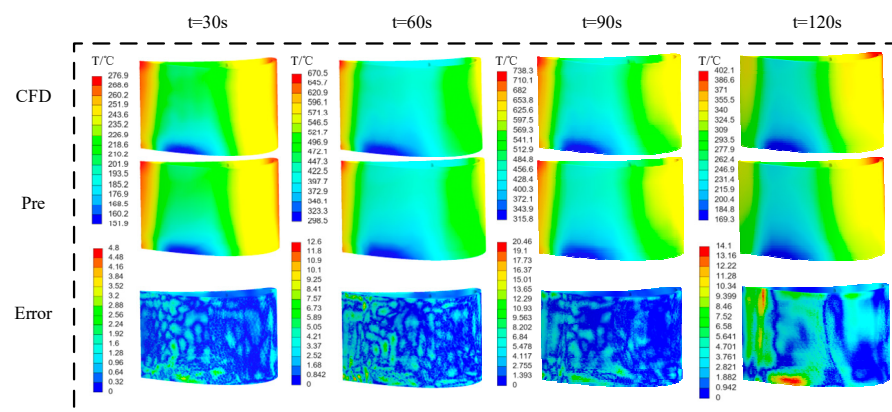


Figure 19. The temperature field of the suction side of the blade over time under operating condition Case 1.

In the late stage of the transient process ($t = 120$ s), the temperature field gradually stabilizes, but there are still relatively obvious temperature gradients in local regions. The error in some regions increases slightly, especially near the leading edge and trailing edge of the blade. This is mainly because the temperature changes in these regions are affected by complex heat transfer and flow coupling mechanisms, resulting in stronger nonlinear characteristics of the temperature field, thereby increasing the difficulty of model Reconstruction.

A statistical analysis was performed on the RMSE between the predicted temperature fields and the CFD calculation results at different time points ($t = 30$ s, 60 s, 90 s, and 120 s), as shown in Figure 20. Overall, the error probability distributions at each time point all exhibit a relatively obvious bell-shaped distribution characteristic. In the initial stage of the transient process ($t = 30$ s), the RMSE distribution is relatively concentrated, with errors mainly distributed within a small range, and the peak of the probability density curve is high and the distribution is relatively symmetrical. When $t = 60$ s, the range of the error distribution expands somewhat, and the peak of the probability density curve

decreases relatively. At $t = 90$ s, the error distribution further expands, the error distribution density drops below 0.15, and the range of RMSE values increases. At $t = 120$ s, the error distribution still maintains an approximately normal distribution shape, but its width is increased compared to the initial stage. This indicates that under high-temperature conditions, the uncertainty of the model Reconstruction slightly increases. However, from the overall distribution, most errors are still concentrated within a small range.

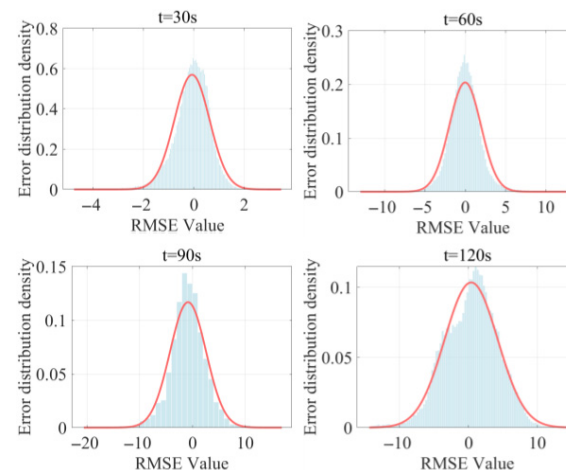


Figure 20. Error distribution of Case 1 at different time points.

In summary, the proposed CNN-LSTM model based on the attention mechanism can effectively learn the spatiotemporal characteristics of the temperature field and exhibits high Reconstruction accuracy at multiple time points throughout the transient process. This method can not only accurately reconstruct the overall distribution structure of the blade surface temperature field but also well capture the variation trend of local high-temperature regions, indicating that the model has good applicability and engineering application potential under complex transient thermal environments.

3.4. Comparison of Different Prediction Models

To further compare the performance differences of different models in transient temperature field reconstruction, this paper selects the sparse transient data of the temperature field under the Case 1 working condition to analyze four different models, which are shown in Table 7. Among them, Model A is a model containing only CNN, Model B is a model containing only LSTM, Model C is the basic CNN-LSTM model, and Model D is the attention-enhanced CNN-LSTM model proposed in this paper.

