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Research on the Application of Topology Optimization Algorithm in Landscape Design and Spatial Layout Planning

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Abstract With the development of resource-saving and environment-friendly concepts, lightweight, high-strength, high-performance and low-consumption structures have become a design trend. Topology optimization, as an optimization design method, can achieve the optimal performance of structures under the satisfaction of constraints, and has been widely used and concerned in many fields. This paper discusses the application of topology optimization algorithms in landscape design and spatial layout planning. The optimal design of node structure is realized by establishing a multi-scale model and a topology optimization method applicable to spatial structure. The study adopts the SIMP interpolation model in the variable density method, takes the minimum structural strain energy as the optimization objective, and constrains the volume ratio before and after optimization. In the multi-case analysis, the flexibility value of the optimized node under the 30% volume constraint is lower than that of the original node in most of the cases, and the final flexibility of Case 3 is 9.18 mm, which is improved by 28.8% compared with that of the original node; and in the case of the similar material usage (volume of the optimized node 7,652 cm³, volume of the original node 7,450 cm³) In the case of similar material usage (optimized node volume 7652cm³, original node volume 7450cm³), the optimized node reduces the flexibility value by 8.2% in Case 4, and the structural stiffness is significantly improved. The design scheme generated by topology optimization not only meets the engineering requirements, but also presents the characteristics of bionic organic structure and the aesthetics of flowing space, which provides new ideas and methods for landscape design and spatial layout planning.

Index Terms topology optimization, spatial structure, multi-scale model, variable density method, node optimization, SIMP model

I. Introduction

Topology optimization algorithm is a mathematical model-based optimization method, which optimizes the topology of the design space to achieve the optimal design solution [1], [2]. This algorithm can help engineers to minimize material consumption and cost under the premise of guaranteeing product performance and quality, and is widely used in various network topologies, such as computer networks, communication networks, and logistics networks [3]-[6]. Its basic principle is to change the structure of the network by adjusting the connection relationship between network nodes, so as to achieve the purpose of optimizing network performance [7], [8]. And topology optimization algorithms also play an important role in landscape design and spatial layout planning [9].

In landscape design, topology optimization algorithms help designers to better understand the formation and operation of spatial structures, so that the needs and requirements of human activities can be better taken into account in the design and planning process [10]-[12]. In landscape design, space is divided into areas of various sizes, each of which has a specific function and use, and can also be interconnected by specific paths and sequences [13]-[15]. Landscape design emphasizes the wholeness and coherence of the spatial structure, and through careful layout and design, it enables people to travel freely through the landscape and linger [16], [17]. Moreover, the landscape usually contains several different landscape areas, such as lawn, woods, gardens, etc. By connecting these landscape areas, designers can create a good spatial layout [18]-[20].

Structural optimization design, as an important research direction in the field of engineering, has seen an increasing demand for lightweight, high-strength, high-performance and low-consumption structures in recent years, driven by the concepts of resource conservation, environmental friendliness and technological competitiveness enhancement. Among the three main methods of structural optimization (size optimization, shape optimization, and topology optimization), topology optimization shows unique advantages due to its feature of no limitation on the size of the input form. Topology optimization can be applied to a wide range of scales from macroscopic structures, such as large bridges and buildings, to micro- and nanoscale structures, providing new technical support for spatial layout and landscape design. Based on the theory of topology optimization, this study explores its application value in landscape design and spatial layout planning. The study firstly combs through the main methods of topology optimization, including the homogenization method and the variable density method, and analyzes the advantages and disadvantages of each. The homogenization method calculates the macroscale stiffness matrix through the material density distribution at the microscale, but the computational complexity is high and there may be errors when dealing with nonlinear problems; the variable density method optimizes the structural performance by controlling the change of the material density, which is computationally efficient, but there may be noise and discontinuities. This study focuses on the SIMP model in the variable density method, which filters the intermediate density by a penalty function to approximate it to 0 or 1. In terms of mathematical modeling, the study establishes a hierarchical optimization method for spatial structures based on a multiscale model, which includes two main steps: structural multiscale modeling and node topology optimization. The multiscale modeling couples the overall model with the local fine model for collaborative computation, which solves the problems of fine model area and cross-scale interface connection for large-span spatial mesh and shell structures; while the node topology optimization takes the minimum strain energy of the overall structure as the primary optimization objective, and at the same time constrains the volume ratio before and after the optimization. In order to verify the effectiveness of the methodology, the study takes three 80m scaled-down models of K6 single-layer spherical mesh-shell structures as the objects of study, and conducts numerical simulations of multi-scale models and experiments of nodal topology optimization. The experimental results show that the optimized nodes exhibit different characteristics and performance under different volume constraints. In particular, under 30% volume constraint, the core region of the node presents a clearer feature of material separation between the upper and lower parts, and the surface thickness is uniform and smooth, with no obvious redundant structure, while the static stiffness is improved under most working conditions. This finding provides an important reference for space structure design. This study also explores the aesthetic characteristics of topology optimization, including the bionic organic structural features, the flowing spatial aesthetics, and the regular and rigorous logical aesthetics, which enriches the dimensions of the application of topology optimization in landscape design. By studying the application of topology optimization algorithms in landscape design and spatial layout planning, this paper aims to provide theoretical support and practical guidance for related fields and promote the application of topology optimization technology in a wider range of fields.

