

Article

Multi-Physics Digital Twin Modeling of Turbine Blades with Small Samples via Multitask Generative Adversarial Networks

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Abstract

In the digital twin modeling of aero-engine turbine blades, traditional CFD requires extensive computational time. Existing data-driven models also struggle to achieve multi-physics decoupling and high-accuracy predictions with extremely small sample constraints. To overcome these challenges, a multitask generative adversarial network (M-GAN) is proposed for multi-physics digital twin modeling. By incorporating a multi-branch attention mechanism into the U-Net generator, this method achieves the decoupling and prediction of multi-physics fields. Additionally, a multi-objective adaptive loss optimization strategy based on uncertainty weighting is proposed to mitigate gradient interference and mode collapse during the joint training of multiple coupled physical fields. Based on the proposed M-GAN, a high-performance digital twin model for turbine blades is developed using only 10 training samples, achieving accurate predictions of pressure, temperature, and airflow angle fields. The test results demonstrate that, on a test set comprising 90 different operating conditions, the average prediction error across all physical fields is only 1.85%, indicating strong cross-physics prediction capability, generalization, and robustness. This approach provides a solid algorithmic foundation for real-time, high-precision mapping in turbine blade digital twin systems.

Keywords: aero-engine turbine blade; digital twin; multitask generative adversarial network; small sample learning; multi-physics field prediction

1. Introduction

Aero-engine turbine blades operate under extreme service environments characterized by high temperatures, high pressures, and strong swirling flows. Their complex aerodynamic and thermodynamic characteristics directly affect engine efficiency and blade service life [1–4]. The accelerating digital transformation of aviation power systems has driven increasing research interest in digital twin modeling of turbine blades for achieving lifecycle-wide virtual–physical mapping [5,6]. According to Grieves’ conceptual framework, a digital twin comprises three fundamental components: a physical entity, its virtual representation, and the bidirectional data and information connections between them [7]. For turbine blades, the physical entity refers to an actual blade, while the virtual representation integrates physics-based and data-driven models to predict its multi-physics response under different operating conditions. Through data exchange, measured

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operating data can be used to update the virtual model, whose predictions provide feedback for performance assessment and engineering decisions. During the design stage, rapid multi-physics field prediction can reduce repeated CFD calculations and accelerate design iterations. During experimental testing, digital twins integrated with measurement data can provide early warnings of potential anomalies and support safer test planning, thereby reducing the need for costly, high-risk destructive tests when exploring performance limits. To support these applications, the virtual model must provide accurate multi-physics predictions while maintaining high computational efficiency. Currently, high-fidelity computational fluid dynamics (CFD) simulation remains the primary method for obtaining detailed physical field data of turbine blades [8,9]. However, traditional CFD demands substantial computational resources and long solution times, limiting its application in rapid performance prediction and real-time digital twin modeling [10]. Therefore, developing a high-fidelity surrogate model that balances prediction accuracy and computational efficiency is essential for overcoming the computational bottleneck of CFD and supporting the practical application of turbine blade digital twins [11].

In recent years, surrogate modeling has played a key role in the aerodynamic optimization and reduced-order modeling of physical fields for aero engines. Traditional data-driven surrogate models, such as Kriging models and response surface methodologies, have been widely applied in the performance prediction and design optimization of various aero-engine components. For example, Goulos et al. [12] utilized a Kriging-based polynomial response surface to perform global aerodynamic optimization on an exhaust system. Cheng et al. [13] achieved high-dimensional global optimization of a compressor by combining a multi-model ensemble strategy. Lian et al. [14] predicted the heat transfer characteristics of a turbine casing under multi-parameter coupling using a Kriging surrogate model. However, as physical constraint dimensions and geometric complexity increase dramatically, traditional low-order surrogate models struggle with strongly nonlinear aerodynamic and thermodynamic fields. This limitation often leads to a sharp decline in interpolation accuracy [15].

To overcome this limitation, high-order data-driven paradigms represented by deep learning have been widely introduced, demonstrating outstanding nonlinear representation potential in surrogate modeling [10,16,17]. Kiyik et al. [18] proposed a surrogate model based on a pyramidal deep regression network for accurate and efficient wing structural analysis and optimization. Abucide-Armas et al. [19] proposed the DeepCFD and further confirmed the significant efficiency advantages of deep convolutional networks in steady-state flow field approximations, thereby improving reconstruction accuracy. Vlahostergios et al. [20] developed a micro-network surrogate model to quickly evaluate the internal cooling effectiveness of turbine blades. Ma et al. [21] constructed a locally enhanced physics-informed neural network, achieving high-precision and ultra-fast assessment of engine nozzle wall temperatures. Chen et al. [22] reconstructed transient temperature fields of turbine blades from sparse measurement data using an attention-augmented CNN-LSTM framework, achieving high accuracy with maximum reconstruction errors below 19 °C. Among various deep learning methods, generative adversarial networks (GANs) [23] and its variants, e.g., conditional generative adversarial networks (cGANs) [24], have shown strong potential for aerodynamic performance evaluation and physical field prediction owing to their powerful high-resolution mapping and data generation capabilities. Li et al. [25] proposed a cGAN-based correction method for turbine blade scaling criteria, reducing the prediction error of high-temperature cooling effectiveness by approximately one order of magnitude compared with traditional methods. Yang [26] employed cGANs to learn and augment features from aero-engine flight data, significantly improving the accuracy of a support vector machine in detecting abnormal engine vibrations. Ge et al. [27] proposed a dynamic adversarial domain adaptation transfer

network based on an improved GAN to accurately predict the remaining useful life of aero engines under multiple operating conditions and fault modes.

Despite the remarkable results achieved by deep learning models in the above studies, their direct application to turbine blade digital twin modeling remains subject to three major limitations. Firstly, high-fidelity CFD simulations are computationally expensive, while most deep learning models require large datasets to achieve satisfactory generalization capabilities [28]. Secondly, a high-fidelity turbine blade digital twin system needs to synchronously map multiple strongly coupled physical fields, such as pressure, temperature, and airflow angle. Existing research mostly focuses on a single scalar field, such as cooling effectiveness [20] and temperature field [22], lacking explicit decoupling mechanisms for high-dimensional multi-physics features. As a result, when predicting multiple physical fields simultaneously, existing models are susceptible to feature entanglement and uneven prediction accuracy due to discrepancies in both gradient directions and magnitudes across different physical fields. Thirdly, under extremely small sample constraints, conventional deep learning models lacking implicit physical constraints and robust regularization mechanisms are highly susceptible to severe mode collapse [29]. This prevents the model from learning the global distribution laws of the genuine multi-physics fields, rendering its extrapolation prediction capabilities under extreme operating conditions completely ineffective.

