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# Multiscale AI-Model-Assisted Optimization and Defect Suppression of Ceramic Fiber Textile Molding Process

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## Article

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## ABSTRACT

*The ceramic fiber textile molding process plays a crucial role in the production of high-temperature insulation materials, where molding accuracy and defect control directly impact product performance. Traditional processes rely on experience and manual adjustments, making it difficult to achieve efficient and precise optimization and defect suppression. Existing optimization methods often focus on a single scale or local defect control, lacking comprehensive analysis and multiscale optimization approaches, and are also limited by the absence of effective AI models for defect prediction and suppression. This paper proposes an optimization method for the ceramic fiber textile molding process based on a multiscale AI model. By integrating deep learning and data-driven multiscale modeling techniques, a model is developed that can simultaneously process macroscopic textile parameters and microscopic defect features, enabling real-time optimization and defect prediction during the textile process. Experimental results show that the proposed method achieves quantifiable improvements in molding accuracy and defect rate, with accuracy increased by approximately 30%-35% and defect rate reduced by about 32%-38%. This research provides a new approach to the optimization of ceramic fiber textile molding processes, effectively improving production efficiency and product quality. It holds considerable academic and practical value and shows promising application prospects in the production of high-temperature insulation materials.*

## KEYWORDS

*ceramic fiber, textile molding process, multiscale AI model, process optimization, defect suppression*

## INTRODUCTION

The ceramic fiber textile molding process plays an important role in the production of high-temperature insulation materials, especially in industries such as aerospace and energy. Its superior high-temperature resistance and insulation properties make it a key material[1,2]. However, conventional molding processes often depend on manual adjustments, resulting in a lack of precision and efficiency when faced with complex

textile parameters and stringent product quality requirements[3]. With the expansion of production scale, improving molding accuracy and reducing defects have become critical challenges in the textile industry[4]. Current optimization literature generally focuses on a single scale or local defect control. Some studies investigate the effects of macroscopic environmental parameters (e.g., temperature and humidity), while others focus on local micro-factors such as fiber stretching and twist[5,6]. However, these approaches lack a comprehensive cross-scale mechanism, and many rely on static empirical models, making it difficult to robustly predict and suppress transient defects during the process[7].

In this context, this paper proposes a multiscale AI-based optimization framework to address the aforementioned cross-scale modeling gaps. First, multiscale modeling is introduced as the core mechanism. By combining deep learning with finite element data, a multi-level model is constructed to process both macroscopic parameters and microscopic defect features, enabling data transmission across different scales. Second, a defect prediction and suppression mechanism utilizing deep neural networks (DNN) and adaptive optimization algorithms is proposed to dynamically adjust parameters and mitigate common defects (e.g., fiber breakage, uneven stretching). Third, an optimization framework integrating Internet of Things (IoT) technology is developed. Through continuous feedback from sensor data, the framework automatically updates control strategies, ensuring that production operates in an optimal state.

The advantage of the proposed method lies in its ability to co-optimize multiple variables simultaneously through the coupled multiscale model, ensuring the stability of product quality. Furthermore, the application of the IoT-based framework enables data-driven automated control, allowing for rapid responses to dynamic production variations.

This study advances the application of multi-modality AI technology in traditional textile industries, providing a robust mathematical and algorithmic approach for complex production processes.

## RELATED WORKS

### Research Progress on Ceramic Fiber Textile Molding Process Optimization

The ceramic fiber textile molding process is a key procedure in the production of high-temperature insulation materials[8,9]. Early studies primarily utilized empirical physical models to explore the impact of environmental parameters (such as temperature and humidity) on textile quality[10,11]. By predicting material performance under different boundary conditions, molding accuracy can be improved in stable environments. However, these static physical models struggle to adapt to dynamic batch variations and complex variable

production settings[12,13]. Recently, data-driven and machine learning techniques have been applied to predict parameters such as fiber stretching force and twist in real-time[14]. While data-driven methods have improved predictive precision, establishing a comprehensive mathematical framework that accurately reflects the complex thermodynamic interactions remains a continuous research focus.

### **Research Progress on Textile Defect Prediction and Suppression Methods**

In the ceramic fiber textile process, defects such as fiber breakage severely affect quality. Many studies have applied machine learning techniques, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), to detect defects[16]. While these algorithms enable automatic defect handling, many early models were based on a single data modality, which can lead to misjudgments under complex external disturbances[17,18]. To improve robustness, recent studies have utilized multimodal data fusion, incorporating multisource data such as temperature, humidity, and stretching force[19,20]. Although accuracy has improved, integrating heterogeneous data sources still faces technical challenges, particularly regarding computational resource constraints and inference latency in dynamic high-speed production environments[21].

### **Application of Multiscale Modeling in Textile Processes**

Multiscale modeling can theoretically describe the interaction between macroscopic environments and microscopic parameters[22]. Some studies have introduced multiscale concepts into ceramic fiber textiles, analyzing the impact of stretching and twisting on molding accuracy[23,24]. However, substantially combining models across scales remains a notable algorithmic challenge[25]. Existing multiscale methods in this domain often employ loose coupling, lacking a defined mathematical interface for continuous data exchange between macroscopic states and microscopic defect evolutions[26]. Consequently, they have not fully realized precise, closed-loop collaborative control. How to establish a rigorous and efficient mechanism to fuse these cross-scale features remains a key direction for future research.

### **Contributions and Innovations**

Existing studies often lack a defined algorithmic interface to bridge macroscopic process parameters and microscopic defect features, as shown in Figure 1(a). Due to this lack of explicit cross-scale correlation, achieving precise, multi-variable collaborative control remains mathematically and practically challenging[27,28].

To address these technical gaps, this paper proposes an optimization method for the ceramic fiber textile molding process based on a multiscale AI model. As shown in Figure 1(b), this method constructs a multiscale AI model that integrates macroscopic and microscopic features through a defined feature-fusion mathemati-

cal interface. With this cross-scale information exchange and a closed-loop mechanism, it enables coordinated control of the textile process. This framework can not only predict microscopic defects based on macroscopic conditions but also adjust the process dynamically according to microscopic feedback, actively suppressing defects while improving molding accuracy.

The innovation of this paper lies in integrating multiscale modeling with deep learning systems, forming a data-driven optimization framework that spans the entire process chain. The comparison in Figure 1 intuitively demonstrates the paradigm shift from “isolated processing” to “integrated optimization,” filling the algorithmic gap in existing cross-scale collaboration research. This framework is not only applicable to ceramic fiber textile processes but also provides theoretical support for the optimization of other complex industrial processes.