II. Topology optimization design and mathematical modeling

II. A. Overview of topology optimization design

II. A. 1) Optimization methods

In topology optimization, different optimization methods have their own advantages and disadvantages, and it is necessary to choose the appropriate method according to the characteristics of the specific problem. After obtaining the optimal material distribution, post-processing and computational optimization are also needed to achieve more accurate and practical results.

The following lists several optimization methods most commonly used for topology optimization, as well as their respective advantages and disadvantages:

Homogenization method: The method of designing an optimized material distribution by transforming the microscale material density distribution into the macroscale equivalent material density, and designing the optimized material distribution through the nature of the equivalent material. The basic idea is to calculate the macro-scale stiffness matrix through the micro-scale material density distribution, which in turn inverts the equivalent material density. On this basis, the equivalent material density is adjusted through the change of material density distribution, and then the optimization objective is minimized. However, due to the need to carry out the calculation of equivalent material density, its computational complexity is high, and at the same time, there may be errors and loss of accuracy when dealing with nonlinear problems.

Variable density method: a method to optimize the structural performance by controlling the change of material density. This method optimizes the structural performance by setting different values of material density at different locations inside the structure. The variable density method is usually calculated using an optimization algorithm. The variable density method is widely used in the field of structural optimization, such as the optimal design of aircraft, automobile and other structures. The method has high computational efficiency and computational accuracy, and at the same time can flexibly control the variation of material density. However, its computational complexity is high due to the need to adjust the material density of each unit, while the results may have noise and discontinuity [21].

II. A. 2) Aesthetic analysis of topological optimization

(1) The topology optimization method can generate forms with bionic organic structure by simulating gene mutation

and natural selection process in nature, which have similar forms of branches, grids, pores and so on with living organisms, so the forms generated by the topology optimization method often have the characteristics of bionic organic structure.

(2) The beauty of flowing space refers to the natural, flowing and beautiful feeling in space. In interior design, the flowing spatial aesthetics can be achieved through a series of design techniques, such as the use of natural light, the flexibility of the spatial layout, smooth line design, soft color matching, appropriate green planting arrangements.

Topology optimization can optimize the curves and forms of objects through automated algorithms to make them more smooth and natural. During topology optimization, the distribution of materials is adjusted according to the laws of stress transfer and energy distribution. This makes the optimized structure have a continuous and smooth spatial form, with a natural transition between lines and surfaces, giving people a beautiful visual experience. This flowing spatial aesthetics reflects the harmony and balance of the structure, which makes the topologically optimized structure have high aesthetic value while meeting the performance requirements. This aesthetic sense is especially obvious in the application of bridges, building s and other fields, which provide people with a beautiful living environment.

(3) As an optimization method based on the principles of mathematics and mechanics, the aesthetic characteristics of topology optimization are also reflected in the aesthetics of regular and rigorous logic. The topology optimization process follows certain mathematical formulas and physical laws, which makes its results highly rational and scientific. This logical beauty reflects the rigor and precision of topology optimization technology in solving practical problems.

II. B.Overview of topology optimization

II. B. 1) Structural optimization

The purpose of structural optimization is to achieve the optimal performance of a structure while meeting other constraints. The concepts of resource conservation, environmental friendliness and technological competitiveness have led to the development of lightweight, high-strength, high-performance and low-consumption structures, and thus structural optimization has gradually gained the attention of various sectors.

Structural optimization can be divided into three categories: size optimization, shape optimization and topology optimization.

In the case of continuum structures, optimization is achieved by determining the optimal location and shape of the cavities in the design domain. Unlike other optimization methods, topology optimization of continuum structures has no restriction on the size of the input form, and can be applied to both large-scale structures such as bridges and buildings, as well as micro- and nanoscale structures.

The Asymptotic Structure Optimization (ESO) algorithm is one of the most widely adopted algorithms. Its basic concept is to gradually remove inefficient parts from a structure. In this process, the optimized structure gradually “evolves” towards the optimal shape and topology.