In view of this, this study aims to overcome the technical bottlenecks of multi-physics turbine blade digital twin modeling under extreme small-sample limitations by proposing the M-GAN. First, a multi-branch attention mechanism is introduced into the generator to implicitly decouple the features of multiple physical fields. This architecture enables task-specific feature extraction and parallel prediction of pressure, temperature, and airflow angle fields, while reducing feature interference among different tasks. Consequently, it significantly reduces the reliance on large sample sizes. Second, a multi-objective adaptive loss optimization strategy based on uncertainty weighting is proposed to mitigate gradient interference during the joint training of multiple physical fields. This strategy dynamically adjusts the weight of each physical field task in the global gradient, fundamentally reinforcing convergence stability under extremely small sample constraints and effectively preventing mode collapse. Using this approach, a high-performance multi-physics digital twin model for turbine blades was trained using only 10 CFD samples. Test results show that the overall average prediction error across the 90 different operating conditions in the test set was only 1.85%. This result demonstrates the potential of the proposed method for digital twin modeling under small sample conditions.

In the following sections, Section 2 introduces the M-GAN; Section 3 details the training process of the multi-physics digital twin model for turbine blades; Section 4 presents the test results and analysis; and Section 5 outlines the conclusions.

2. Multitask Generative Adversarial Network

Extremely small sample availability and strong multi-physics coupling remain major challenges in digital twin modeling. To address these challenges, a multitask generative adversarial network (M-GAN) is proposed by substantially redesigning the conventional conditional generative adversarial network (cGAN) [24]. To minimize data dependency and prevent mode collapse under small sample constraints, M-GAN incorporates three key designs: a multi-branch attention mechanism in the generator (see Section 2.2), a patch-based discriminator to improve local flow-field reconstruction fidelity (see Section 2.3), and a multi-objective adaptive loss optimization strategy based on uncertainty weighting to stabilize gradient updates (see Section 2.4). The details are introduced as follows.

2.1. Overall Algorithm Framework

As shown in Figure 1, the framework of the M-GAN algorithm inherits from the cGAN structure. It consists of four main functional modules: the inputs processing, a generator (G), a discriminator (D), and a composite loss function. Through an adversarial training process, the network learns the complex mapping relationship between input conditions and target physical distributions.

The inputs consist of geometric features and operating parameters, which are determined according to the specific prediction task. Geometric features are represented by two-dimensional feature maps, while operating parameters are scalar variables describing the corresponding boundary conditions. To integrate these different types of data, the scalar parameters are mapped into spatial feature maps with the same resolution as the geometric features. These feature maps are then concatenated along the channel dimension to form the input tensor for the generator.

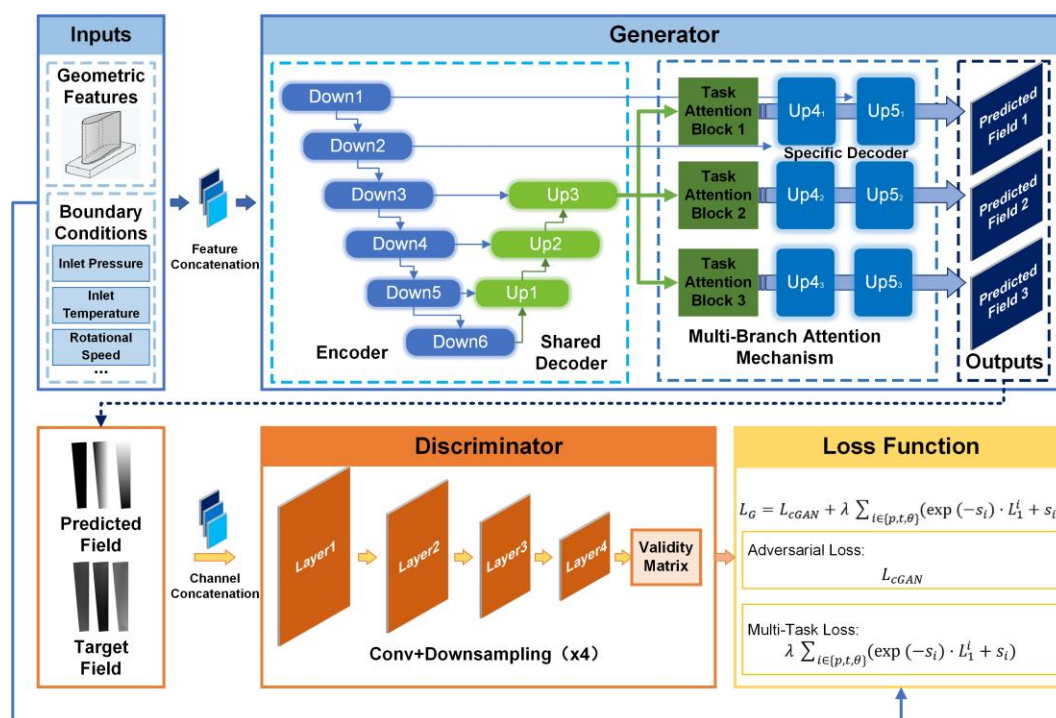


Figure 1. Overall architecture schematic of the proposed M-GAN algorithm.

Generator primarily outputs specified physical field prediction results based on input conditions, which include the geometric structures and operating parameters of the physical field to be predicted (see Figure 1). In this algorithm, generator inherited the classic U-Net fully convolutional neural network [30] as its backbone. The core advantage of U-Net is its symmetric encoder–decoder structure paired with a skip connection mechanism. Given the input x , the encoder progressively extracts high-level features through successive convolution and downsampling operations. The decoder then progressively restores the spatial resolution of the feature maps through transposed convolution and upsampling operations. The mathematical transfer processes of encoding and decoding are represented by Equation (1) and Equation (2), respectively:

$$h_i^{(enc)} = \sigma(W_i^{(enc)} * h_{i-1}^{(enc)} + b_i^{(enc)}) \quad (1)$$

$$h_j^{(dec)} = \sigma(W_j^{(dec)} * [h_{j-1}^{(dec)} \oplus h_{N-j}^{(enc)}] + b_j^{(dec)}) \quad (2)$$

Here, $h_i^{(enc)}$ is the output of the i -th layer encoder; $*$ denotes the convolution operation; σ is the activation function; and $\oplus$ represents feature concatenation along the

channel dimension. Through skip connections, U-Net fuses shallow features containing spatial localization information from the encoder with deep semantic features from the decoder, effectively preventing the loss of detail during reconstruction. To achieve high-accuracy multi-physics field prediction, a multi-branch attention mechanism is introduced at the back end of the U-Net. As shown in Figure 1, the shared features are fed into independent task-attention blocks and decoding branches to reconstruct the pressure, temperature, and airflow angle fields in parallel. The detailed architecture of the multi-branch task-attention generator is presented in Section 2.2.