Table 7. Performance Comparison of Different Models.

Model	Architecture	Time [min]	Training Loss	Test Loss
A	CNN	40	2.1×10^{-4}	5.4×10^{-4}
B	LSTM	38	1.65×10^{-4}	3.8×10^{-4}
C	CNN + LSTM	21	7.9×10^{-5}	2.18×10^{-4}
D	Attention-enhanced CNN-LSTM	26	7.04×10^{-5}	2.13×10^{-4}

From the perspective of training time, there are relatively obvious differences in computational efficiency among different models. Model A(CNN) and Model B(LSTM), which adopt a single structure, have training times of 40 min and 38 min respectively, both remaining at a relatively high level. In contrast, the basic CNN-LSTM model (Model C)

has its training time significantly reduced to 21 min, representing a decrease of 47.5% and 44.7% compared with Model A and Model B respectively. This result indicates that in the current temperature field reconstruction task, relying solely on spatial feature extraction or time series modeling cannot efficiently organize and express temperature field information. When CNN and LSTM are coupled, the model can more effectively establish spatiotemporal correlations between sparse temperature inputs and global temperature responses, thereby improving the efficiency of feature extraction during the training phase. The attention-enhanced CNN-LSTM model (Model D) proposed in this paper has a training time of 26 min, an increase of approximately 23.8% compared with Model C. This shows that the introduction of the attention mechanism does bring additional computational overhead, yet its time cost is generally controllable and does not significantly weaken the engineering application potential of the model.

In terms of loss results, the performance differences among various models are quite significant, showing a clear progressive trend. The training loss and test loss of Model A are 2×10^{-4} and 5.4×10^{-4} respectively, presenting the worst performance among the four models. This indicates that although relying solely on CNN can extract certain spatial distribution features, it is difficult to identify the temporal evolution rules in the transient thermal response process. The training loss and test loss of Model B drop to 1.65×10^{-4} and 3.8×10^{-4} , which are reduced by 21.4% and 29.6% compared with Model A respectively. It demonstrates that temporal modeling is more critical for transient temperature field reconstruction, as the blades are in an unstable state and the temperature field changes continuously over time. However, due to the lack of effective representation of spatial structures, its overall accuracy remains limited. After combining CNN with LSTM, the training loss and test loss of Model C are further reduced to 4.9×10^{-5} and 2.18×10^{-4} , decreasing by 76.7% and 59.6% relative to Model A. This proves that spatio-temporal joint modeling can significantly enhance the model's ability to characterize complex thermal response features. On this basis, although the training loss of Model D proposed in this paper is slightly higher than that of Model C at 5.84×10^{-5} , its test loss is further lowered to 2.13×10^{-4} , a decrease of approximately 2.3% compared with Model C. This reveals that the attention mechanism does not simply strengthen the fitting ability on the training set, but improves the model's capability to identify key spatial regions and important temporal features, thereby further boosting the reconstruction accuracy and stability during the testing phase.

To further compare the performance differences of various models in transient temperature field reconstruction, this paper conducts research at specific moments under the Case 1 working condition. Figures 21 and 22 present the temperature field prediction results and error distribution of different models under the Case 1 working condition at the corresponding moments.

Further analysis based on the maximum error results enables a more intuitive comparison of the performance of different models. The maximum errors of Model A, Model B, Model C and Model D are 76.12 °C, 45.39 °C, 28 °C and 17.54 °C respectively. It can be seen that LSTM reduces the maximum error by approximately 40.4% compared with CNN, indicating that time series information can significantly alleviate the distortion problem of pure spatial models in transient responses; CNN-LSTM further reduces the maximum error by about 38.3% in comparison with LSTM, which shows that spatiotemporal joint modeling can effectively suppress local high-error regions; and the proposed model in this paper cuts down the maximum error by an additional 37.4% relative to the basic CNN-LSTM, demonstrating that the enhancement effect of the attention mechanism on key regions is not a partial modification but a further optimization of the overall error structure. It is particularly noteworthy that although the improvement in test loss is relatively limited,

the maximum error keeps decreasing significantly. This proves that the advantages of the model proposed in this paper are reflected not only in the improvement of accuracy, but more importantly in its ability to effectively enhance the prediction reliability of the model in complex high-gradient regions.