II. B. 2) Topology optimization numerical solutions

Taking the ESO method as an example, the following describes the computation process of the topology optimization algorithm based on stress level and based on structural stiffness, respectively.

Computational process of ESO topology optimization based on stress level:

Firstly, the concept of stress level is introduced, which is a reliable indicator for assessing the efficiency of material use in a particular part of the structure, and the stress level in any part of the structure can be solved by the finite element method. Ideally, the stresses in each part of the structure should be close to the same value, i.e., the safe stress level. This concept leads to a negative criterion based on localized stress levels: material sections with low stress levels are not used and they are removed. This can be achieved by removing elements in a finite element model. Stress levels are determined by comparison. For example by comparing the vonMises stress σ_e^{vm} of an element with the maximum vonMises stress $\sigma_{\max}^{vm}$ of the entire structure. After each element has been analyzed, elements that satisfy the following conditions are removed from the finite element model. i.e:

$$\frac{\sigma_e^{vm}}{\sigma_{\max}^{vm}} < RR_i \tag{1}$$

where RR_i is the current rejection rate. This finite element analysis and element deletion loop is repeated using the same rejection rate RR_i until a steady state is reached.

That is, no more elements can be deleted using the current rejection rate RR_i. At this stage the evolution rate E will be added to the rejection rate. I.e:

$$RR_{i+1} = RR_i + ER \tag{2}$$

With progressively increasing rejection rates, the iteration will continue until a new steady state is reached. This progressive optimization process will continue until an optimized solution that satisfies the requirements is obtained. For example, when there is no material cell stress level in the structure below 25% of the maximum value. The above topology optimization calculation process can be summarized in the following 5 steps:

Step 1: Discretize the structure using a good quality finite element mesh.

Step 2: Finite element analysis of the structure.

Step 3: Remove the elements that satisfy the conditions in (1).

Step 4: If a steady state is reached, increase the rejection rate according to equation (2).

Step 5: Repeat steps 2 to 4 until the desired topology optimization design result is obtained.

Structural stiffness is a key parameter in the design of building or bridge structures. This parameter is usually considered through its inverse measure-mean flexibility. The mean flexibility can be defined as the total strain energy generated by the external loads acting on the structure:

$$C = \frac{1}{2} f^T u \tag{3}$$

where f is the external force vector and u is the displacement vector.

In finite element structural analysis, the static equilibrium equation can be described as:

$$Ku = f \tag{4}$$

where K is the global stiffness matrix.

When the i th element is removed from the structure, its stiffness matrix changes to:

$$\Delta K = K^* - K = -K_i \tag{5}$$

where K^* is the stiffness matrix of the structure after the material unit is removed and K_i is the stiffness matrix of the i th material unit. From this, the amount of change in the displacement vector can be obtained:

$$\Delta u = -K_i \Delta K u \tag{6}$$

It follows from Eqs. (5) and (6):

$$\Delta C = \frac{1}{2} f^T u = -\frac{1}{2} f^T K^{-1} \Delta K u = \frac{1}{2} u_i^T K_i u_i \tag{7}$$

where u_i is the displacement vector of the i th cell.

Therefore, the sensitivity coefficient of the average flexibility value can be defined as:

$$\alpha_i^e = \frac{1}{2} u_i^T K_i u_i \tag{8}$$

The above equation shows that the increase in average flexibility due to the removal of the i th cell is equal to its cell strain energy. In order to minimize the average flexibility (i.e., maximize the stiffness) when removing cells, the most efficient way is to eliminate the cell with the smallest value of α_i. The number of removed cells is determined by the cell removal ratio. The cell removal ratio is defined as the ratio of the number of cells removed in each iteration to the total number of cells in the current finite element model. The above optimization process can be summarized as follows:

Step 1: Discretize the structure using a finite element mesh.

Step 2: Finite element analysis of the structure.

Step 3: Calculate the sensitivity factor for each element.

Step 4: Remove a certain number of elements with low sensitivity coefficients based on a predetermined unit removal ratio (ERR).

Step 5: Repeat steps 2 through 4 until the average flexibility value (or maximum displacement) reaches a preset limit value.

II. C. Topology optimization analysis

II. C. 1) Computational Principles of Topology Optimization

Topology optimization is performed to ensure that the objective function and constraints are perfectly recognized by the optimization algorithm. Continuously varying density variables are introduced in the design domain, usually ranging from 0 to 1. The constraints aim to optimize the material distribution to achieve the objective function optimization.

