

# Parametric Structural Design for Mycelium and Seaweed Fiber: Sustainable Furniture Component Optimization Method Based on Physical Simulation and Reinforcement Learning

Chun Wang<sup>1</sup>, Xiaoyu Liang<sup>2</sup>

<sup>1</sup>Department of Product Design, Wuchang Shouyi College, Wuhan 430064, Hubei, China

<sup>2</sup>Department of Visual Communication Design, Hubei Business College, Wuhan 430079, Hubei, China

Corresponding author: Xiaoyu Liang (e-mail: cecilia\_wang1989@163.com)

**ABSTRACT** This study presents a parametric structural design framework for sustainable furniture components fabricated from mycelium and seaweed fibers by integrating Proximal Policy Optimization (PPO) with continuum-mechanics-based physical simulation. Fiber orientation angle, porosity distribution, and layer thickness are encoded as continuous state variables, enabling the policy network to generate adaptive parameter adjustment strategies during the optimization process. Finite element analysis is employed to evaluate stress distribution, deformation behavior, and failure probability, while reward functions are formulated to improve structural stiffness and stress uniformity. Under a compressive load of 2.5 kN, the optimized structure achieves a stress standard deviation of 2.98 MPa, a displacement norm integral of  $5.93 \times 10$  mm/N, and a failure probability of 12.17%, indicating enhanced mechanical stability and microstructural controllability. Transferability analysis further demonstrates improved elastic recovery and breathability regulation in smart textile applications across different porosity levels. The proposed framework establishes a quantitative relationship between microstructural parameters and macroscopic performance, providing an efficient design methodology for porous bio-based materials and functional material architectures. The approach also offers potential value for the optimization of structurally adaptive components used in intelligent material systems and electromagnetic-responsive engineered structures.

**INDEX TERMS** mycelium and seaweed fiber, parametric structural design, reinforcement learning, functional material architectures

## I. INTRODUCTION

**S**USTAINABLE materials science is an integral solution to the global environmental crisis, with advancements in fields like the textile industry being crucial for mitigating the pollution and resource depletion associated with traditional material production. Mycelium and seaweed fiber represent new renewable bio-based alternatives to standard synthetic materials, having lightweight, biodegradable, and self-healing properties [1,2]. Reducing carbon emissions through their usage promotes a circular economy within furniture design. However, controlled microstructure remains a significant challenge impacting the stable performance of sustainable furniture components, demonstrating unique application utility in the textile sector as well [3,4]. While mycelium and seaweed fiber have application potential in multiple fields by conversion into environmentally friendly leather alternatives and as substrate for the development of

smart textiles incorporating integrated sensing functions to react to the dynamic needs of the human body [5,6], the significant concern of unstable mechanical properties as a consequence of insufficiently parameterization of microstructure is an issue in but more pronounced in furniture component design. Promotion of interdisciplinary integration can promote the green transformation of processes within the furniture industry, ensure sustainable fabric solutions for the apparel industry whilst being a beneficial outlet for reducing dependency on petroleum-based synthetic fibers [7-9]. Given increasing consumer awareness of environmental issues, addressing this core issue is a significant link to promote the application of bio-based materials within the context of green manufacturing, transitioning to global resource use [10].

Existing research faces technical challenges in the parameterization of the microstructure of mycelia and seaweed