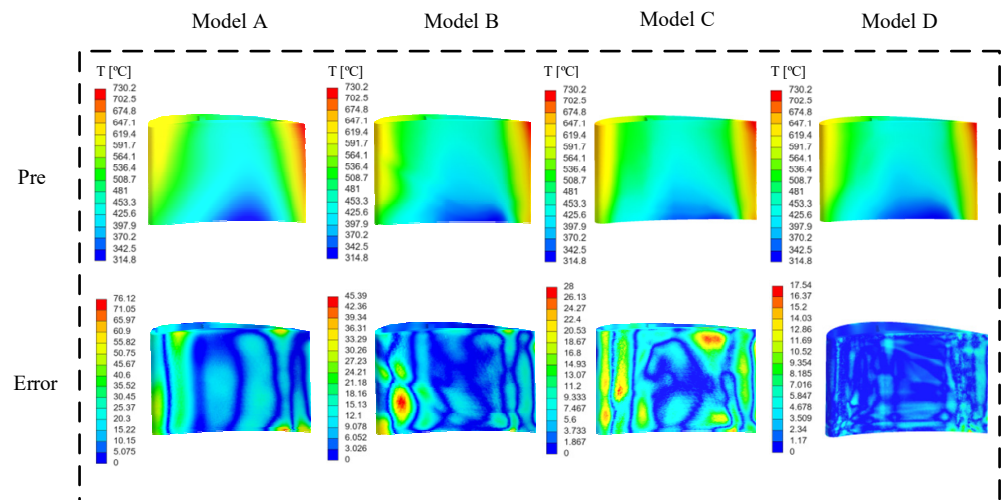


Figure 21. Reconstruction results of the temperature field on the pressure surface of turbine blades of different models under Case 1 working condition.

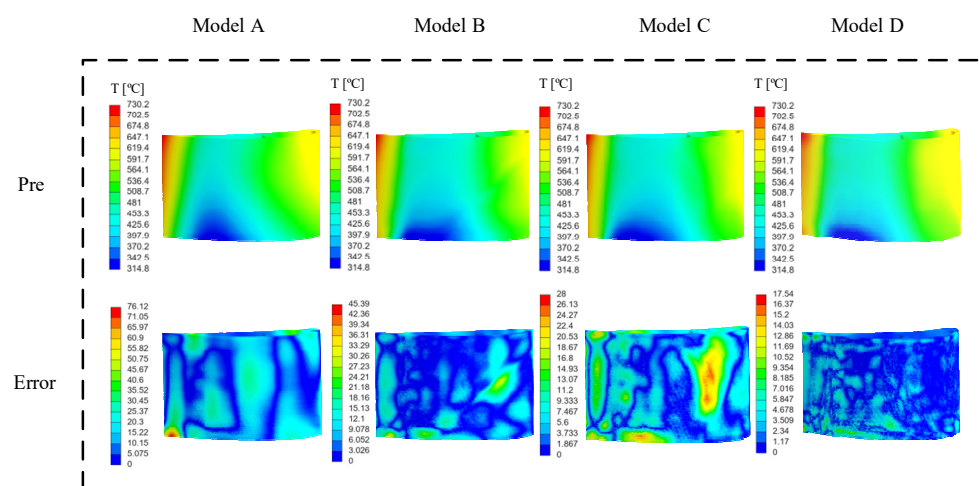


Figure 22. Reconstruction results of temperature field on the suction surface of turbine blades of different models under Case 1 working condition.

3.5. Influence of the Number of Measuring Points on the Reconstructed Model

In actual experiments, there may be issues such as limited sensor deployment, failure of local measuring points, and measurement noise. These factors will ultimately result in a reduction in the volume of input data for the model. Therefore, analyzing the impacts of the aforementioned uncertainties helps to further evaluate the robustness and applicable scope of the proposed model under practical application conditions. For the uncertainty caused by insufficient input data volume, this paper gradually reduces the number of input measuring points on the basis of the benchmark measuring point layout scheme to investigate the influence of missing measuring points on the accuracy of temperature field reconstruction. Taking the original measuring point scheme as a reference, different sparse input conditions are constructed by retaining 100%, 80%, 60% and 40% of the measuring points respectively. To avoid the accidental impact caused by a single deletion of measuring points, multiple random samplings are carried out under each retention ratio

of measuring points, and the average results are taken as the evaluation indicators under the corresponding working conditions.