The role of the discriminator is to distinguish between genuine and generated physical fields. The predicted physical fields and the corresponding target fields are separately concatenated with the input conditions and fed into the discriminator. Through successive convolution and downsampling operations, the discriminator outputs a validity matrix to distinguish between real CFD results y and generated physical fields $\hat{y}$ (detailed in Section 2.3).

As shown in Figure 1, the loss function combines the adversarial loss with a multi-task loss based on uncertainty weighting. The adversarial loss guides the generator to produce realistic physical fields, while the multi-task loss adaptively balances the prediction errors of different physical fields. The detailed loss function and optimization strategy are presented in Section 2.4.

2.2. Multi-Branch Task-Attention Generator

When conventional U-Net generators handle parallel prediction tasks for multi-physics fields, physical features from different physical fields are forced into reconstruction within the same feature space. This can cause severe feature entanglement during the decoding stage, subsequently leading to model convergence difficulties. To achieve the implicit decoupling of physical fields, this paper proposes a multi-branch attention mechanism for the generator.

This generator adopts a topological architecture comprising three key stages: shared encoding, multi-branch feature extraction, and independent decoding (see Figure 2). In the encoder and first three layers of the decoder (i.e., layers up1 to up3), the network captures the global topological structure and macroscopic evolution patterns of the flow field through shared parameters. After the shared feature layer up3, the generator splits into multiple parallel decoupled branches corresponding to different prediction tasks, e.g., pressure field p , temperature field t and airflow angle θ .

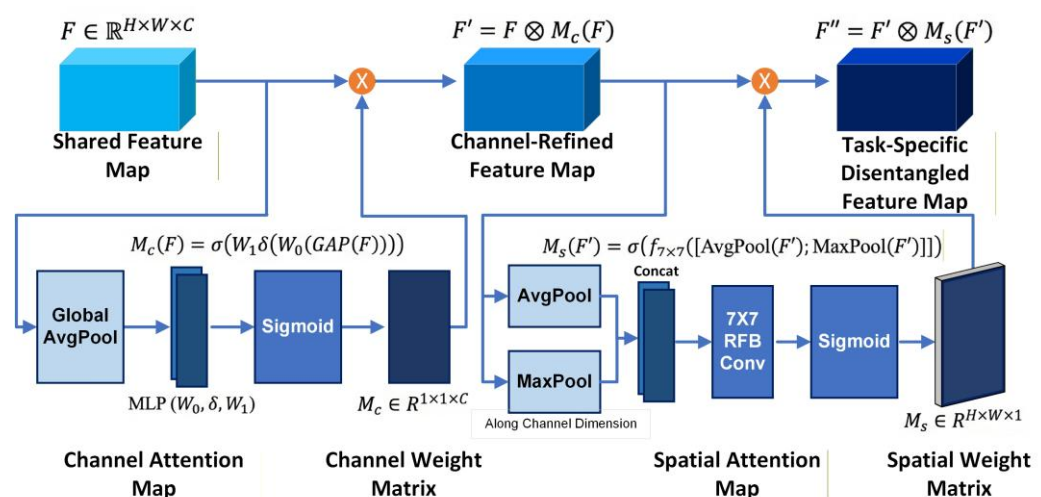


Figure 2. Schematic diagram of the task attention block.

As shown in Figure 2, to achieve more precise feature extraction within each branch, a task attention block (TAB) is introduced at the start of the branches. Each TAB performs targeted physical feature extraction on the shared feature map $F \in \mathbb{R}^{H \times W \times C}$ through an internal dual attention mechanism covering both channel and spatial dimensions. The specific process is as follows:

- (1) Channel attention mapping: The mechanism is designed to guide each branch to adaptively focus on the feature channels that are most relevant to the corresponding physical field. The feature map is first compressed into a channel descriptor through global average pooling. A bottleneck mapping consisting of two 1×1 convolution layers is then used to learn nonlinear dependencies between channels, generating the channel attention weight $M_c \in \mathbb{R}^{1 \times 1 \times C}$ (3)

$$M_c(F) = \sigma(W_1 \delta(W_0(\text{GAP}(F)))) \quad (3)$$

where σ is the sigmoid activation function, δ is the ReLU activation function, and W_0 and W_1 are weight parameters. The recalibrated feature is expressed as $F' = F \otimes M_c(F)$, where $\otimes$ denotes element-wise multiplication.

- (2) Spatial attention mapping: Aimed at localizing critical spatial regions in the flow field that are highly sensitive to specific physical quantities (such as shock edges or blade wake zones). The channel-refined feature F' undergoes average pooling and max pooling along the channel dimension, and the concatenated features are subjected to a 7×7 convolution operation to generate the spatial weight matrix $M_s \in \mathbb{R}^{H \times W \times 1}$:

$$M_s(F') = \sigma(f^{7 \times 7}([\text{AvgPool}(F'); \text{MaxPool}(F')])) \quad (4)$$

Finally, task-specific feature output is $F'' = F' \otimes M_s(F')$.

An independent branch is assigned to each physical field to extract field-specific features from the shared parameters through dual filtering. The resulting feature maps are then fed into independent decoding paths to reconstruct the pressure, temperature, and airflow angle fields. This architecture promotes task-specific feature extraction and reduces feature interference during decoding, while the shared encoder remains jointly optimized. Consequently, it facilitates more stable learning of the nonlinear characteristics of each physical field and improves prediction accuracy under small-sample conditions.

2.3. Patch-Based Discriminator

This paper adopts a fully convolutional PatchGAN as the discriminator [24] to enhance the network's perceptual capability of flow field details. Unlike a standard global discriminator outputting a single probability indicating whether the input is real or generated, PatchGAN produces a spatial matrix $N \times N$ of local authenticity scores, with each score corresponding to a specific image patch. In this way, it effectively penalizes local structural distortions and encourages the generator to preserve fine-scale flow-field features.