fibers. The microporous network of mycelia is affected by the growth environment, resulting in batch-to-batch fluctuations in mechanical properties [11,12]. Current design tools do not have the accuracy to control parameters, including porosity distribution and fiber orientation angle, creating concerns of local stress concentration and eventual structural failure under load [13,14]. Under conditions of humidity and heat, the mechanical response of seaweed fibers becomes unstable, and nonlinear effects related to layer thickness and crystallinity on structural stiffness have not been adequately quantified [15,16]. Without adequate microstructure parameterization, furniture component structural reliability and service life are compromised. Mycelial-based fabrics are prone to brittle fracture when repeatedly deformed [17]. When the porosity exceeds the critical threshold, the compressive strength of mycelia drops sharply, and uneven layer thickness causes structural instability, resulting in local stress concentration and early structural failure under load. These technical bottlenecks seriously restrict the large-scale application of bio-based materials in the field of sustainable furniture [18,19]. Existing parametric modeling tools generate complex geometries but fail to integrate the microstructural features of biomaterials, resulting in design configurations that cannot reflect the dynamic evolution of mycelial pore networks. Physical simulation methods rely on preset boundary conditions to predict stress distribution [20,21], making it difficult to handle the nonlinear behavior during the growth of mycelia and seaweed fibers, and high computational costs limit the depth of design space exploration. Reinforcement learning frameworks such as DQN (Deep Q-Network) are used for parameter optimization [22,23], but discrete action space design cannot adapt to fine adjustments of continuous variables such as fiber orientation angles, resulting in low strategy convergence efficiency. These methods fail to establish a dynamic correlation model between microscopic parameters and macroscopic mechanical properties and lack a real-time feedback mechanism for material deformation, causing parametric designs of mycelia and seaweed fibers to fail to meet the stringent mechanical stability requirements of sustainable furniture components.

Recognizing the need for stable, predictable feedstock for the sustainable textile industry, this paper applies an optimization framework integrating the PPO algorithm and a continuum mechanics physical simulation model to address the unstable mechanical properties caused by insufficient parameterization of the microstructure of mycelia and seaweed fibers. The framework defines a design parameter vector, including variables such as fiber orientation angle, porosity distribution, and layer thickness as inputs to the agent's state. A policy network processes the state data to generate parameter adjustment instructions in a continuous action space. The instructions engage a finite element solver in the physical simulation environment to conduct stress-strain calculations, effectively providing real-time feedback regarding the component's mechanical response. The reward function is adjusted in real-time to ensure that structural

stiffness and stress distribution constraints converge efficiently. Finally, a parameterized design configuration is provided in order to control mechanical properties quickly. This provides a defined design pathway for sustainable furniture components, while establishing a closed-loop optimization method between microscopic parameters and macroscopic responses.

## II. PARAMETERIZED STRUCTURE OPTIMIZATION METHOD BASED ON REINFORCEMENT LEARNING

### A. DESIGN PARAMETERIZATION AND STATE SPACE CONSTRUCTION

A continuous parameterization approach accurately defines the microstructural features of mycelium-seaweed composites, resulting in a verifiable state-space model. The fiber orientation angle  $\theta$  refers to the angle produced by the fiber principal axis and reference coordinate system. The porosity distribution function  $P(x, y, z)$  defines the pore volume ratio at a structural point  $(x, y, z)$ , and it is established as part of the Gaussian process regression model [24,25], with the constraint being  $P(x, y, z) \in [0, 1]$ . Layer thickness  $T$  is established as a geometric parameter in the direction of material stacking.

Figure 1 presents the central steps of the parametric design process, such as micro-parameter input, state encoding processes and parametric characterization methods that describe microstructural features.

Figure 1 illustrates the workflow of establishing a mapping relation between micromechanical characteristics and macroscopic mechanical properties. These parameters represent structured input for the following physical simulation and optimization through reinforcement learning, ensure continuity and operating characteristics of the parameter space, and ultimately form the fundamental input layer of the closed-loop optimization framework.