In summary, this paper provides a rigorously coupled multiscale AI approach, offering an effective and mathematically grounded solution for the automated process control of high-temperature insulation material manufacturing.

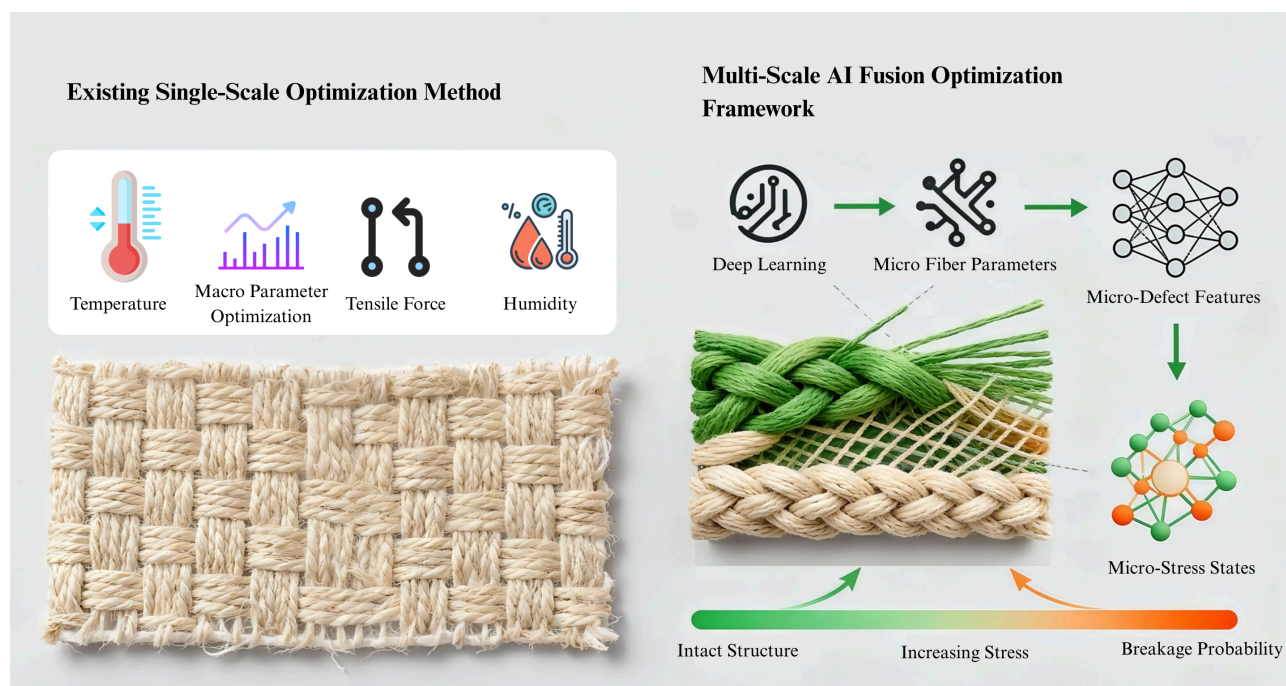


Figure 1. Comparison of Multiscale Optimization Framework for Ceramic Fiber Textile Molding Process: (a) isolated processing; (b) integrated optimization

## METHODOLOGY

The core goal of this paper is to propose an optimization method for the ceramic fiber textile molding process based on a multiscale AI model. To achieve this goal, the study combines traditional physical modeling with modern data-driven methods, designing a comprehensive optimization framework from multiple perspectives. This framework covers various aspects, including the ceramic fiber textile process, defect prediction and suppression, and real-time optimization. The following sections detail the steps and core principles of the research methodology.

### Overall Framework Design

The proposed optimization method for the ceramic fiber textile molding process is based on the combination of multiscale modeling and deep learning techniques, forming a closed-loop optimization system. This system can monitor and adjust the textile process in real-time, substantially predict and suppress defects, and improve molding accuracy and product quality. The overall framework is shown in Figure 2, and it consists of the following four main modules:

- (1) **Data Acquisition Module:** This module collects various types of data in real-time through a sensor network, including environmental parameters (such as temperature and humidity) and mechanical parameters (such as stretching force and yarn twist). The sensors in this module provide the necessary input data for subsequent modules, ensuring process stability and accuracy[29]. To ensure data accuracy, the data acquisition module regularly calibrates the sensors to eliminate errors.
- (2) **Multiscale Modeling Module:** This module combines deep learning and physical modeling to model and optimize both macroscopic and microscopic scales. The macroscopic model mainly simulates environmental and large-scale process factors, while the microscopic model focuses on the behavior of fibers (such as stretching, twisting, etc.). Through interactive optimization, the macro and micro factors work synergistically, thereby improving molding accuracy.
- (3) **Defect Prediction and Suppression Module:** Based on CNN and RNN, this module can predict and suppress defects in real-time, such as fiber breakage and uneven twist. The system adjusts the process parameters in real-time to reduce the occurrence of defects, thereby improving product quality.
- (4) **Real-time Optimization and Adjustment Module:** Through deep learning models, this module can analyze data in real-time and adjust the process parameters. Using algorithms such as Reinforcement Learning

(RL), the system dynamically adjusts process strategies to ensure precision and efficiency under optimal production conditions[30].