The discriminator concatenates the input operating conditions with the multi-physics results $\hat{y}$ output by the generator (or the real physical fields y) along the channel dimension. The concatenated tensor successively passes through 4 layers of downsampling convolutions with a stride of 2 and a terminal linear activation layer to output the discrimination result. This design encourages the generator to preserve local flow-field structures and improves reconstruction fidelity.

2.4. Multi-Objective Adaptive Loss Optimization

In the prediction of multi-physics fields for turbine blades, there are often immense characteristic disparities among the different physical fields. If the joint L_1 loss is constructed by directly summing the losses of all physical fields with equal weights, a physical field with a relatively large loss can dominate the optimization process. This imbalance may lead to severe mode collapse, particularly under small-sample conditions. To address this, multi-physics prediction is regarded as a multitask learning problem, and an uncertainty weighting mechanism based on homoscedastic task uncertainty is introduced in M-GAN [31]. Using maximum likelihood estimation, an adaptive loss function L_G incorporating uncertainty-driven learnable weights is constructed for the generator:

$$L_G = L_{cGAN} + \lambda \sum_{i \in \{p, t, \theta\}} (\exp(-s_i) \cdot L_1^i + s_i) \quad (5)$$

$$L_{cGAN} = \min_G \max_D V(D, G) = E_{x,y} [\log D(x, y)] + E_x [\log (1 - D(x, G(x)))] \quad (6)$$

where L_{cGAN} is the foundational conditional adversarial loss [22]. λ is the regularization coefficient; $L_1^i = E_{x,y} [|y_i - G_i(x)|]$ is the mean absolute error of the i -th physical field. $s_i = \log(\sigma_i^2)$ is the learnable log-variance parameter for the corresponding physical field.

The key advantage of the uncertainty weighting strategy lies in its adaptive weighting mechanism. The log-variance parameter s_i represents the model's uncertainty associated with the i -th physical field and is automatically updated during backpropagation. When the prediction error L_1^i of a specific physical field is exceptionally large, indicating high task uncertainty, the network tends to increase s_i . Consequently, the adaptive weight $\exp(-s_i)$ decreases, reducing that challenging field's contribution to the total loss. This effectively prevents a single difficult task from dominating the overall gradient direction. Meanwhile, the penalty term $+s_i$ at the end of the formula acts as a regularization constraint, preventing the network from trivializing the loss by infinitely increasing the uncertainty. This dynamic uncertainty weighting mechanism enables the network to adaptively balance the optimization rates of different physical fields. As a result, it improves convergence stability and mitigates mode collapse under extremely limited sample conditions.

3. Multi-Physics Digital Twin Model for Turbine Blades

Based on the proposed M-GAN algorithm, a digital twin model is constructed for the two-dimensional (2-D) multi-physics fields of turbine blades. Given the operating parameters, including inlet temperature, inlet pressure, exit pressure, and rotational speed, the model rapidly predicts the corresponding 2-D temperature, pressure, and airflow angle fields. The training process for the digital twin model is detailed below.

3.1. Preparation of the Dataset

Here, the third-stage power turbine blade of a specific turboshaft engine is utilized as a case study. Multi-physics field data for this power turbine blade under 100 different operating conditions were obtained by CFD simulation. The operating conditions of the turbine blade are defined by 4 parameters: inlet temperature, inlet pressure, exit pressure, and rotational speed. The distribution characteristics of the 100 samples within the aforementioned four-dimensional parameter space are depicted in Figure 3. Each sample includes the aforementioned operating condition parameters and their corresponding 2-D steady-state pressure field (p), temperature field (t), and airflow angle field (θ). The resolution of the 2-D physical fields is 512×256 .

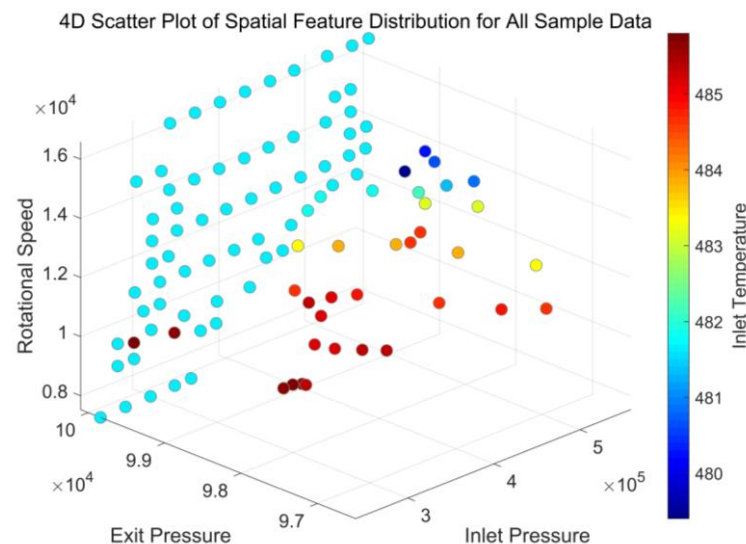


Figure 3. Distribution characteristics of all samples in the four-dimensional parameter space.

3.2. Feature Encoding Preprocessing

The data fed into the model includes both discrete scalar parameters and 2-D images of the turbine blades. To enable the neural network to synchronously parse scalar and 2-D image data, the Min-Max scaling method is utilized to normalize the 4 scalar parameters to the $[-1,1]$ interval. Through a global broadcasting mechanism, the normalized scalars are mapped into spatial dimensions, generating $512 \times 256 \times 4$ physical feature maps that match the resolution of the geometric features. Finally, the geometric features and the broadcast scalar parameters are concatenated along the channel dimension, establishing the $512 \times 256 \times 5$ fused input tensor required by the digital twin model. This ensures that every spatial pixel in the flow field is accurately mapped to its corresponding geometric location while simultaneously embedding the operating condition information.

3.3. Model Training

During the training process, the 100 samples are partitioned into mutually exclusive training and testing sets. As shown in Figure 4, 10 samples are randomly selected as the training set. The model relies solely on 10 training samples to update network weights. The testing set, which remains unseen during training, is utilized to evaluate the model's generalization capability and multi-physics reconstruction capabilities. For the training hyperparameters, the initial learning rate is set to 2×10^{-4} , the first-order momentum decay rate β_1 is 0.5, and the batch size is 8. The adversarial training process iterates for a total of 2000 Epochs. Throughout the training process, the algorithm actively logs the data for various loss functions.