The state space vector  $S$  above is comprised of the aforementioned metrics, representing a continuous n-dimensional vector space:

$$S = [\vartheta, P(x, y, z), T, H] \quad (1)$$

$\vartheta \in [0, \frac{\pi}{2}]$  represents the radian value of  $\vartheta$ ;  $P(x, y, z) \in C^3(\Omega)$  represents the continuously differentiable porosity distribution function defined on the three-dimensional spatial domain  $\Omega$ ;  $T \in [T_{\min}, T_{\max}]$  represents the range of layer thickness values;  $H \in [30\%, 90\%]$  represents the environmental humidity level as a percentage relative humidity value. The environmental humidity parameter  $H$  directly influences the material constitutive relations through moisture-dependent elastic modulus adjustments. The physical simulation environment now incorporates humidity-dependent material property variations through real-time database calls during the FEM analysis process. This state vector comprehensively defines the geometric, topological, and environmental properties of the material's microstruc-

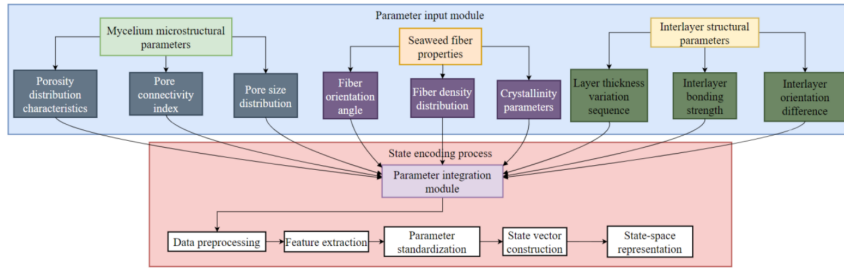


FIGURE 1. Parametric design flow framework

ture and maintains parameter space continuity to accommodate reinforcement learning agent optimization components.

The parametric design approach to the behavior of a microstructure maps microstructural features to the macro-mechanical response by defining a relationship mathematically between parametric variables and material constitutive relations [26-27].  $\theta$  directly affects anisotropic properties of the material;  $P(x, y, z)$  is important because it determines the path the stresses are transmitted through the material; the layer thickness  $T$  affects the amount of overall stiffness distribution in the structure. This suite of parameters defines the basic dimensions of the state space and provides an operable input representation of the space for the subsequent policy network. The continuous nature of the state vector allows the reinforcement learning agent to perform differential operations, and assesses and optimizes the parameter space at a higher resolution. Therefore, the parametric approach to structural design is a framework that establishes an unambiguous mapping from the microstructural features of the material to the mechanical function at a macro-level, to define an initial input space for optimization.

### B. PHYSICAL SIMULATION ENVIRONMENT MODELING

The physical simulation setting uses a finite element method (FEM) module that is grounded in continuum mechanics theory to evaluate the stress-strain field of mycelium and seaweed fiber composite materials, dynamically. Overall, this FEM module uses tetrahedral elements to provide an adaptive mesh of the three-dimensional geometric model, with element edge lengths ranging from 0.5 mm to 1.2 mm, balancing computational efficiency with accurate representation of the composite material's structural features. The mesh size is appropriate for capturing the macroscopic structural characteristics, including porosity distribution, fiber orientation, and layer thickness, which are parameterized inputs in the simulation rather than resolving individual fiber microstructures. The material constitutive relation represents a model for extended anisotropic elastics that uses  $\theta$ ,  $P(x, y, z)$ , and  $T$  as input variables for real-time updates during simulation.

Boundary conditions are set according to ASTM D695, and compressive loads are applied at a constant loading rate of 1 mm/min from 0.5 to 3.0 kN of force. The 2.5 kN load level was selected as the primary validation point because it represents the upper limit of typical furniture

usage scenarios while maintaining structural integrity. This load level corresponds to the maximum load tested in experimental validation as presented. During the simulation, preset parameters like the elastic modulus of seaweed fibers, along with the critical threshold of mycelial porosity, are called in real-time from the material property database. The contact algorithm employing the principle of augmented Lagrangian is used to track interlayer interactions [28-29]. The coefficient of friction is set at 0.25 to accurately simulate interlayer slip behavior.