Figure 23 presents the box plot distribution of temperature field reconstruction errors under different retention ratios of measuring points. It can be observed that as the retention ratio of measuring points increases from 40% to 100%, the overall error distribution shows an obvious convergence trend. Under the 40% condition, the error distribution is relatively scattered, with the range of upper and lower whiskers extending approximately from -90 to $+80$, and there are many outliers, indicating that the model output has strong uncertainty when measuring points are severely missing. Under the 60% condition, the interquartile range is about -5 to $+25$, which means although the extreme error range has narrowed, the main distribution of errors is still wide and shows a certain positive skewness. This indicates that an increase in the number of measuring points does not necessarily bring a synchronous improvement in reconstruction performance. In contrast, under the 80% condition, the interquartile range is significantly reduced to approximately -4 to $+1$, and the range of upper and lower whiskers also converges remarkably, proving that the model can stably reconstruct the main characteristics of the temperature field under this condition, yet the errors still remain relatively large. Under the 100% condition, the box almost shrinks into a line, with the median and interquartile range basically concentrated near zero, suggesting that the model achieves the optimal reconstruction stability at this time. Overall, the retention ratio of measuring points exerts a significant impact on model performance, especially when the retention ratio rises from 60% to 80%, the convergence trend of error distribution becomes more prominent. In practical applications, it is necessary to maximize the coverage of measuring points in key heat transfer areas to reduce the uncertainty caused by insufficient input data and enhance the reliability of temperature field reconstruction results.

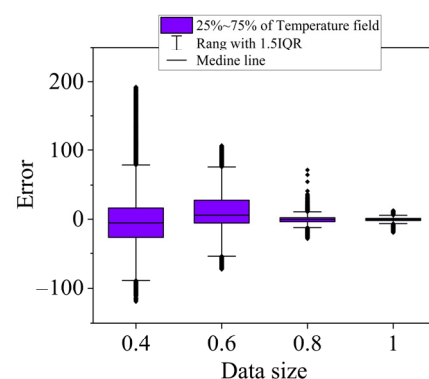


Figure 23. The Impact of Measurement Point Quantity on Model Performance.

4. Conclusions

This study focused on the key challenge of reconstructing transient turbine-blade temperature fields under sparse measurement conditions and developed an attention-augmented CNN-LSTM framework for this purpose. In the proposed model, SE channel attention was introduced to adaptively recalibrate feature responses, while temporal attention was incorporated to enhance the extraction of critical transient thermal features. By combining CFD simulations with thermal shock experiments, the proposed method was systematically validated. The main conclusions are summarized as follows:

- (1) By adjusting the temperature variation process of the mainstream gas, the blade temperature fields under three different transient operating conditions were established. Meanwhile, the CFD model was verified through thermal shock tests, which provides a reliable foundation for dataset construction and subsequent model validation.

- (2) By comparing the reconstruction performance of the model under different working conditions, it can be seen that the training and test losses remain at a low level under all working conditions, indicating that the established model possesses favorable training stability and reconstruction capability under various transient thermal load conditions. A comparison between the reconstructed temperature field at the same moment and the CFD results reveals that the maximum error is 19 degrees Celsius and the error distribution follows a normal distribution. This demonstrates that the model can accurately reproduce the main temperature distribution characteristics on the blade surface.
- (3) Taking the typical working condition Case 1 as the research object, the transient prediction performance of the model at different moments is analyzed. The results show that the reconstruction model has certain errors in local areas with significant temperature gradients such as the leading edge and trailing edge of the blade, but the overall error is always maintained at a low level, with the maximum reconstruction error being 20.46 °C; the model can still achieve high-precision temperature field reconstruction in most areas. In conclusion, the proposed model can effectively characterize the temporal evolution law of the blade temperature field and reconstruct the high-gradient temperature changes with relatively high accuracy.
- (4) A comparison of the analysis results of different models shows that the enhanced CNN-LSTM model integrated with the attention mechanism (Model D) outperforms single-structure models and the basic CNN-LSTM model without the attention mechanism introduced. This verifies that the attention module can effectively improve the model's capabilities in feature extraction and time series modeling.