After training, the trained network can be integrated as a rapid multi-physics prediction module in a digital twin system. Given measured operating parameters, a single forward pass can generate the corresponding quasi-steady pressure, temperature, and air-flow angle fields within milliseconds.

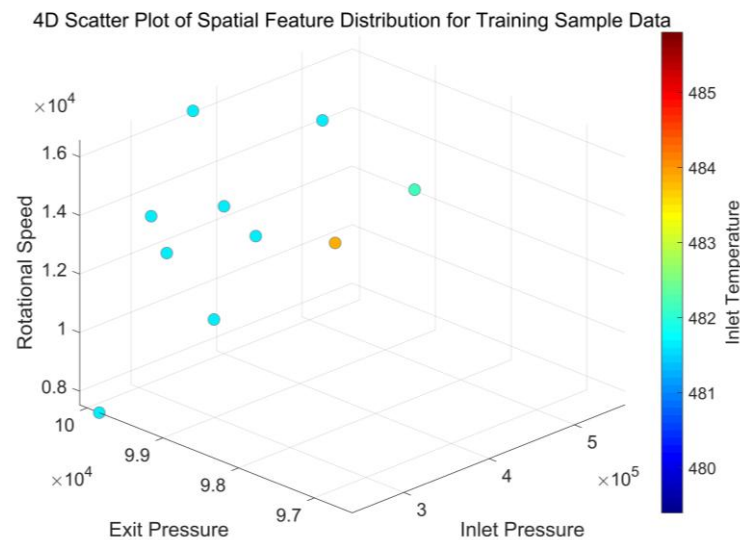


Figure 4. Distribution characteristics of the training samples in the four-dimensional parameter space.

4. Results and Discussion

This section evaluates M-GAN in four aspects: prediction accuracy and inference efficiency under unseen operating conditions (Section 4.1), the effectiveness of adaptive loss optimization (Section 4.2), the interpretability and contribution of the task-attention block (Section 4.3), and interpolation and extrapolation performance under small-sample conditions (Section 4.4).

4.1. Performance Evaluation

To evaluate the generalization capability of the proposed digital twin model and its ability to reconstruct complex flow fields, six representative test conditions (Samples 1, 16, 39, 70, 82, and 99) are selected for visual comparison. As shown in Figure 5, M-GAN reproduces the pressure, temperature, and airflow angle fields across the six test cases. The absolute error fields show low errors over most spatial regions, with larger deviations mainly occurring in strongly nonlinear regions, such as blade wakes. These results demonstrate good reconstruction fidelity across the three physical fields. The model's interpolation and extrapolation performance is further quantified in Section 4.4.

To quantitatively evaluate the real-time inference capability of the proposed M-GAN, its performance was tested on an NVIDIA RTX3080 GPU. The model achieved a single-field prediction time of 17.5 ms and required only 3368 MB of GPU memory, comfortably satisfying the millisecond-level real-time constraints for online digital twin deployments.

To quantitatively evaluate the prediction accuracy of the M-GAN, the CFD results are used as the reference, and the prediction error err_p is defined using the normalized mean absolute error:

$$err_p = \frac{\text{mean}(|\bar{P} - \bar{R}|)}{\bar{R}_{max} - \bar{R}_{min}} \times 100\% \quad (7)$$

where $\bar{R}$ signifies the ground truth CFD physical field, $\bar{P}$ is the predicted physical field, mean indicates the averaging operation, and $\bar{R}_{max}$ and $\bar{R}_{min}$ denote the maximum and minimum values of the authentic physical field, respectively.

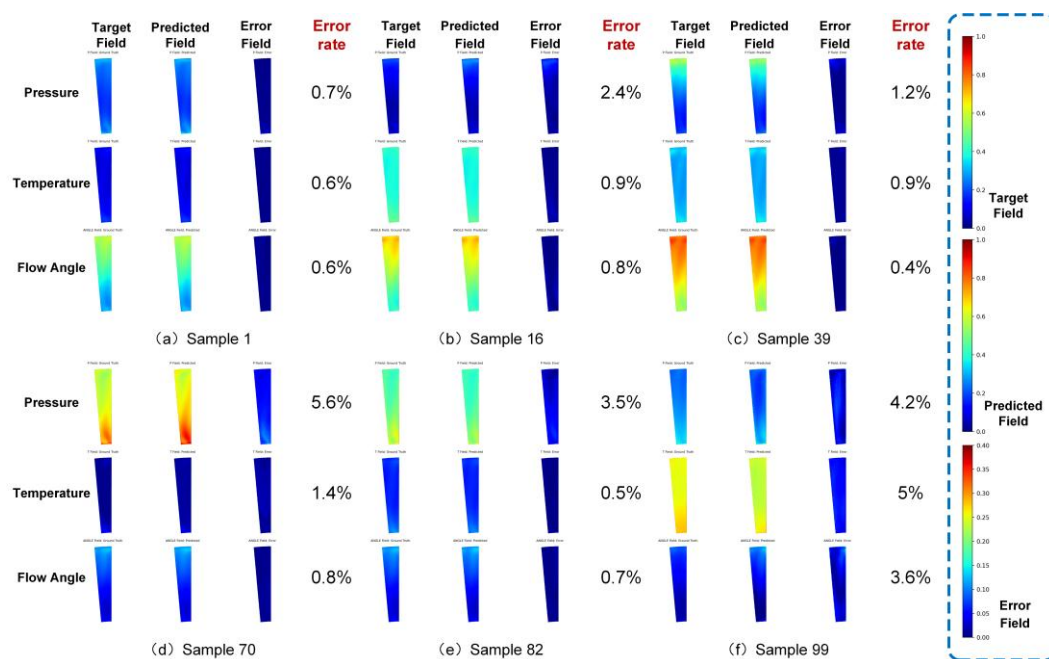


Figure 5. Performance evaluation and test results of the M-GAN algorithm.

For comparison, the original cGAN [24] and the widely recognized DeepCFD [19] were selected as comparative baselines. All three models were trained using the same 10 CFD samples and evaluated on the same 90 test samples. As summarized in Table 1, M-GAN achieves an overall average error of 1.85%, compared with 6.54% for cGAN and 3.72% for DeepCFD. M-GAN achieves average prediction errors of 2.26%, 1.96%, and 1.32% for the pressure, temperature, and airflow angle fields, respectively, all lower than those of DeepCFD and cGAN for the corresponding fields. Defining a prediction failure as a field prediction error exceeding 5%, M-GAN yields only 10 failures among the 270 test fields, compared with 159 for cGAN and 53 for DeepCFD. These results demonstrate that the proposed M-GAN achieves higher prediction accuracy and fewer prediction failures than both baseline models under the same small-sample training conditions.