The relationship between stress and strain is correctly defined with the use of an anisotropic tensor, which mathematically relates microscopic parameters to macroscopic mechanical response. The formula to compute the material stiffness matrix  $C$  is:

$$C = C_0(1 - \phi)^n + k(\vartheta) \cdot C_1 \quad (2)$$

$C_0$  is the basic stiffness matrix;  $\phi$  is the value of  $P(x, y, z)$  in the spatial domain;  $n$  is the porosity influence index;  $k(\vartheta)$  is a function of the fiber orientation angle;  $C_1$  is the orientation-related stiffness correction term. The failure probability  $P_f$  is calculated based on the maximum principal stress criterion and statistical damage theory, using the Weibull distribution model to assess the failure risk of local regions [30-31]. The formula for calculating  $P_f$  is:

$$P_f = 1 - \exp \left[ - \left( \frac{\sigma_{\max}}{\sigma_0} \right)^m \right] \quad (3)$$

$\sigma_{\max}$  is the maximum principal stress of the element;  $\sigma_0$  is the material characteristic strength;  $m$  is the Weibull modulus, which is 8.2 for mycelial composite materials and 12.5 for seaweed fiber composite materials. The simulation module interacts with ANSYS Mechanical via the Python API (Application Programming Interface) to facilitate the automation of the input parameter, execution of computations, and extraction of results [32-33]. This physical simulation environment supplies the reinforcement learning algorithms with instantaneous and accurate mechanical response data that produces closed-loop feedback between the micro-parameter level adjustments and the macro-performance level assessment.

### C. IMPLEMENTATION OF PPO STRATEGY OPTIMIZATION MECHANISM

The policy network takes in the parameterized design state vector, undergoes processing through a fully connected neural network, and outputs the incremental parameter adjustment for the continuous action space. The physical simulation environment processes a structural mechanics analysis based on the adjusted parameter configuration, and outputs characteristic performance indicators such as stress distribution, deformation, and failure probability. The reward function combines constraints in terms of structural stiffness and stress uniformity, and its form is:

$$r_t = \alpha \cdot \frac{1}{\int_{\Omega'} \|u(x)\| dx} + \beta \cdot \frac{1}{\sigma_s(\sigma_{ij})} - \gamma \cdot P_f \quad (4)$$

$r_t$  denotes the instantaneous reward at time  $t$ ;  $\alpha$  and  $\beta$  are the weighting coefficients;  $\gamma$  is the failure penalty coefficient;  $\int_{\Omega'} \|u(x)\| dx$  denotes the integral value of the displacement norm over the structural domain  $\Omega'$ ;  $\sigma_s(\sigma_{ij})$  denotes the standard deviation of the stress tensor  $\sigma_{ij}$ .

The optimization process employs the PPO objective function pruning mechanism to avoid excessively large policy update magnitudes.

$$L^{CLIP}(\vartheta') = E_t \left[ \min \left( r_t(\vartheta') \cdot A_t, \text{clip}(r_t(\vartheta'), 1 - \epsilon, 1 + \epsilon) \cdot A_t \right) \right] \quad (5)$$

$L^{CLIP}(\vartheta')$  is the pruning objective function;  $\vartheta'$  is the policy network parameter;  $r_t(\vartheta')$  is the probability ratio of the old and new policies;  $\epsilon$  is the pruning range parameter;  $A_t$  is the estimated value of the dominance function. The algorithm enforces constraints of Kullback-Leibler divergence to avoid a mutation of the policy, and the parameters of the policy network are updated iteratively using the Adam (Adaptive Moment Estimation Optimizer) [34-35]. In this way, it provides a dynamical connection between micro-parameter adjustment and macro-mechanical performance, establishing a closed-loop optimization link for the parameterized design.

## III. EXPERIMENTAL SETUP AND RESULTS

### A. EXPERIMENTAL PLATFORM AND DATA CONFIGURATION

The experimental geometry was defined as a cylindrical support column with 30 mm diameter and 60 mm height, representative of load-bearing furniture components such as chair legs or table supports, which are subjected to compressive loads in typical usage scenarios.