Although the attention-enhanced CNN-LSTM model proposed in this paper exhibits favorable capability for reconstructing transient temperature fields under sparse measurement conditions, the research still has certain limitations. The reconstruction performance remains sensitive to the density and coverage of measurement points. Therefore, future work will focus on introducing governing physical equations into the model to improve physical consistency and reconstruction robustness with limited measurements.

Author Contributions: Conceptualization, Y.C. and L.L.; methodology, Y.C. and L.L.; software, Y.C.; validation, Y.C., L.L. and D.S.; formal analysis, Y.C. and L.L.; investigation, Y.C.; resources, H.L.; data curation, Y.C.; writing—original draft preparation, Y.C.; writing—review and editing, L.L.; visualization, Y.C.; supervision, L.L.; project administration, J.Y.; funding acquisition, J.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Joint Program of Liaoning Provincial Science and Technology Plan (Key Research and Development Program), grant number 2025JH/101800079.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Rajabi, T.; Tabrizi, H.; Hafezi, M.; Partovipour, H. Failure analysis of the CM186LC gas turbine blade. *Eng. Fail. Anal.* **2026**, *188*, 110653. [\[CrossRef\]](#)
2. Salehnasab, B.; Poursaeidi, E.; Mortazavi, S.A.; Farokhian, G.H. Hot Corrosion Failure in the First Stage Nozzle of a Gas Turbine Engine. *Eng. Fail. Anal.* **2016**, *60*, 316–325. [\[CrossRef\]](#)
3. Ogiriki, E.A.; Li, Y.G.; Nikolaidis, T.; Isaiah, T.E.; Sule, G. Effect of Fouling, Thermal Barrier Coating Degradation and Film Cooling Holes Blockage on Gas Turbine Engine Creep Life. *Procedia CIRP* **2015**, *38*, 228–233. [\[CrossRef\]](#)
4. Huda, Z. Metallurgical Failure Analysis for a Blade Failed in a Gas-Turbine Engine of a Power Plant. *Mater. Des.* **2009**, *30*, 3121–3125. [\[CrossRef\]](#)