The main formulation for topology optimization can usually be expressed in the following form:

$$\begin{cases} find & \gamma \\ min & f(\gamma) \\ s.t. & f_i(\gamma) \le 0 \quad i = 1, 2, \cdots, n \quad find \\ & V = \int_{\Omega} \gamma d\Omega - V^* \le 0 \\ & 0 \le \gamma_v \le 1, \quad v = 1, 2, \cdots, n \end{cases} \tag{9}$$

where γ_v denotes the relative density of the v th cell. V^* denotes the fluid region volume fraction. $f_i(\gamma)$ denotes the i th constraint, and the constraints are mostly expressed as inequalities. $f(\gamma)$ denotes the objective function of the design object, and the size of the objective function depends on γ and its related formula.

During the optimization process, multiple such constraints can be set to ensure the rationality and feasibility of the design. Overall, the goal of topology optimization is to satisfy specified performance requirements by searching for the optimal material distribution in the design space and to satisfy various constraints and boundary conditions in the process.

II. C. 2) Generalized model for material interpolation

In the variable density method, SIMP and RAMP interpolation models are usually used, which are used to establish the relationship between density and material properties and play a key role in topology optimization.

(The (Brinkman) model is used to simulate the frictional resistance with the expression:

$$F = -\alpha^* u \tag{10}$$

where α^* denotes the pore reverse permeability of a porous medium.

where α^* reflects the permeability of the fluid. When the value of α^* is 0, it means that the fluid is not hindered in the porous medium and can pass freely. On the contrary, when α^* is infinite, it means that the fluid cannot be distributed in the medium and the resistance becomes infinite. Therefore, by adjusting the value of α^*, the distribution of fluid and solid regions in topology optimization can be effectively controlled.

SIMP and RAMP interpolation models are respectively:

SIMP [22]:

$$\alpha(\gamma) = \alpha_{\max}(1-\gamma)^p \tag{11}$$

RAMP:

$$\alpha(\gamma) = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min})\frac{q(1-\gamma)}{q+\gamma} \tag{12}$$

where p, q denote the interpolation parameters. $\alpha_{\max}$ denotes the maximum value of reverse permeability, denoted as solid phase. $\alpha_{\min}$ denotes the minimum value of reverse permeability, denoted as liquid phase.

From the above equation, when γ is taken as 0, $\alpha(\gamma)$ is equal to $\alpha_{\max}$, which indicates that the fluid flow is extremely restricted and no fluid passes through the design domain, which is then embodied as a solid material. When γ is taken as 1, $\alpha(\gamma)$ is equal to $\alpha_{\min}$, which indicates that at this time, the fluid is not restricted, and the fluid is allowed to flow freely within the design domain, and therefore represents a fluid state. In scholarly studies, $\alpha_{\max}$ depends mainly on the Darcy number and the magnitude of the viscous force, expressed as:

$$\alpha_{\max} = \frac{\mu}{Da \cdot L^2} \tag{13}$$

where Da represents the Darcy number, which indicates the relationship between friction and viscous forces in porous media. In porous media, the larger the Darcy number, the greater the permeability, the permeability of the media used in this paper is small, so the smaller Darcy number is selected.

II. C. 3) Numerical instability and treatment

When the phenomenon of numerical instability occurs in topology optimization design, it is not only difficult to process and manufacture, but also more difficult to meet the practical applications. To solve this kind of problem, the main application of filtering method, filtering method has the advantages of simplicity, convenience and reliability. Filtering method can be specifically divided into sensitivity filtering and density filtering. Currently, density filtering and projection methods are often used to solve the phenomenon of numerical instability in topology optimization. The expression of density filtering is:

$$\gamma_e = \frac{\sum_{i \in N_e} w(X_i) v_i \gamma_i}{\sum_{i \in N_e} w(X_i) v_i} \tag{14}$$

where v_i denotes the cell volume, X_i denotes the center of cell i, and $w(X_i)$ denotes the weighting function.

The linear or exponential decay with increasing distance can be expressed as:

$$w(X_i) = r_{filter} - \|X_i - X_e\| \tag{15}$$

where r_{filter} is the filtration radius. Ne is the set of filter ranges in the center of the cell, i.e:

$$Ne = \left\{ i \middle| \|X_i - X_e\| \le r_{filter} \right\} \tag{16}$$

Topology optimization often uses filtering techniques to obtain information about neighboring cells, but it is not easy to apply this method for some special designs, especially when the design domain is divided into multiple non-overlapping regions. Density filters are usually defined as solutions of Helmholtz-type partial differential equations, i.e., density filtering is achieved by solving Helmholtz-type partial differential equations:

$$-r^2 \nabla^2 \tilde{\gamma} + \tilde{\gamma} = \gamma \tag{17}$$

where r denotes the reference length. γ , $\tilde{\gamma}$ denote unfiltered and filtered design variables.