As shown in Figures 6 and 7, the test error heat maps further support the above conclusions. The original cGAN exhibits dense warm-colored regions with relatively high errors in the temperature and airflow angle fields, suggesting insufficient decoupling among the physical fields (see Figure 7a). Compared with cGAN, DeepCFD exhibits fewer high-error regions. However, relatively large prediction errors remain in the pressure field (see Figure 7b). In contrast, M-GAN exhibits predominantly cool-colored regions, indicating generally low prediction errors, with few areas of large errors (see Figure 6). These results further demonstrate that M-GAN achieves more consistent prediction accuracy across different operating conditions and physical fields.

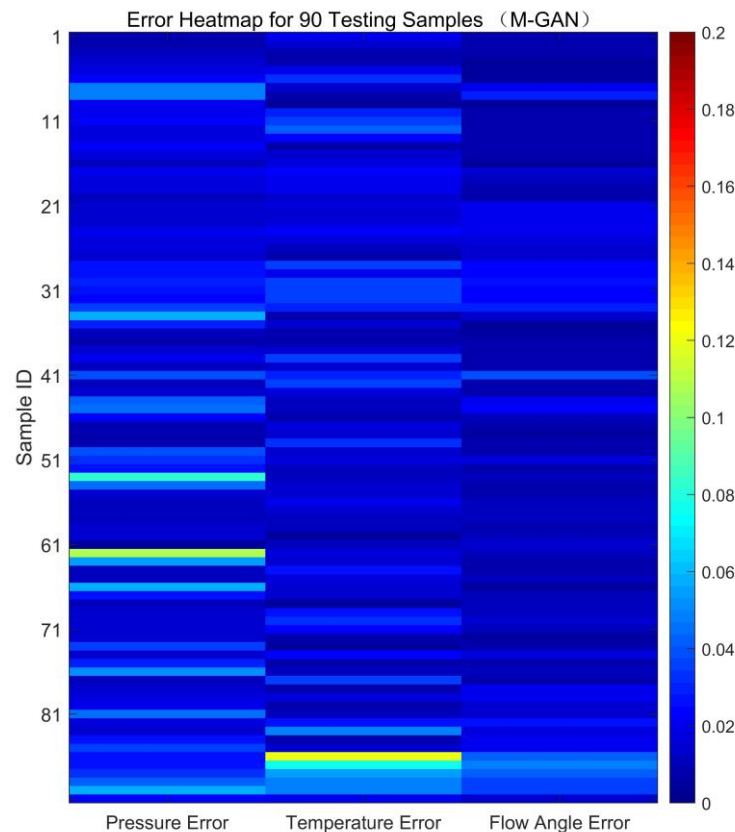


Figure 6. Heatmaps of test errors for the M-GAN algorithm.

Table 1. The test results of the M-GAN, cGAN, and DeepCFD.

	M-GAN	cGAN	DeepCFD
Average error rate of pressure	2.26%	4.92%	4.67%
Average error rate of temperature field	1.96%	8.98%	3.17%
Average error rate of airflow angle field	1.32%	5.71%	3.33%
Overall average error rate	1.85%	6.54%	3.72%
Number of physical fields with error rates > 5%	10	159	53

Compared with the original cGAN, a multi-branch attention mechanism and an adaptive loss optimization strategy are proposed for M-GAN to improve task-specific feature extraction and balance the joint optimization of multiple physical fields. DeepCFD provides a non-adversarial approach for multi-physics field prediction, but its prediction accuracy is relatively limited under the extremely small sample conditions considered in this study. In contrast, M-GAN combines adversarial learning with task-specific feature extraction to improve the reconstruction accuracy of multiple physical fields. Nevertheless, the proposed method requires additional attention branches and adversarial optimization, resulting in a more complex training process than the non-adversarial DeepCFD model.

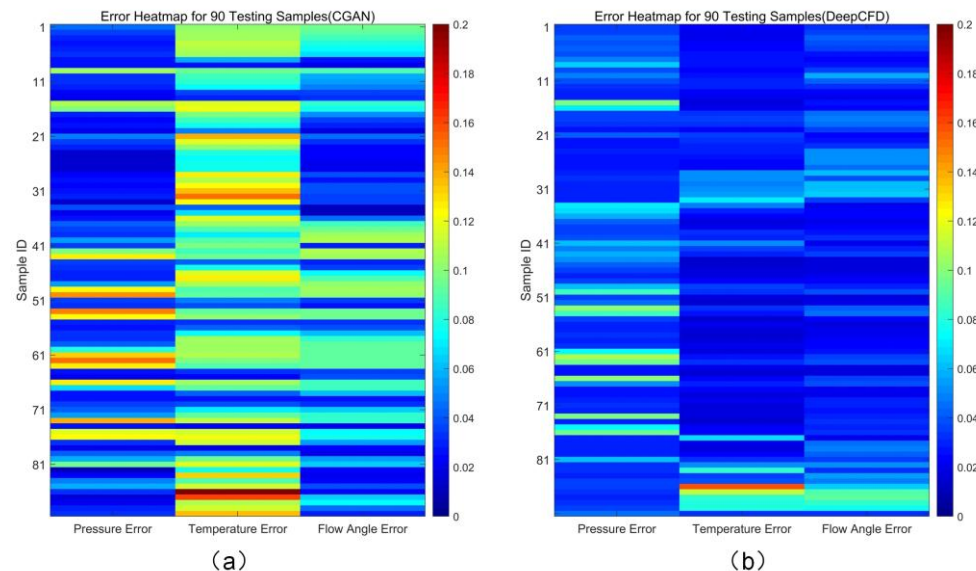


Figure 7. Heatmaps of test errors for the baseline algorithms: (a) cGAN; (b) DeepCFD.

4.2. Evaluation of the Adaptive Loss Optimization Strategy

In the construction of multi-physics digital twin models, discrepancies in gradient magnitudes and optimization directions among different fields are prone to inducing optimization imbalance in multitask learning. To investigate how the proposed adaptive loss optimization strategy affects gradient interference and prediction accuracy, this section compares it with a conventional fixed-weight strategy. In the traditional strategy, s_i in Equation (5) is fixed. Furthermore, the loss evolution and adaptive parameter changes during training are analyzed.