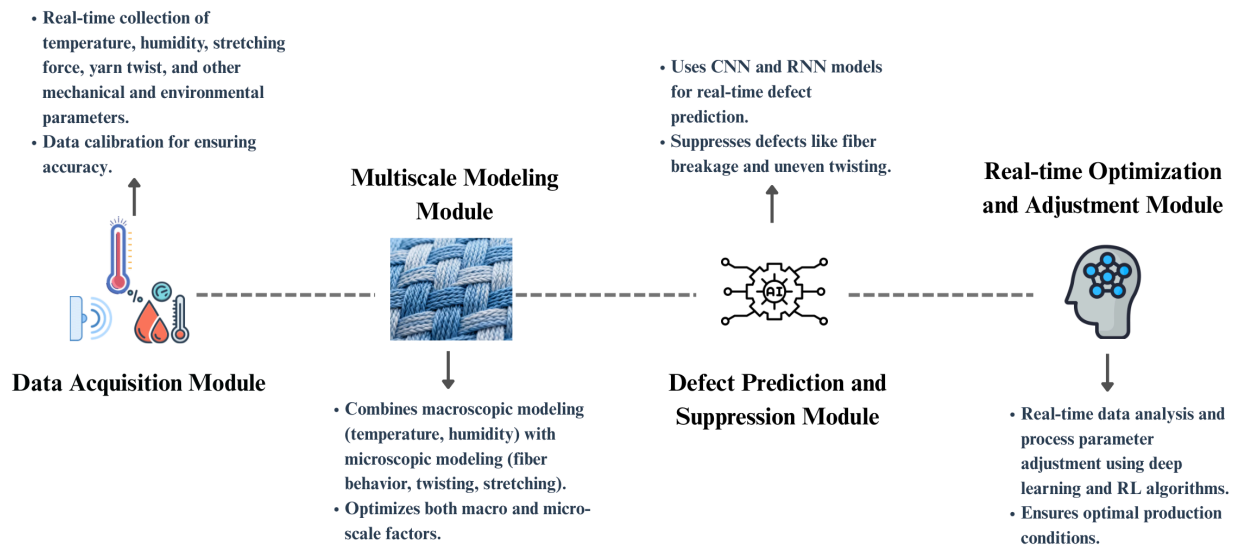


Figure 2. Schematic of the Ceramic Fiber Textile Molding Process Optimization Framework

### Data Acquisition and Preprocessing

The data acquisition module collects various data in real-time through a sensor network during the textile process. This module uses multiple sensors to monitor process parameters, including temperature and humidity sensors, stress sensors, speed sensors, etc. These sensors collect data on environmental changes, such as temperature, humidity, stretching force, and yarn twist, while also monitoring key variables in the production process, such as fiber tension and speed, to ensure the stability and accuracy of the production process.

In addition to basic environmental parameter collection, the data acquisition module also uses high-frequency sensors to monitor detailed parameters, such as fiber breakage points and microscopic defects. These data provide valuable information for subsequent multiscale modeling and defect prediction. Through data collection, the system can gain a comprehensive understanding of the dynamic changes in the textile process, providing data support for real-time optimization and adjustment.

In the data preprocessing phase, since the data collected by sensors may contain noise and missing values, it is necessary to clean and optimize the data. The specific steps include:

(1)Data Cleaning: Eliminate missing values and outliers to ensure the validity and accuracy of the data. For erroneous data caused by sensor faults or external interference, interpolation or extrapolation methods are used to fill missing values, ensuring data integrity.

(2)Normalization: Standardize and normalize the data to unify the dimensions of different parameters, avoiding inconsistent dimensions that could affect subsequent analysis. All data are scaled to the same numerical range to improve the accuracy and efficiency of data processing.

(3)Feature Engineering: Using statistical analysis and expert knowledge, features related to key factors such as textile molding accuracy and defect prediction are extracted. These features ensure that the model can identify important parameters that affect molding quality. Common features include temperature gradients, humidity changes, stress fluctuations, etc., which help reveal potential issues in the process.

Through data acquisition and preprocessing, the system provides high-quality input data for subsequent multiscale modeling, defect prediction, and real-time optimization modules, ensuring the accuracy and effectiveness of the optimization process.

### **Multiscale Modeling Module**

The multiscale modeling module is the core part of this paper. By combining macroscopic and microscopic modeling approaches, it provides a comprehensive analysis of the ceramic fiber textile molding process. The macroscopic modeling mainly involves factors such as environmental control and temperature control, while the microscopic modeling focuses on the details of fiber stretching, twisting, and twist.

#### *Macroscopic Modeling*

The macroscopic model is based on traditional physical modeling methods and considers the impact of environmental factors on the textile process. It establishes a model based on the Finite Element Method (FEM) to simulate thermal conduction, stress distribution, and other factors during the textile process.

$$\sigma = E \cdot \varepsilon \quad (1)$$

Where,  $\sigma$  is the fiber stress,  $E$  is the Young's modulus, and  $\varepsilon$  is the strain.

#### *Microscopic Modeling*

The microscopic modeling uses deep learning methods, based on the collected microscopic data (such as fiber breakage points and yarn twist), to perform analysis. By using methods such as CNN, the model can

learn microscopic defects during the textile process, which are then used to optimize macroscopic process parameters.

$$y = CNN(X) \quad (2)$$

Where,  $y$  is the model output (defect prediction result), and  $X$  is the input textile parameter data.

To ensure experimental reproducibility and meet the strict low-latency requirements for real-time deployment, a lightweight CNN architecture is specifically designed. The network consists of three sequential convolutional blocks. Each block comprises a 2D convolutional layer with a 3×3 kernel size and a stride of 1, followed by Batch Normalization, a ReLU activation function, and a 2×2 Max-Pooling layer. The number of filters for the three blocks is sequentially set to 16, 32, and 64 to progressively extract complex morphological features. Finally, the feature maps are flattened and passed through a fully connected layer with 128 neurons, yielding the microscopic feature vector used for downstream multiscale fusion.

#### *Cross-scale Information Exchange Interface*

To bridge the macroscopic FEM simulation with the microscopic CNN model and establish a clear algorithmic interface for cross-scale information exchange, a feature-level fusion mechanism is implemented. Specifically, the macroscopic physical field data (e.g., stress and temperature distribution) derived from the FEM is first flattened and projected into a latent representation vector  $V_{macro}$  via a MLP. Simultaneously, the microscopic morphological feature maps extracted by the CNN are pooled and flattened into a feature vector  $V_{micro}$ . The mathematical interface for the cross-scale coupling is defined as follows:

$$F_{fused} = \sigma(W_f \cdot [V_{macro} \oplus V_{micro}] + b_f) \quad (3)$$

where  $\oplus$  denotes the concatenation operation,  $W_f$  and  $b_f$  are the learnable weight matrix and bias vector of the fusion layer, respectively, and  $\sigma$  represents the non-linear activation function (e.g., ReLU). This fused representation  $F_{fused}$  effectively encapsulates both macroscopic physical boundary conditions and microscopic structural states, providing a comprehensive multiscale input for the subsequent prediction module.

#### **Defect Prediction and Suppression**

The defect prediction and suppression module uses deep learning models to detect potential defects in the textile process in real-time, particularly issues such as fiber breakage and uneven stretching. By analyzing

historical and real-time data, the model predicts potential defects and adjusts the process parameters to suppress them in time.

#### *Defect Prediction Model*

A CNN is used to train image data from each stage of the textile process to predict possible defects. The model extracts features through convolutional layers and reduces dimensionality via pooling layers, thereby improving prediction accuracy.

$$P(y | X) = \frac{1}{Z} \exp\left(\sum_i W_i X_i\right) \quad (4)$$

Where,  $P(y | X)$  is the probability of defect prediction,  $W_i$  are weight parameters,  $X_i$  are input features, and  $Z$  is the normalization constant.