Finally, applying the projection at the filter can be good to reduce the gray units. In the variable density method, the hyperbolic tangent function is applied to control the degree of projection. Namely:

$$\theta = \frac{\tanh\left[\beta_1 \cdot (\gamma_i - \eta_1)\right] + \tanh(\beta_1 \cdot \eta_1)}{\tanh\left[\beta_1 \cdot (1.0 - \eta_1)\right] + \tanh(\beta_1 \cdot \eta_1)} \tag{18}$$

where θ denotes the projection point, β_1 denotes the projection slope, and η_1 denotes the projection threshold, with values from 0 to 1. If the final density value is greater than η_1 the curve is projected in the direction of 1, and vice versa for 0.

III. Topology optimization-based hierarchical optimization method for spatial structures

III. A. Structural multiscale modeling

The purpose of structural multiscale modeling calculation is to couple the overall model with the local fine model for collaborative calculation in order to obtain the overall response of the structure while obtaining the local response information of the structure. Different multi-scale models can be established according to different purposes, for example, in order to obtain the results of the stress response of the local units, the response analysis of the local details is modeled using shell units to establish a fine model. The rest of the structure is modeled using beam units. Therefore, the first step in multiscale modeling should be to determine the analysis objectives, and according to the different analysis objectives, the components of the structure are divided into multiple regions. Different scale models are established in different regions according to the needs of analysis, and finally the multi-scale unit models are coupled and analyzed collaboratively in order to obtain the overall and local responses of the structure at the same time. The large-span space mesh-shell structure belongs to large engineering structures with a huge number of bars and nodes, and the two basic problems of the refined modeling region of the structure and the connection of the cross-scale interface need to be considered in the establishment of the multiscale model of the structure.

(1) Determination of macroscopic units

In the establishment of structural multiscale model, the overall structure is firstly analyzed for dynamic response to determine the key parts of the structure. The key position of the structure is simulated by the fine-scale unit, and the non-critical position is simulated by the macroscopic unit. Generally, the microscopic unit is the shell unit and the macroscopic unit is the beam unit. The structure is modeled by the consistent unit method, and the amplitude of the input seismic acceleration is gradually increased, and the relationship curve between the proportion of structural plastic rods and the amplitude of the acceleration is obtained. According to the distribution of plastic rods at the corresponding acceleration of the curve, the weak parts of the structure are determined. And a fine-scale multi-scale model is established.

(2) Cross-scale connection

Reasonable and scientific establishment of multi-scale model connection interface is the key to multi-scale model calculation. According to the physical continuity of multi-scale interface units and nodes, the deformation-based physical connection equations are established to realize the connection between cross-scale units. In fact, the connection between cross-scale can be roughly categorized into three major types: the connection between beam unit and shell unit, the connection between shell unit and solid unit, and the connection between beam unit and solid unit, and the basic principles of these three types are the same in essence. In this paper, the MPC method is applied to illustrate the connection between beam unit and shell unit as an example of cross-scale connection. Both are usually rigid connections.

At the cross-scale interface, different types of unit nodes can be connected through the displacement constraint equations of the nodes, so as to realize the displacement coordination at different scales. The constraint equations are adopted in the form of:

$$u_n^{(1)} = \sum_{i=1}^{n} X_i u_m^{(2)} \tag{19}$$

where $u_n^{(1)}$ and $u_m^{(2)}$ are the number of node degrees of freedom in the large-scale domain (beam unit) and small-scale domain (shell unit), respectively, and n is the total number of nodes. X_i is the constraint coefficient of node i at the connection interface.

The simplified multipoint constraint equation is in polynomial form:

$$u_n^{(1)} = c_1 u_1^{(2)} + c_2 u_2^{(2)} + \cdots + c_m u_m^{(2)} + C \tag{20}$$

where c_i is the weight coefficient. C is a constant.

III. B. Node topology optimization based on multi-scale model optimization results

III. B. 1) Spatial structure optimization based on multi-scale theory

In order to accurately extract the force conditions in the node design domain as the boundary conditions for node topology optimization, the hollow ball nodes and the rods connected to the ball nodes with 0.9 times of the outer diameter of the rods are taken as the areas to be modeled in a refined way.

With the angle between the rods connected to the nodes, the nodes can be roughly divided into the following three categories.

The first category: nodes intersected by radial rods, the angle between the rods is 45°.

The second category: nodes intersected by ring, radial and diagonal rods, with rod angles of 65°, 70° and 45°.

The third category: the node intersected by inclined rod and ring rod, the angle of the rod is 40°, 60°, 80°.