As shown in Figure 8a, the traditional loss optimization strategy exhibits pronounced oscillations during the first 50 epochs, reflecting the optimization difficulties associated with multi-task learning under extremely small-sample conditions. In contrast, the proposed adaptive loss optimization strategy produces a significantly smoother total-loss curve. It indicates improved convergence stability during the early training stage. As training progresses to 2000 epochs (see Figure 8b), the branch losses for the pressure, temperature, and airflow angle fields decrease steadily and gradually converge. No divergence caused by the dominance of a single physical-field gradient is observed. These results demonstrate that adaptive loss weighting alleviates gradient interference and improves convergence stability during the joint training of multiple physical fields.

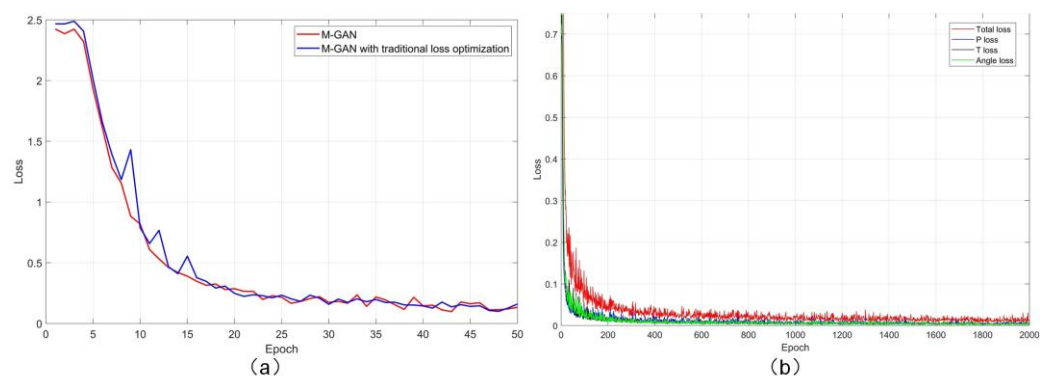


Figure 8. Evolution of training losses for the adaptive strategy versus the fixed-weight strategy: (a) The first 50 epochs with different loss optimization strategy. (b) The entire training process of M-GAN.

The quantitative evaluation results further demonstrate the effectiveness of the adaptive loss optimization strategy. Statistical analysis shows that the overall average prediction error increases from 1.85% to 3.2% when the traditional loss optimization strategy is used. Without the adaptive loss optimization strategy, the prediction error rate for the temperature field surges to 4.6%, which is considerably higher than the error levels of the pressure and airflow angle fields. Under the traditional loss optimization strategy, gradient interference and optimization competition among different physical fields can bias the optimization toward certain fields, subsequently reducing the prediction accuracy of certain fields (e.g., the temperature field). By dynamically adjusting the weights of individual tasks, the multi-objective adaptive loss optimization strategy reduces competition among physical fields and improves the balance of the joint optimization.

As shown in Figure 9, the absolute values and relative weights of the adaptive log-variance parameters s_p , s_t and s_{angle} (See Equation (5)) are tracked during training. Although the three parameters exhibit similar overall downward trends, their relative values change at different rates, particularly during the early training stage. This dynamic adjustment of the relative weights allows the network to respond to changes in the optimization of different physical fields. When a physical field exhibits increased prediction error or slower convergence during training, its gradient contribution is adjusted accordingly. This helps maintain a balance among the different tasks during joint optimization. Combined with the convergence and ablation results, these observations further demonstrate that the uncertainty weighting mechanism helps balance multi-task optimization and improve training stability under extremely small-sample conditions.

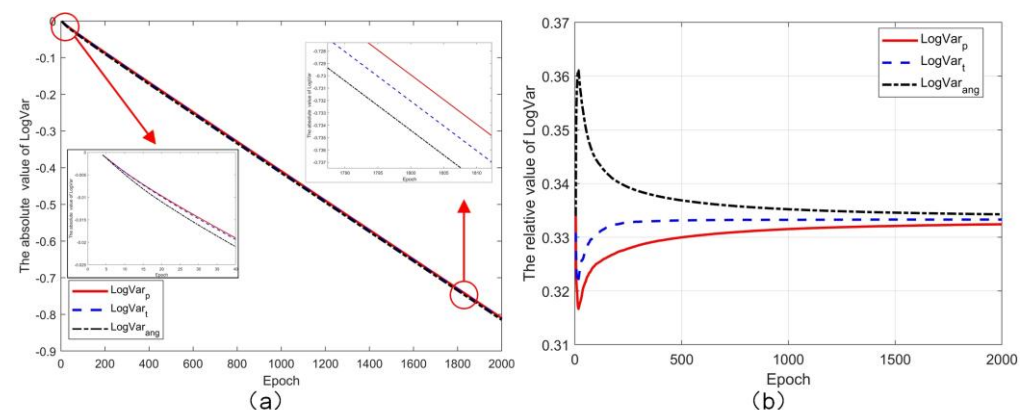


Figure 9. Evolution trajectories of the absolute values and relative weights of the adaptive log-variance parameters throughout the training cycle: (a) Absolute value; (b) Relative value.

4.3. Evaluation of the Task-Attention Block

To investigate the physical interpretability of TAB, we visualize spatial-attention maps, which reveal task-specific regions more intuitively than channel attention. As shown in Figure 10, the CFD results, M-GAN predictions, and corresponding spatial-attention maps are compared for Samples 39 and 61. The red ellipses highlight regions where the learned attention weights correspond to characteristic physical-field variations. For the pressure branch, relatively high attention weights are concentrated near the leading and trailing edges (upper and lower boundaries), where pronounced pressure gradients occur. The temperature branch exhibits a distinct distribution, localizing its focus near the thermal boundary layers and convective heat transfer zones at the flow boundaries. In contrast, the airflow angle branch exhibits distinct longitudinal patterns of spatial weighting, where the airflow angle varies along the flow direction. These differences indicate that the three branches learn task-specific spatial weighting patterns rather than applying identical attention to all physical fields. The observed correspondence between

attention distributions and physical-field characteristics supports the effectiveness of TAB in task-specific feature extraction and implicit multi-physics decoupling.