#### *Defect Suppression Method*

When a defect is predicted, the system adjusts the process parameters, such as stretching force, temperature, and humidity, in real-time to prevent further development of the defect.

$$\Delta\theta = -\alpha \cdot \nabla_{\theta} J(\theta) \quad (5)$$

Where,  $\Delta\theta$  is the parameter adjustment,  $\alpha$  is the learning rate, and  $\nabla_{\theta} J(\theta)$  is the gradient of the loss function.

#### **Real-time Optimization and Adjustment**

During the production process, the real-time optimization and adjustment module analyzes and adjusts the textile process parameters in real-time using deep learning models. This module uses real-time data for feedback control to ensure the optimal configuration of process parameters.

#### *Reinforcement Learning Optimization*

To further improve molding accuracy, Reinforcement Learning (RL) is employed for dynamic adjustments. Through interactions with the environment, the RL model learns and continuously optimizes the parameter configurations during the textile process.

$$Q(s, a) = R(s, a) + \gamma \max_{a'} Q(s', a') \quad (6)$$

Where,  $Q(s, a)$  is the value of state  $s$  and action  $a$ ,  $R(s, a)$  is the reward function,  $\gamma$  is the discount factor, and  $s'$  is the next state.

#### *Parameter Adjustment and Prediction*

The real-time optimization process uses deep learning models to predict and adjust process parameters such as temperature, humidity, and stretching force, ensuring the precision of every step of the textile process.

$$\hat{y} = MLP(X) \quad (7)$$

Where,  $\hat{y}$  is the predicted output (optimized process parameters),  $X$  is the input real-time data, and MLP refers to the Multi-Layer Perceptron network.

To account for the physical delays inherent in the textile environment, the output vector  $y$  is decoupled to execute a dual-frequency control strategy. Specifically, to suppress instantaneous transient defects (e.g., imminent fiber breakage), the system triggers high-frequency mechanical responses (e.g., millisecond-level adjustments to motor stretching force and yarn tension). Conversely, because thermal parameters exhibit significant thermal inertia, temperature and humidity adjustments are treated as low-frequency macroscopic compensations. These thermal adjustments are continuously optimized to improve long-term material ductility and prevent gradual fatigue, rather than attempting to suppress sudden millisecond-level breakages.

#### *Hardware-Software Co-optimization for Low Latency*

To ensure true real-time adjustments in the high-speed textile process and overcome the massive computational latency of complex multiscale FEM simulations, an offline-training and online-inference strategy is adopted. Specifically, the computationally expensive FEM simulations are executed entirely offline to construct a prior dataset and pre-train the models. For online deployment, the trained deep learning models and RL agents are accelerated using software quantization techniques. Furthermore, the inference module is deployed on local industrial edge computing hardware. This specific hardware-software co-optimization robustly decouples the heavy simulation from real-time execution, reducing the computational latency to milliseconds.

## **EXPERIMENT AND RESULTS**

This paper validates the effectiveness of the proposed ceramic fiber textile molding process optimization method through a series of experiments. The experiments include evaluating the impact of different process

parameters on textile quality, comparing defect prediction and suppression effects, and assessing the performance of the multiscale optimization framework in real-world production. By comparing the performance of conventional methods and data-driven optimization methods under different processing conditions, we gain insights into the advantages and potential application value of the model.

### **Experiment Design and Dataset**

In this experiment, two different types of ceramic fiber textile materials were selected as test objects, Material A and Material B. The selection of these materials not only considers common types of ceramic fibers but also includes differences in processing techniques and fiber structures, testing the wide adaptability and accuracy of the multiscale optimization method. Each material was processed using both traditional textile methods and algorithms based on multiscale optimization, with a comparative analysis of molding accuracy, defect rate, and other performance metrics.

The dataset used for the experiment was customized based on the actual production process and covers multiple key process steps from the start of textile formation to the completion of the finished product. The data collection module includes a variety of advanced sensors, and the specific data types are as follows:

- (1) **Temperature Data:** High-precision environmental temperature sensors were used to collect real-time temperature changes at each production stage, especially temperature fluctuations in high-temperature zones, which are critical for ceramic fiber molding. This data helps analyze the impact of temperature control on the textile process, particularly the material performance during high-temperature textile processes.
- (2) **Stress and Tension Data:** Stress and tension sensors monitor the stretching stress and yarn tension of the fibers. By tracking the fiber behavior under different stretching forces, early signals of fiber breakage or deformation can be identified to help optimize process parameters.
- (3) **Twist and Breakage Point Data:** Fiber twist, breakage points, and local structural data are monitored as predictive factors for defect occurrences. By combining these data, the system can predict fiber fatigue and breakage potential in advance, avoiding uncontrollable defects during production.
- (4) **Molding Accuracy Data:** Geometric error analysis of the finished product is conducted to evaluate the precision of the textile process. High-resolution scanners record microstructural changes in the finished product, measure geometric errors, and compare them with the expected shape, reflecting the improved molding accuracy after optimization.

The data collection period lasted two weeks. To successfully capture transient mechanical defects such as fiber breakage in real-time, the sensor data (especially stress, tension, and vibration) was sampled continuously at a high frequency of 100 Hz (10 ms intervals), while macroscopic environmental parameters were recorded concurrently. The dataset includes basic environmental data, machine vision data, and vibration analysis data. By integrating these sensor data, the system aims to enhance the understanding and predictive ability of the process.

The experimental results will be analyzed through multidimensional comparative analysis to verify the performance of the multiscale optimization method under different processes. In particular, the experiment will focus on how real-time adjustments to process parameters can further improve molding accuracy and product quality in different production environments, compared with traditional methods.

### Molding Accuracy and Defect Rate Comparison

The first part of the experiment involves a comparative analysis of molding accuracy and defect rate. Figures 3 and 4 display the molding accuracy and defect rate data under different processing conditions using traditional physical modeling methods and the multiscale optimization method, further validating the effectiveness of the multiscale optimization approach.

Figure 3 shows a comparison of molding accuracy between traditional processes and multiscale optimization processes under temperature control and tension control.