This multiscale model is optimized for sizing under multiple operating conditions. In the optimized model because of the introduction of hollow ball nodes. One more constraint to be considered here is the determination of the outer diameter and wall thickness of the welded hollow ball. The specification states that the wall thickness of the single-layer mesh shell hollow sphere should not be less than 4mm. It is appropriate to take 2.4~3.0 for the outer diameter/wall thickness of hollow ball nodes. Ball node wall thickness/maximum pipe wall thickness should be 1.5~2.0. The following constraint equation can be established:

$$D_{\min} = (d_1 + 2a_n + d_s) / \theta \tag{21}$$

$$t_{\min} = \max(\frac{D_{\min}}{3}, 4) \tag{22}$$

where d_1 is the maximum outer diameter (mm) of the two neighboring steel pipes. d_s is the smaller outer diameter (mm) of the two neighboring steel pipes. a_n is the clear distance between two adjacent steel pipes, taken as 10 mm. θ is the angle between the axes of two adjacent bars, and $D_{\min}$ is the minimum outer diameter of hollow ball node. $t_{\min}$ is the minimum wall thickness of the hollow sphere node.

Since the single-layer mesh shell does not have enough bending stiffness provided by the inner web in space, and the connection between the members is mostly a rigid connection with welded hollow sphere nodes. Therefore, the axial force and bending moment in the node design domain need to be extracted as the boundary conditions for the next step of node topology optimization. In this paper, the axial force and bending moment envelope values obtained from the multi-scale model under multiple working conditions are used as the boundary conditions.

III. B. 2) Node Optimization Design

The topology optimization method used in this paper is the variable density method commonly used in optimal design, and its mathematical model can be expressed as:

$$\overline{G}(\rho) = \rho^P G \tag{23}$$

where $\overline{G}$ represents the penalty function of the cell, G represents the solid filled cell stiffness of the cell, ρ is the cell density, and P is a penalty coefficient that takes a value greater than 1.

Through the sensitivity analysis, the sensitivity of each cell corresponding to the optimization objective function is obtained. By processing the results of the sensitivity analysis and iterating using the optimization criterion method (OC), the density distribution of the next result can be obtained, i.e.:

$$\rho^{k+1} = OC(\rho^k) G \tag{24}$$

where ρ^{k+1} and ρ^{k} are the structural unit densities at the k th generation optimization step and the $k+1$ th optimization step, respectively.

The SIMP method is one of the most commonly used variable density methods. It realizes the filtering of the intermediate density by using the method of penalty function, which makes it approach to 0 or 1 until it finally becomes 0 or 1. The correspondence between the relative density of the material unit and the elastic modulus of the material for the SIMP method in the variable density method is as follows:

$$E(x) = E_{\min} + \rho(x)^{p}(E - E_{\min}) \tag{25}$$

where E is the elastic modulus of the solid filled cell. $E_{\min}$ is the elastic modulus of the null cell (low strength cell). $\rho(x)$ takes any value between $[\rho_{\min}, 1]$. The value of $\rho_{\min}$ is taken to be a very small and non-zero value with the aim of making the equation hold.

In this paper, the overall structural strain energy minimization (stiffness maximization) is adopted as the primary optimization objective, and at the same time, in order to achieve the lightness of the node mass, the volume ratio before and after the optimization is constrained not to exceed a certain limit value, then this optimization model can be expressed:

$$\begin{aligned} &Find: \rho = \{\rho_1, \rho_2, \rho_3 ..., \rho_n\}^T \in \Omega \\ &Minimize: C = F^T U \\ &Subject: V^* \le fV, F = KU \\ &0 < \rho_{\min} \le \rho_i \le 1 (i = 1, 2, 3..., n) \end{aligned} \tag{26}$$

where C is the overall flexibility of the structure. K is the structural stiffness matrix and U is the overall deflection matrix. F is the external load. V is the original structural volume and V^* is the optimized structural volume.

The original node is a conventional welded hollow ball node. Because all the rod end forces converge to the node core, the node core is most likely to be damaged, and the deformation of the node core is most significant, and the stiffness of the node core has a particular impact on the mechanical properties of the node. In this paper, TOSCA is used to optimize the topology of the nodal core, and the optimization interpolation model used is SIMP method, in which the size of the nodal core is determined by the original hollow sphere node outer diameter and height. No material nonlinearity is involved in the topology optimization problem and all the optimizations are within the elastic phase. In order to find the optimal distribution of the material, the constrained volume fraction of the model is set to be only 30% of the pre-optimization one, and the penalty factor is taken as 3.0. while the objective function is the minimum overall strain energy of the structure. The optimization model can be expressed as:

$$\begin{aligned} &Find: \rho = \{\rho_1, \rho_2, \rho_3 ..., \rho_n\}^T \in \Omega \\ &Minimize: C = F^T U \\ &Subject: V^* \le fV, \Delta \le [\Delta_{\max}], \sigma \le [\sigma_{\max}] \\ &0 < \rho_{\min} \le \rho_i \le 1 (i = 1, 2, 3..., n) \end{aligned} \tag{27}$$

where Δ is the nodal core displacement, $A_{\max}$ is the displacement limit value of 196mm, σ is the nodal core stress, and $\sigma_{\max}$ is the nodal core stress limit value.