**TABLE 1.** Experimental platform and data configuration

| Category               | Setting                | Description                                                                                           |
|------------------------|------------------------|-------------------------------------------------------------------------------------------------------|
| Computing environment  | Hardware configuration | Intel Xeon Gold 6248R processor / NVIDIA Tesla V100 GPU (Graphics Processing Unit) / Ubuntu 20.04 LTS |
| Simulation System      | Simulation Tools       | ANSYS Mechanical 2022 R2 physical simulation environment                                              |
| Optimization Algorithm | Policy Network         | PPO algorithm, 128 hidden unit network structure                                                      |
| Comparison Methods     | Benchmark scheme       | Traditional manual design, parametric scanning method, DQN reinforcement learning                     |

Table 1 shows the hardware configuration: Intel Xeon Gold 6248R processor/NVIDIA Tesla V100 GPU/Ubuntu 20.04 LTS. The simulation tool used is ANSYS Mechanical 2022 R2. The optimization algorithm employed is the PPO algorithm with a 128 hidden unit network structure. Three benchmark schemes are included in the comparison method.

### B. STRESS UNIFORMITY INDEX

To evaluate the impact of different design methods on the stress uniformity of mycelium-seaweed fiber composites, this study systematically compares the performance of four methods within a compressive load range of 0.5 to 2.5 kN. The stress standard deviation is the core indicator for measuring stress distribution uniformity; the stress concentration factor reflects the risk of localized high-stress areas forming in the material under load. These indicators are particularly important for bio-based materials like mycelium and seaweed fibers, which are sensitive to microstructural parameters, as subtle changes in porosity distribution and fiber orientation angle can affect macroscopic mechanical properties, and stress concentration is often a key factor leading to early material failure. Figure 2 shows a comparison of stress uniformity indicators for mycelium-seaweed fiber composites under different compressive loads.

In Figure 2, under a load of 0.5 kN, the stress standard deviation of the PPO method is 0.58 MPa, a 29.3% reduction compared to the 0.82 MPa of the manual design, and the stress concentration factor is 2.31, lower than the 2.85 of the manual design. When the load increases to 2.5 kN, the stress standard deviation of the PPO method remains at 2.98 MPa, and the stress concentration factor is 3.32. The PPO method shows a lesser range of error, which reflects its superior stability in controlling the microstructural parameters. The PPO algorithm achieves continuous action space for fine adjustment of the fiber orientation angle to significantly improve the interrelatedness of the porosity distribution and fiber orientation while minimizing the formation of stress concentration regions. Whereas the parameter scanning method is superior to the manually designed, it does not have an intuitive mechanism for a dynamic response to the nonlinear relationship between parameters, thus causing performance to degrade under high load conditions. Since the DQN method operates under a discrete action space, it does not facilitate continuous fine adjustment the micro-parameters, which has resulted in little improvement in stress uniformity. Experimental results have confirmed that the proposed PPO-based parametric design framework is a

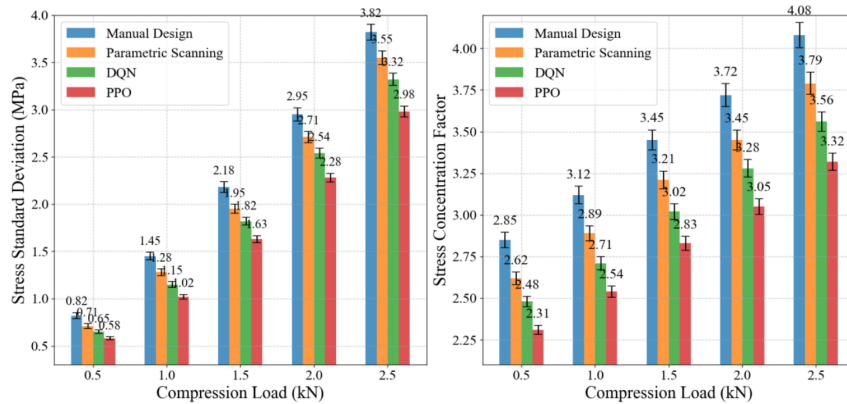


**FIGURE 2.** Comparison of stress uniformity indices of mycelium and seaweed fiber composite materials under different compressive loads