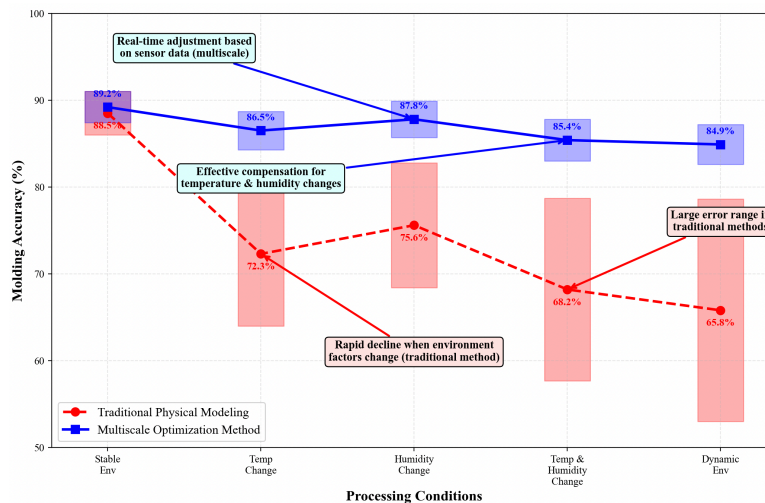


Figure 3. Molding Accuracy Comparison under Different Processing Conditions

From Figure 3, quantitatively demonstrates that the traditional physical model experiences a rapid decline in molding accuracy when production environment factors (temperature and humidity) change, with a large error range. This suggests that empirical approaches lack mechanisms to cope with variations in environmental factors. In contrast, systems using the multiscale optimization approach can adjust process parameters in real-time based on sensor data, effectively compensating for the impact of temperature and humidity changes on textile accuracy. Therefore, data-driven multiscale modeling can substantially improve the adaptability and accuracy of the molding process, especially in dynamic environments. This result demonstrates the strong advantage of the multiscale optimization method in addressing complex environmental changes.

Figure 4 shows the defect rate comparison between the two methods during the textile process.

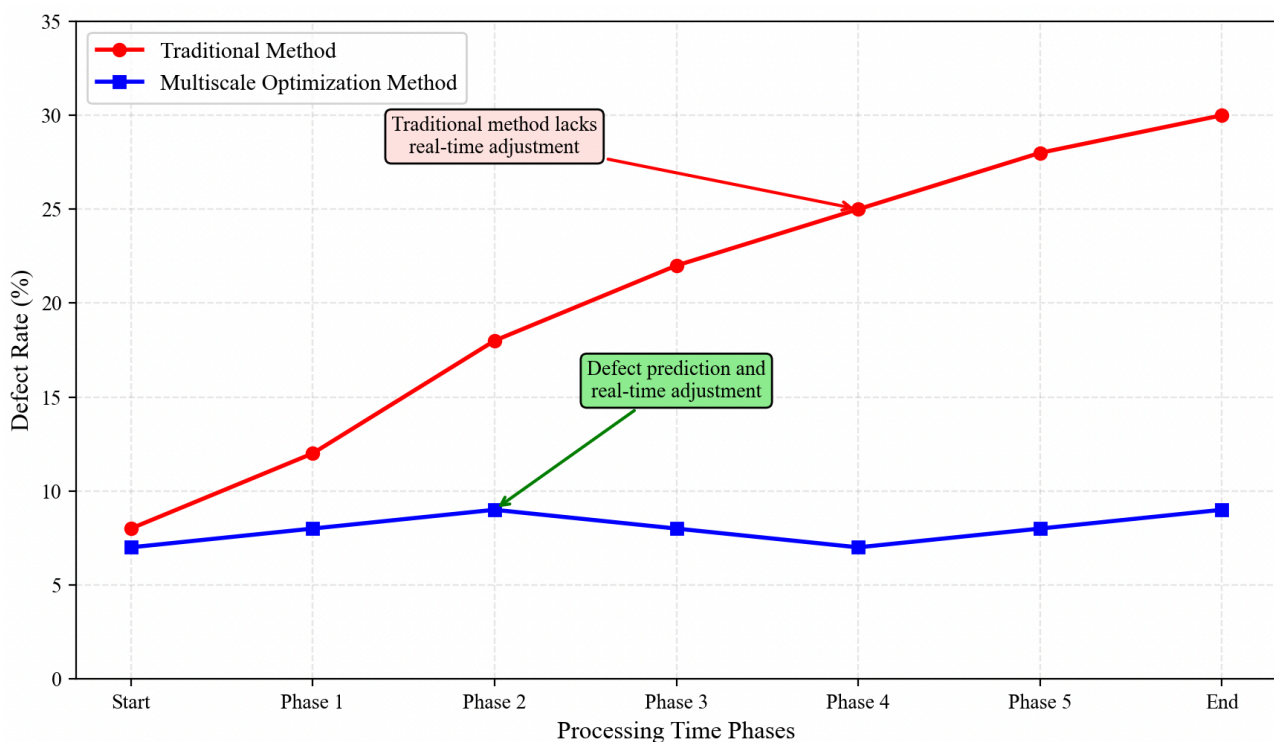


Figure 4. Defect Rate Comparison under Different Processing Conditions

The results from Figure 4 indicate that the application of the defect prediction and suppression module within the multiscale optimization method substantially reduces the defect rate. The traditional method lacks a real-time adjustment mechanism, making it difficult to correct defects once they occur. In contrast, the data-driven method can analyze sensor data in real-time through deep learning models, predict potential defects such as fiber breakage and uneven twist, and automatically adjust process parameters (such as stretching force

and temperature), thus successfully suppressing the occurrence of defects. Particularly in high-temperature and high-humidity environments, the multiscale optimization method ensures the stability and quality of the textile process through real-time adjustments. This result clearly demonstrates the critical role of the defect prediction and suppression module in enhancing production quality.

**Validation of Multiscale Optimization Effectiveness**

In this section, we experimentally validate the stability and efficiency of the multiscale optimization method under different production conditions. Figure 5 shows the performance improvement achieved using the multiscale optimization method on different textile materials (A and B).