5. Cai, L.; He, Y.; Wang, S.; Li, Y.; Li, F. Thermal-Fluid-Solid Coupling Analysis on the Temperature and Thermal Stress Field of a Nickel-Base Superalloy Turbine Blade. *Materials* **2021**, *14*, 3315. [[CrossRef](#)] [[PubMed](#)]
6. Wang, X.M.; Hui, Y.Z.; Hou, Y.Y.; Yu, Z.Y.; Li, L.; Yue, Z.F.; Deng, C.H. Direct Investigation on High Temperature Tensile and Creep Behavior at Different Regions of Directional Solidified Cast Turbine Blades. *Mech. Mater.* **2019**, *136*, 103068. [[CrossRef](#)]
7. Rani, S.; Agrawal, A.K.; Rastogi, V. Failure Analysis of a First Stage IN738 Gas Turbine Blade Tip Cracking in a Thermal Power Plant. *Case Stud. Eng. Fail. Anal.* **2017**, *8*, 1–10. [[CrossRef](#)]
8. Sun, H.; Yang, X.; Chen, Y.; Ai, Y.; Zhang, W. Study on the Impact of Cooling Air Parameter Changes on the Thermal Fatigue Life of Film Cooling Turbine Blades. *Aerospace* **2025**, *12*, 512. [[CrossRef](#)]
9. Gorgulu, Y.F. CFD-based cooling performance of gas turbine blades. *Aircr. Eng. Aerosp. Technol.* **2026**, *98*, 154–168. [[CrossRef](#)]
10. Zacharko, B.; Kuźniar, M.; Orkisz, M. CFD Analysis for Thermal Design of Low-Pressure Turbine Uncooled Blade. *Heat Transf. Res.* **2021**, *52*, 45–54. [[CrossRef](#)]
11. Tunçil, İ.; Çakır, M.T. Analysis and optimization of film cooling parameters for turbine blades using CFD. *Appl. Therm. Eng.* **2025**, *275*, 126850. [[CrossRef](#)]
12. Ji, Z.; Duan, F.L.; Xie, Z. Transient Measurement of Temperature Distribution Using Thin Film Thermocouple Array on Turbine Blade Surface. *IEEE Sens. J.* **2020**, *21*, 207–212. [[CrossRef](#)]
13. Lavagnoli, S.; De Maesschalck, C.; Paniagua, G. Uncertainty analysis of adiabatic wall temperature measurements in turbine experiments. *Appl. Therm. Eng.* **2015**, *82*, 170–181. [[CrossRef](#)]
14. Tan, X.; Li, W.; Dong, H.; Leng, Y. Rapid Reconstruction of cooling performance in dual-layer wall turbine blades using deep learning approaches. *Aerosp. Sci. Technol.* **2025**, *167*, 110675. [[CrossRef](#)]
15. Hao, M.; Li, Z.; Li, J. Transient Temperature Field Inversion of Turbine Based on Physics-Encoded Neural Networks. *J. Turbomach.* **2026**, *148*, 031008. [[CrossRef](#)]
16. Li, J.; Wang, Y.; Qiu, Z.; Zhang, D.; Xie, Y. Fast performance prediction and field reconstruction of gas turbine using supervised graph learning approaches. *Aerosp. Sci. Technol.* **2023**, *140*, 108425. [[CrossRef](#)]
17. Li, Z.; Wen, F.; Wan, C.; Zhao, Z.; Luo, Y.; Wen, D. A pyramid-style neural network model with alterable input for reconstruction of physics field on turbine blade surface from various sparse measurements. *Energy* **2024**, *308*, 132828. [[CrossRef](#)]
18. Mi, J.; Qiu, L.; Tong, Z.X.; Zhang, Y.; Zhu, J. A multi-condition spectral proper orthogonal decomposition approach for reconstruction of transient temperature fields in turbine blades. *Appl. Therm. Eng.* **2025**, *279*, 127506. [[CrossRef](#)]
19. Kala, S.; Jose, B.R.; Mathew, J.; Nalesh, S. High-performance CNN accelerator on FPGA using unified winograd-GEMM architecture. *IEEE Trans. Very Large Scale Integr. (VLSI) Syst.* **2019**, *27*, 2816–2828. [[CrossRef](#)]
20. Lees, T.; Buechel, M.; Anderson, B.; Slater, L.; Reece, S.; Coxon, G.; Dadson, S.J. Benchmarking data-driven rainfall-runoff models in Great Britain: A comparison of long short-term memory (LSTM)-based models with four lumped conceptual models. *Hydrol. Earth Syst. Sci.* **2021**, *25*, 5517–5534. [[CrossRef](#)]
21. Genzel, M.; Macdonald, J.; März, M. Solving Inverse Problems with Deep Neural Networks—Robustness Included. *IEEE Trans. Pattern Anal. Mach. Intell.* **2022**, *45*, 1119–1134. [[CrossRef](#)]
22. Yin, Y.; Feng, Y.; Song, C.; Wang, X. FCFCNN: Frequency coupled fusion convolutional neural network for hyperspectral and LiDAR data classification. *Appl. Intell.* **2026**, *56*, 105. [[CrossRef](#)]
23. Tang, K.; Cui, Y.; Chen, P. A deep learning method for addressing the scarcity of experimental data in composite structures: Multi-Fidelity Triple LSTM. *Thin-Walled Struct.* **2025**, *211*, 113106. [[CrossRef](#)]
24. Boccato, T.; Ferrante, M.; Duggento, A.; Toschi, N. Beyond multilayer perceptrons: Investigating complex topologies in neural networks. *Neural Netw.* **2024**, *171*, 215–228. [[CrossRef](#)] [[PubMed](#)]
25. Cui, X.; Zhu, J.; Jia, L.; Wang, J.; Wu, Y. A novel heat load Reconstruction model of district heating system based on hybrid whale optimization algorithm (WOA) and CNN-LSTM with attention mechanism. *Energy* **2024**, *312*, 133536. [[CrossRef](#)]
26. Li, Y.; Liu, W.; Sun, C.; Cui, M.; Ren, J.; Nikolaitchik, M.A. A physics-informed LSTM framework for solving fluid flow and heat transfer coupling problem of the turbine vane as well as the internal cooling optimization. *Aerosp. Sci. Technol.* **2026**, *168*, 111300. [[CrossRef](#)]
27. Menter, F.R. Review of the shear-stress transport model experience from an industrial perspective. *Int. J. Comput. Fluid Dyn.* **2009**, *23*, 305–316. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.