practical means to improve the stress distribution characteristics in the mycelium/seaweed fibre composite materials and nevertheless provides a much-needed reliable technical pathway for the structural improvement of sustainable furniture developments.

### C. STRUCTURAL STIFFNESS PERFORMANCE AND FAILURE PROBABILITY ASSESSMENT

To assess the structural stability of mycelium-seaweed fiber composites under various loads, this study systematically evaluates and contrasts the performance of four design approaches. The displacement norm integral, as a quantitative indicator of structural stiffness, reflects the overall deformation of the material under a unit load; a lower value indicates higher stiffness. The failure probability, calculated based on the Weibull distribution model, characterizes the likelihood of structural failure under a given load. Figure 3 shows a comparison of structural stiffness and failure probability for the four methods.

In Figure 3, the displacement norm integral of the PPO method under a high load of 2.5 kN is  $5.93 \times 10^{-4}$  mm/N, with a failure probability of 12.17%. As the load increases, both the displacement value and failure probability of all methods show an increasing trend, but the growth rate of the PPO method is relatively slow. In the 2.0 to 2.5 kN range, the displacement value of the manual design increases more than that of the PPO method. The difference in performance results from the flexible and finer control on the fiber orientation angle afforded by the PPO algorithm and the enhanced synergistic relationship of the porosity distribution and layer thickness parameters to alleviate stress concentration in mycelial materials subjected to high loads. The lower failure probability indicates the method's adaptability to batch-to-batch variability in the mechanical properties of mycelium and its avoidance of risk of a dramatic drop in the compressive strength due to porosity being above the critical threshold. The PPO method is able to maintain a low structural failure risk under high load conditions, providing a reliable assurance of mechanical performance for sustainable furniture component designs.

### D. SMART TEXTILE ADAPTABILITY VALIDATION: METHOD TRANSFERABILITY ASSESSMENT

The purpose of this study is to assess the applicability of the proposed parametric structural design framework to achieve a switch from sustainable furniture components to smart textiles as an adjustment of the reward function weights. The evaluation systemically tests the performance of the four methods in smart textiles made of mycelium and seaweed fiber. Resilience refers to the material's ability to return to its original form after being deformed, which is key to the durability of mycelium-based fabrics in smart textiles. Breathability uniformity represented as the standard deviation of breathability represents how evenly breathable the different areas of the material are, which directly affects the garment's thermal and humid comfort levels when someone is active. Figure 4 demonstrates the performance of each method across different porosity parameters.

The PPO method presented in Figure 4 achieves the highest rebound rate of 89.3% at 30% porosity, which is 12.5% higher than found for the manual design, and has the lowest breathability uniformity index of 0.28 at 10% porosity, which is 26.3% lower than the manual design. The rebound rate achieves its peak, as seen for all methods, at 30% porosity and declines subsequently. It should be noted that a significant loss in compressive strength occurs when porosity passes the critical threshold. The breathability uniformity index, on the other hand, rises monotonically with higher porosity values, confirming that a high porosity causes an overall more uneven breathability distribution. The PPO method shows overall robustness throughout the porosity spectrum, especially when examining 40% porosity, which still returns a rebound rate of 86.5%, or 14.2% higher than the manual design. This can be attributed to the PPO algorithm's ability to finely control fiber orientation angles and the porosity distribution throughout an ongoing action space, while producing an optimal synergistic relationship between microstructures. The parametric structural design framework enables transfer between furniture component design and smart textiles through targeted adjustment of reward function weights, reflecting the method's adaptability