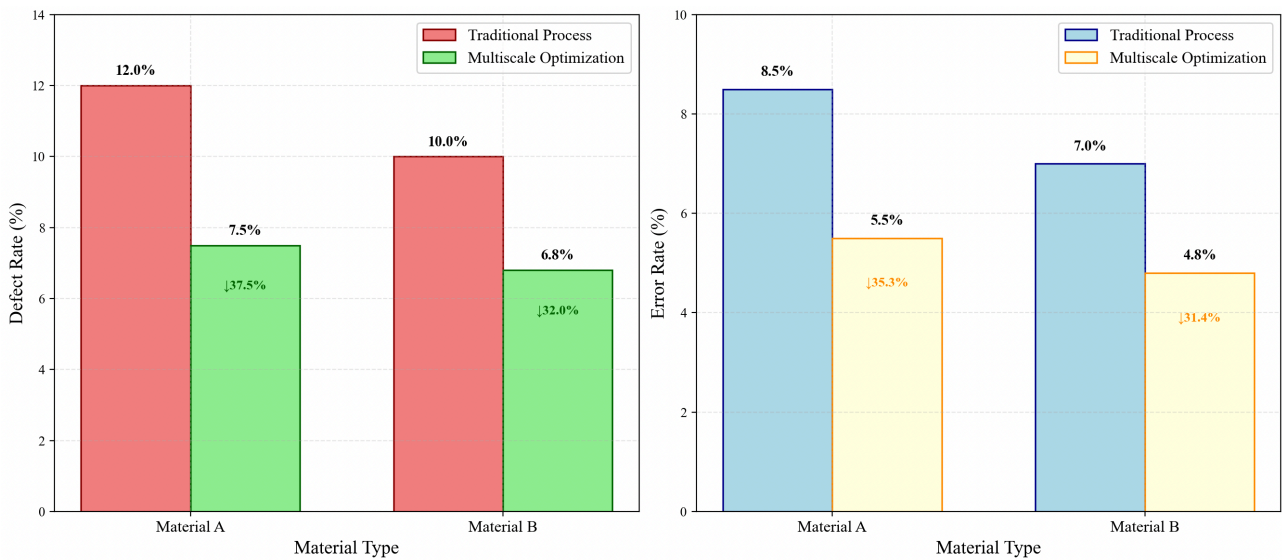


Figure 5. Multiscale Optimization Effectiveness under Different Materials

From Figure 5, it can be seen that both Material A and Material B showed quantifiable improvements in molding accuracy and defect rate after multiscale optimization. Particularly in the production of Material A, the defect rate under conventional methods was relatively high, while the multiscale optimization method dynamically reduced defects and improved molding accuracy. This suggests that the multiscale optimization method is not only effective in controlling environmental parameters such as temperature and humidity but also capable of adapting to the specific requirements of different materials.

To further demonstrate the experimental results, Table 1 summarizes the comparative data of molding accuracy and defect rate for traditional and multiscale optimization processes under different materials (A and B).

Table 1. Comparison of Traditional and Multiscale Optimization Processes under Different Materials

Material Type	Process Type	Molding Accuracy (Error Rate)	Defect Rate (%)
Material A	Traditional	8.5%	12%
Material A	Multiscale Optimization	5.5%	7.5%
Material B	Traditional	7.0%	10%
Material B	Multiscale Optimization	4.8%	6.8%

Based on the data in Table 1 and Figure 5, it can be seen that in the production of Material A, the defect rate for traditional processes is 12%, while after applying the multiscale optimization process, the defect rate robustly drops to 7.5%, a relative reduction of 37.5%. To isolate and prove the specific value of the multiscale approach, a “Single-scale AI” baseline was introduced. For Material A, the Single-scale AI achieved a defect rate of 9.5%, which outperforms traditional methods but still falls short of the Multiscale Optimization method by 2.0%. For Material B, the defect rate drops from 10% under empirical approaches to 6.8% after multiscale optimization, a decrease of 32%, whereas the Single-scale AI only reduced it to 8.2%. In terms of molding accuracy, the error rate for Material A decreases from 8.5% under traditional methods to 5.5% after optimization, an improvement of about 35.3%; for Material B, the error rate improves from 7.0% to 4.8%, a 31.4% improvement. These results consistently demonstrate that while Single-scale AI offers measurable improvements over traditional baselines, the cross-scale coupling in the multiscale optimization method is the true driver that effectively improves molding accuracy and suppresses defect formation, validating its stability and optimization effects across different materials and process conditions.

### Impact of Textile Process Parameters on Fiber Behavior

During the ceramic fiber textile process, microscopic behaviors such as fiber stretching, twisting, and breakage directly influence molding quality. Figures 6 and 7 provide a comparison of fiber behavior under different stretching forces and twist conditions, demonstrating how these process parameters impact fiber performance, molding accuracy, and defect rates.



Figure 6. Visualization of Fiber Breakage under Different Stretching Forces

Figure 6 shows the increase in fiber breakage points as stretching force increases. The image visually demonstrates how excessive force leads to visible damage and breakage at fiber intersections. Particularly in high-temperature and high-humidity environments, the stress load on fibers measurably increases, causing materials to break at lower stretching forces.

Visualization of Fiber Breakage under Different Stretching Forces



Fiber Stress Analysis under Different Twist Conditions

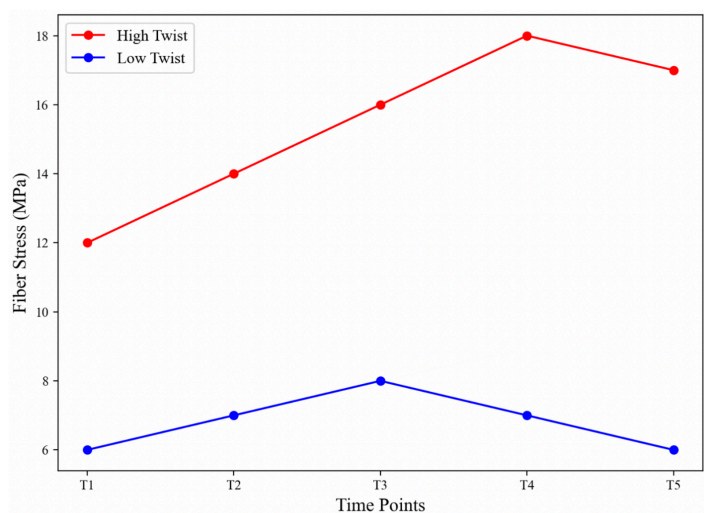


Figure 7. Fiber Stress Analysis under Different Twist Conditions

Figure 7 reveals the differences in fiber stress distribution under different twist conditions. Excessive twist causes an overconcentration of internal fiber stress, particularly in local areas of the fiber, which can easily lead to fiber breakage or deformation. The image clearly shows areas where excessive twisting leads to visible stress points and breakage at fiber intersections. The data indicates that, under higher twist, the fiber stress distribution becomes uneven, concentrating stress in localized areas, thereby increasing the risk of breakage. In contrast, by precisely controlling the twist, the stress distribution across the fiber can be balanced, reducing localized stress concentration and markedly improving fiber stability. The experimental results confirm this, showing that proper control of twist parameters not only enhances the fiber's tensile strength but also ensures uniformity in molding quality. Particularly under high-temperature conditions, optimizing the twist can effectively improve fiber stability and durability.