The density projection technique based on Heaviside function is considered to be an effective method to realize the minimum size constraint in the constraints of additive manufacturing process, and this method can effectively realize the design threshold for increasing the minimum size of the optimized structure, avoiding the appearance of fine rods and holes in the structure that are difficult to print, and guaranteeing the applicability of the printing results.

The size filtering equation based on Heaviside function can be expressed as:

$$\bar{x} = H(x, \eta, \beta) = \begin{cases} \eta(e^{-\beta(1-x/\eta)} - (1 - x/\eta)e^{-\beta}) & 0 \le x \le \eta \\ (1-\eta)(1 - e^{-\beta(x-\eta)/(1-\eta)} + (x-\eta)e^{-\beta} / (1-\eta)) + \eta & \eta \le x \le 1 \end{cases} \tag{28}$$

where η is the cell density filtering threshold. β is the Heaviside function smoothing standardized coefficient. x is the relative density of material units before processing. x is the relative density of material units after processing. When $\eta = 0$, its principle is equivalent to mapping into a threshold penalty function, below the threshold of the relative density of the material unit to penalize, so that it is enlarged to the specified value, in order to achieve the optimization process of the minimum size of the control.

IV. Optimized design of the topology of the nodes of the space structure

IV. A. Numerical Simulation of Multiscale Models

The test models are three 80m scaled-down models of the K6 single-layer spherical mesh shell structure. The dimensions of the rods in model 1 were uniform, and the overall stiffness was evenly distributed. Under the strong seismic action, there is a “symptomatic” strength damage, accompanied by some of the rods going into plasticity. Model 2 has weak zones in the six radial main ribs, and local dynamic instability damage occurs “without signs”. Model 3 has the same geometrical topology as Model 2, with no weak zones, and a strength-damaged collapse mode occurs.

The vector-to-span ratio of all three models was 0.5, and 24 fixed supports were arranged at intervals along the perimeter of the ground floor. According to the test conditions, the geometric similarity coefficients between the test models and the structural prototypes were all 1:10. In order to maximize the similarity of the stress performance between the two, the number of ball nodes and bars of the prototypes were not simplified, i.e., the test models and the structural prototypes had the same topological relationship. On the basis of satisfying the geometrical similarity, the model also needs to satisfy the requirements of load similarity, mass similarity, stiffness similarity and boundary and initial conditions similarity.

In order to compare with the test model, the test model is modeled at multiple scales based on the multi-point constraint method.

Considering that there are many uncertainties in the test (human factors, material factors, environmental factors, etc.), and each model has different configurations and materials, which are prone to local deformations in the process of ground shaking, the multiscale model can only be made as close as possible to the test model in the numerical simulation. In order to visualize the displacement changes of the nodes, the horizontal displacements of eight measurement points are extracted and fitted with peak-displacement curves for analysis. The maximum relative displacements of the nodes of the three multiscale models for each condition are shown below.

The simulated values of model 1 are shown in Table 1, (unit: mm).

In Case 1, the PGA(gal) is 50 and the Dmax is 1.787. In Case 6, the PGA(gal) is 1990 and the Dmax is 34.859. The Dmax of Case 6 is significantly higher than that of Case 1.

Table 1: Model 1 simulation value/(mm)

Operating condition	PGA (gal)	D1	D2	D3	D4	D6	D7	D8	Dmax
1	50	1.529	1.231	1.204	1.787	1.296	1.024	1.525	1.787
2	401.6	3.257	2.751	2.529	3.251	3.524	2.891	3.215	3.524
3	842	8.206	9.805	9.215	8.997	7.263	7.523	6.896	9.805
4	1321	11.336	10.216	8.691	9.859	11.596	10.036	10.143	11.596
5	1550	9.583	10.093	12.663	10.263	9.506	9.787	10.209	12.663
6	1990	24.501	34.159	29.421	20.629	34.859	26.554	23.117	34.859

Comparison of the displacement response values of Model 2 with the simulated values is shown in Table 2, (in mm).

In Case 3, the Dmax is 4.127 and 11.526 with an error of 35.81%. Combining all the conditions, the maximum error rate is 101.60%, which occurs in condition 11 with PGA(gal) of 1194.

Model 3 displacement response values are compared with the simulated values (in mm) as shown in Table 3.