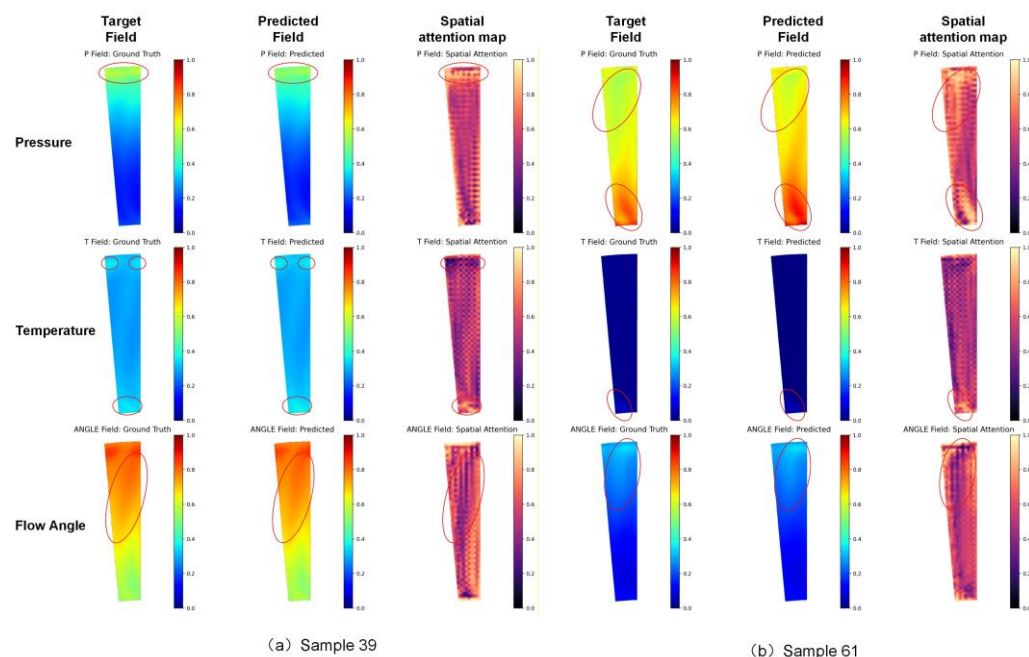


Figure 10. Spatial-attention maps of the pressure, temperature, and airflow-angle branches under two representative operating conditions: (a) Sample 39; (b) Sample 61.

To quantify each attention sub-module's contribution, channel and spatial attention were separately removed from the TAB, with the remaining architecture and adaptive loss strategy unchanged. As shown in Table 2, when spatial attention is removed, the overall average prediction error increases from 1.85% to 2.53%, while the number of failed predictions increases from 10 to 19. In particular, the prediction errors of the pressure and temperature fields increase from 2.26% and 1.96% to 3.29% and 2.83%, respectively. Removing channel attention results in a larger deterioration in prediction performance, with the overall average error increasing to 3.34% and the number of failed predictions reaching 52. The airflow angle field is particularly affected, with its average prediction error increasing from 1.32% to 3.12%. These results demonstrate that both spatial and channel attention contribute to multi-physics reconstruction, while channel attention plays a more significant role in prediction accuracy under the present experimental setting.

Table 2. Ablation results of the channel-attention and spatial-attention sub-modules.

	M-GAN	Without Spatial Attention	Without Channel Attention
Average error rate of pressure	2.26%	3.29%	3.54%
Average error rate of temperature field	1.96%	2.83%	3.36%
Average error rate of airflow angle field	1.32%	1.48%	3.12%
Overall average error rate	1.85%	2.53%	3.34%
Number of physical fields with error rates > 5%	10	19	52

4.4. Generalization Boundary and Extrapolation Analysis

To further evaluate the generalization capability of M-GAN, the 90 test cases were classified using the minimum and maximum values of the four operating parameters in the training set. Cases with all four parameters within the training ranges were defined as range-based interpolation samples; the remaining cases were classified as extrapolation

samples. This criterion yielded 46 interpolation and 44 extrapolation samples, whose prediction errors were evaluated using Equation (7) and are reported in Table 3.

Table 3. Prediction performance of M-GAN for interpolation and extrapolation samples.

	Interpolation	Extrapolation
Number of test samples	46	44
Average error rate of pressure	2.42%	2.09%
Average error rate of temperature field	1.40%	2.54%
Average error rate of airflow angle field	0.88%	1.78%
Overall average error rate	1.57%	2.14%
Number of physical fields with error rates > 5%	4	6

As shown in Table 3, the overall average error increases from 1.57% for interpolation samples to 2.14% for extrapolation samples. The temperature and airflow-angle errors increase to 2.54% and 1.78%, respectively, whereas the pressure error decreases slightly to 2.09%. These results indicate that the influence of extrapolation varies among different physical fields. Note that M-GAN maintains low errors in both groups, showing strong generalization and extrapolation beyond the training ranges.

The reliability of M-GAN far beyond the tested operating envelope remains unverified, as the model lacks explicit physical constraints. In practical applications, operating conditions outside the training range should be identified and assessed using additional CFD simulations, while newly validated CFD cases could support incremental model updates. In addition, measurement noise may also propagate through input normalization to the reconstructed fields. Future work will therefore investigate noise-robust training and sparse-sensor fusion to improve deployment reliability.

5. Conclusions

This paper proposed a multitask generative adversarial network for high-fidelity digital twin modeling of turbine blades under extremely small sample and strongly coupled multi-physics conditions. The major conclusions are summarized as follows.

- (1) A generator based on a multi-branch attention mechanism was developed to achieve implicit feature decoupling and parallel learning of multi-physics fields. The proposed architecture reduces cross-field feature entanglement and improves the accuracy and consistency of simultaneous multi-physics prediction.
- (2) An adaptive loss optimization strategy was introduced to dynamically balance the optimization of multiple prediction tasks. The proposed strategy enhances model precision while significantly reducing the risk of mode collapse.
- (3) Using only 10 training samples, M-GAN achieves an overall average error of 1.85%, with only 10 failed predictions. Its average errors for the interpolation and extrapolation samples are 1.57% and 2.14%, respectively. These results demonstrate strong prediction accuracy and extrapolation capability under extreme small sample constraints.

Overall, the proposed M-GAN enables millisecond-level prediction of coupled physical fields with limited training data, providing an effective approach for multi-physics digital twin modeling of aero-engine components. These advantages make it a promising solution for 2-D multi-physics digital twin modeling of aero-engine components where high-quality simulation data are scarce. However, the current framework is limited to 2-D slice-based physical-field reconstruction and cannot capture three-dimensional flow structures. Future work will extend M-GAN to 3-D multi-physics field prediction for turbine blade digital twins, addressing the increased GPU memory requirements and

computational cost of 3-D adversarial training, as well as the need for larger high-fidelity 3-D CFD datasets.

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