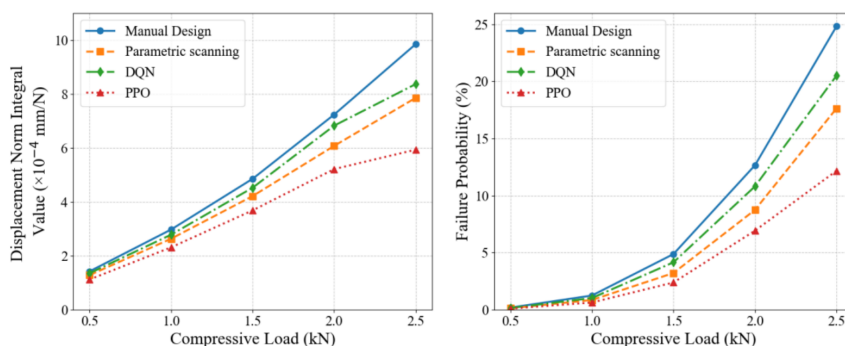


FIGURE 3. Comparison of structural stiffness and failure probability of mycelium and seaweed fiber composite materials under different compressive loads

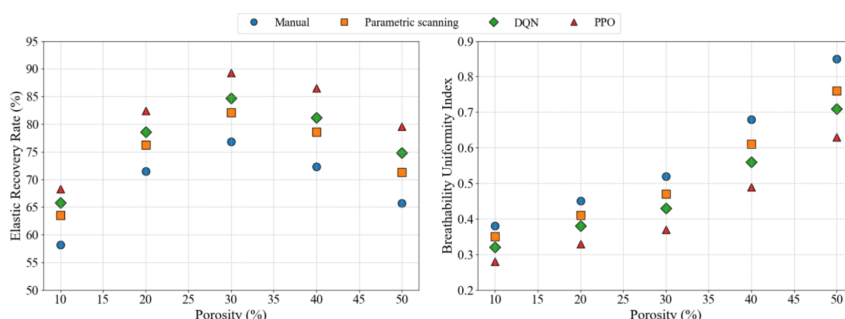


FIGURE 4. Comparison of elastic recovery rate and breathability uniformity under different design methods in smart textiles with varying porosity parameters

to different bio-based material applications with distinct mechanical requirements.

#### IV. CONCLUSIONS

This paper introduces a parametric structural design framework combining the PPO algorithm and a physical simulation model, where an agent receives key material parameter vectors relevant to composite and textile engineering, such as fiber orientation angle, porosity distribution, and layer thickness, as input states. A policy network generates commands for the adjustment of parameters in a continuous action space. Stress distribution and deformation are computed in real time in a finite element simulation. The policy network is updated according to structural stiffness and stress uniformity constraints. Experimental results show that under a compressive load of 2.5 kN, the standard deviation of stress is 2.98 MPa; the integral of the norm of displacement is  $5.93 \times 10^{-4}$  mm/N; the probability of failure is 12.17%, demonstrating the method's capability to optimize microstructural parameters of mycelia and seaweed fibers within the experimental framework. This framework solves the issue of variable mechanical properties of bio-based materials, which is often because parameterization of microstructure has not been sufficient, while improving the uniformity of stress distribution and structural stiffness, demonstrating some reliability of its technical approach to sustainable design of furniture components. The application of this framework in smart textiles demonstrates its adaptability to different biobased material applications, supporting the potential for broader implementation of bio-

based materials in sustainable manufacturing contexts.

#### AUTHOR CONTRIBUTIONS

Conceptualization – Chun Wang and Xiaoyu Liang; methodology – Chun Wang and Xiaoyu Liang; investigation – Chun Wang and Xiaoyu Liang; writing-original draft preparation – Chun Wang and Xiaoyu Liang. 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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