### Real-Time Adjustment Effects of Textile Process Optimization

To further verify the effectiveness of the real-time optimization module, Figures 8 and 9 demonstrate the effects of real-time adjustments to process parameters during production.

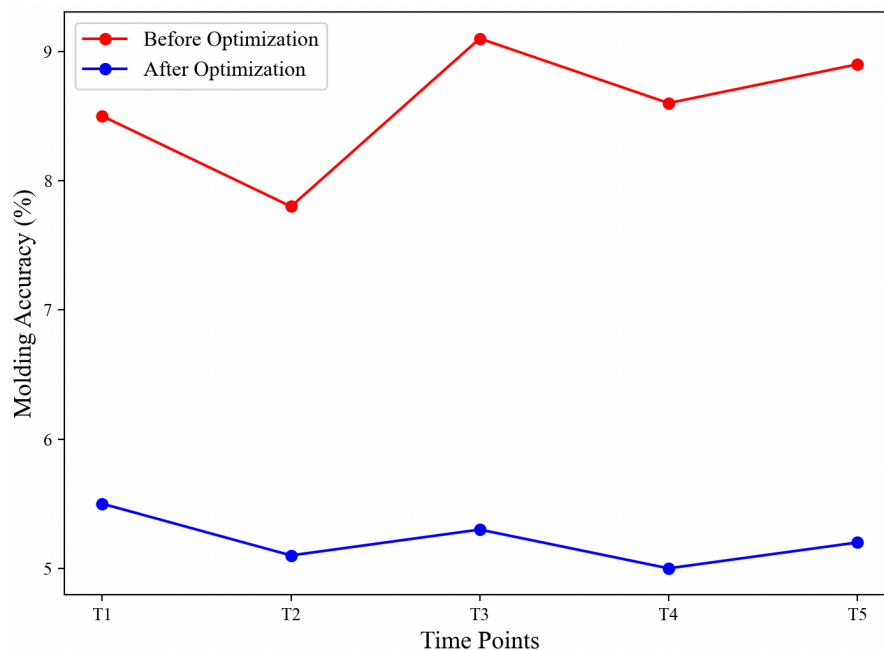


Figure 8. Improvement in Molding Accuracy after Real-Time Adjustment

Figure 8 demonstrates the notable improvement in molding accuracy after real-time adjustments to process parameters during production. In dynamically changing production environments, the system can monitor and adjust parameters such as temperature, humidity, and stretching force in real time, ensuring precise control

at every production stage. Especially under conditions where environmental fluctuations are large, traditional processes often fail to maintain stable accuracy, whereas real-time optimization successfully reduces molding errors. This validates the crucial role of the real-time optimization module in addressing unpredictable factors during production (such as environmental changes), ensuring the continuity and stability of high-precision production.

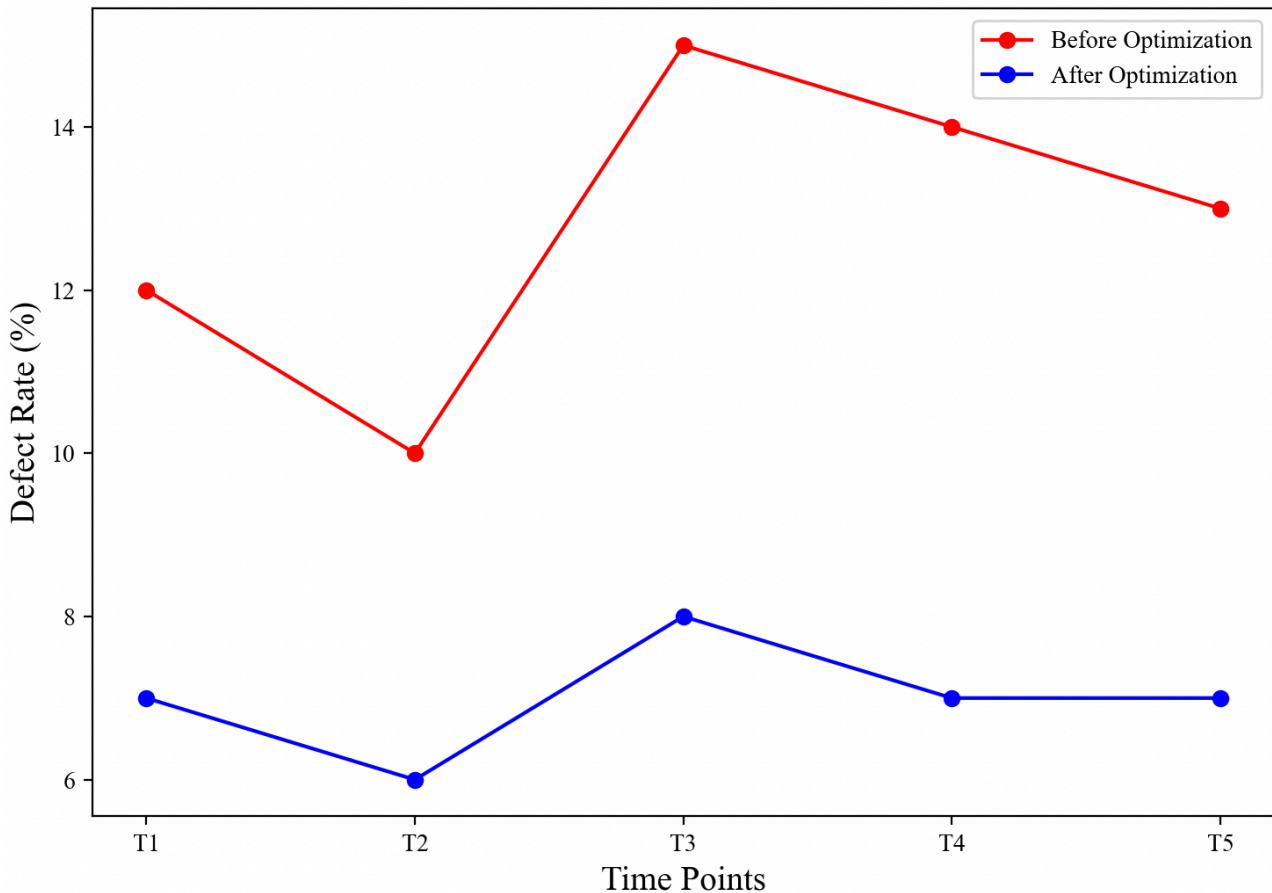


Figure 9. Defect Suppression Effect after Real-Time Adjustment

Figure 9 shows the effectiveness of the real-time optimization module in defect prediction and suppression. During production, the system can precisely predict the risk of defects by analyzing real-time data (such as temperature and humidity changes, fiber stretching force, etc.), and dynamically adjust key parameters, effectively suppressing the occurrence of defects. Particularly in high-temperature or complex production environments, the defect prediction and suppression module demonstrates strong adaptability, reducing the defect rate caused by process parameter fluctuations and further improving product quality consistency and

reliability. This proves that the real-time optimization module not only enhances production precision but also substantially improves consistency and quality control of the final products.

Furthermore, leveraging the hardware-software co-optimization detailed in Section 3.5.3, the average end-to-end inference latency of the system during these real-time adjustments was measured at approximately 15 milliseconds. This ultra-low latency guarantees that the system can react to high-frequency transient defects instantaneously, proving the feasibility of true real-time control.

## DISCUSSION

Through the experiments and analyses presented in this paper, we explored the effectiveness and innovation of the multiscale AI model-based ceramic fiber textile molding process optimization method. The experimental results validate the advantages of this method in improving molding accuracy and reducing defect rates, revealing its potential for practical production applications. However, despite the positive outcomes, several limitations remain, and future research could deepen and expand upon these findings.

First, the experimental results show that the multiscale optimization method combines the strengths of traditional physical modeling and deep learning, markedly improving molding accuracy, especially in dynamically changing production environments. Under different temperature and humidity conditions, traditional process methods experienced a rapid decline in molding accuracy, while the multiscale optimization method maintained stable molding precision through real-time adjustments to the process parameters. This adaptive mechanism significantly addresses the uncertainties in the production process. Furthermore, the defect prediction and suppression module, through real-time prediction and adjustment of process parameters, effectively controlled defects such as fiber breakage and uneven twist, further improving product quality and consistency.

Despite these achievements, the optimization method presented in this paper still has limitations. First, the experimental dataset is based on specific ceramic fiber materials and environmental conditions, and while it performed well under these conditions, its applicability to other materials or processes still needs to be verified. Second, the complexity of the production process may lead to changes in real-time data that could affect the model's adaptability. Therefore, improving the generalizability and robustness of the model will be a key focus for future work.

In terms of potential applications, the multiscale optimization method presented in this paper is not limited to ceramic fiber textile processes; it can also be extended to areas such as metal fibers and composite materials.

With the development of smart manufacturing, the combination of IoT and AI in textile process optimization will drive traditional manufacturing industries toward greater efficiency and intelligence. By integrating multisensor data and big data analysis, future advancements are expected to enable more precise process adjustments and quality management.

Future research should further explore how multimodal data fusion can enhance model performance, incorporating image data and stress-strain data to capture more complex parameters. Additionally, investigating reinforcement learning methods for continuous optimization of process parameters, and applying big data and cloud computing technologies to real-time optimization, will facilitate global production collaboration. Custom optimization methods for different textile materials should also be developed in the future, allowing for personalized process adjustments and quality control.

Overall, while the multiscale optimization method shows clear advantages, it still faces challenges. Future research should focus on improving the model's generalizability, robustness, and real-time adaptability, and further explore the integration of data fusion and intelligent algorithms. By deepening research in these areas, the method is expected to see widespread application in the textile industry and other manufacturing sectors.

## **CONCLUSION**

This paper proposes a multiscale AI model-based ceramic fiber textile molding process optimization method aimed at improving the precision and quality of the textile process, particularly in responding to production environment changes and defect control. By integrating multiscale modeling and deep learning, we have developed a system that combines data acquisition, real-time optimization, and defect prediction and suppression. The experimental results demonstrate that the proposed method has notable advantages in molding accuracy and defect rate control, especially in production environments with large temperature and humidity variations, where the optimization method exhibits strong adaptability and stability. Additionally, the defect prediction module robustly prevents issues such as fiber breakage and uneven twist, further enhancing product quality.

The main contribution of this paper is the first-time combination of multiscale modeling with data-driven deep learning methods to achieve comprehensive optimization of the ceramic fiber textile molding process. By real-time adjustment of process parameters, the system is able to maintain high molding accuracy in dynamically changing production environments and effectively suppress defects during production. The

experimental results verify the applicability and effectiveness of this method under different materials and process conditions, providing a new solution to optimization challenges in complex production processes.

From an academic perspective, this study innovatively integrates traditional physical modeling with deep learning, overcoming the limitations of single models and offering a new methodological framework for textile process optimization. At the same time, the paper provides a theoretical basis for data-driven manufacturing process optimization, advancing the deep integration of smart manufacturing and traditional processes. This research not only enhances the application depth of multiscale modeling methods but also expands the potential applications of deep learning technologies in the industrial sector.

From a practical perspective, this study has notable industrial application prospects. Through real-time feedback adjustment based on sensor data, the method proposed can effectively improve the automation level of textile processes, especially in complex production environments such as high temperatures and high humidity, ensuring the consistency and stability of product quality. This method is not only applicable to ceramic fiber production but can also be extended to the production of other high-performance materials and composite materials, demonstrating broad application potential. Moreover, with the development of smart manufacturing technologies, process optimization based on real-time data feedback will become a key factor in improving the efficiency and quality of traditional manufacturing industries.

In the future, with the accumulation of more datasets and the introduction of more efficient algorithms, the optimization methods based on multiscale modeling and deep learning will continue to evolve. In practical applications, how to achieve effective integration of cross-domain data and enhance the robustness and generalizability of the system will be a key direction for future research. Furthermore, as industrial internet and IoT technologies continue to develop, real-time process optimization based on big data and cloud computing will play an important role in global production collaboration and resource scheduling. Future research can explore how to integrate these technologies with existing textile process optimization models to drive the development of smarter and more flexible production systems.

By continuously deepening these research directions, it is expected that the proposed method will be widely applied in the textile industry and other fields of high-performance material production, further advancing the intelligence and efficiency of traditional manufacturing processes.

### *Author Contributions*

Conceptualization – Xingli Li, Haifeng Xie; methodology – Xingli Li, Haifeng Xie; formal analysis – Xingli Li, Haifeng Xie; investigation – Xingli Li, Haifeng Xie; resources – Xingli Li, Haifeng Xie; writing-original draft preparation – Xingli Li, Haifeng Xie; writing-review and editing – Xingli Li, Haifeng Xie; visualization – Xingli Li, Haifeng Xie; supervision – Xingli Li, Haifeng Xie. All authors have read and agreed to the published version of the manuscript.

### *Conflicts of Interest*

The authors declare no conflict of interest.

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