The three models before entering plasticity (PGA is small), the difference between the experimental and simulated values of the measured point displacements is large, which is due to the fact that the multiscale model did not consider the effect of the initial defects. In the elastic phase, although some rods will be deformed, the deformation is not obvious, and the motion form of the model is basically rigid-body displacement, so the relative displacement between nodes is generally small relative to the bottom measurement point D5. With the increase of PGA, when the model enters plasticity, the displacement of the multiscale model grows faster than that of the experimental model, which offsets part of the error caused by the initial defects, and at this time, the displacement deviation is significantly reduced.

IV. B. Topology optimization of nodes

IV. B. 1) Multi-case optimization analysis results

Integrate the optimization results of single working condition, and further analyze and study the comparison of multiple working conditions. The objective function is a compromise planning expression, and several working conditions are regarded as equally important, taking the same weighting coefficients, i.e., $w_i = 0.3(k = 1, 2, 3, 4)$, and the compromise planning penalty coefficient $q = 2.0$. Set the overall checkerboard lattice control and take the SIMP method density interpolation penalty coefficient $p = 2.0$. In order to avoid excessive accumulation of materials in the local or too small redundant structures appear, change the minimum and maximum member size of the optimization region and carry out trial calculations, a comprehensive comparison of the geometric expression of the results obtained as well as the computational resources consumed, determined to set the topology optimization of the process manufacturing constraints for the following: the minimum member size of 10mm, the maximum member size of 20mm, do not add symmetry constraints, the conditions can be obtained a more Clear topology optimization results can be obtained under this condition.

Table 2: The model 2 displacement response value is compared to the simulated value

Operating condition	Categories	3	4	6	7	10	11	17
PGA (gal)		245	381	633	828	1082	1194	1433
D1	Numerical value	3.098	7.256	11.919	19.782	15.896	21.334	20.253
	Test	4.423	5.943	7.846	7.501	7.829	9.521	10.809
D2	Numerical value	3.897	6.895	12.203	17.413	21.663	17.914	18.454
	Test	4.991	4.787	8.426	7.609	7.895	9.207	12.965
D3	Numerical value	3.996	9.215	11.021	17.251	21.536	22.351	21.223
	Test	6.879	8.745	10.326	12.334	12.238	14.004	12.704
D4	Numerical value	3.335	9.321	17.099	16.877	21.004	21.331	21.821
	Test	5.475	6.809	9.801	9.859	11.452	14.526	12.552
D6	Numerical value	4.127	8.012	10.336	17.253	17.596	26.845	23.936
	Test	11.526	16.784	18.956	22.007	24.351	26.421	24.232
D7	Numerical value	3.898	8.795	12.902	20.135	21.895	20.754	24.101
	Test	4.754	5.428	6.040	6.859	7.569	9.486	9.565
D8	Numerical value	3.212	6.454	13.284	17.578	23.895	19.521	19.254
	Test	6.829	8.501	12.993	11.604	15.632	12.324	11.027
Dmax	Numerical value	4.127	9.321	17.099	20.135	23.895	26.845	24.101
	Test	11.526	16.784	18.956	22.007	24.351	26.421	24.232
Error/%		35.81	55.54	90.20	91.49	98.13	101.60	99.46

Table 3: The model 3 displacement response value is compared to the simulated value

Operating condition	Categories	3	11	14	16	19	23	24
PGA (gal)		246	1232	1597	1922	2105	2180	2290
D1	Numerical value	3.01	19.35	37.15	51.57	69.57	98.04	102.55
	Test	12.32	17.89	27.30	50.13	54.24	95.13	103.48
D2	Numerical value	3.01	20.72	35.42	52.89	70.54	96.52	96.25
	Test	10.15	17.23	28.75	49.76	56.58	86.04	82.13
D3	Numerical value	3.36	19.12	38.75	54.25	75.69	97.55	98.75
	Test	14.25	12.36	21.45	44.63	49.22	66.04	24.07
D4	Numerical value	3.25	22.23	37.84	53.75	76.42	98.96	97.31
	Test	14.96	14.39	20.72	44.28	48.56	67.12	24.15
D6	Numerical value	2.96	19.52	40.25	59.12	80.42	96.15	107.21
	Test	9.75	15.36	25.36	52.36	65.76	84.62	89.33
D7	Numerical value	3.11	21.22	38.79	52.43	73.45	95.89	111.05
	Test	12.36	15.689	26.34	53.46	60.19	78.53	25.43
D8	Numerical value	3.15	20.34	40.52	56.32	83.57	90.42	116.09
	Test	11.79	26.25	38.91	49.85	76.10	84.79	60.72
Dmax	Numerical value	3.36	22.23	40.52	59.12	83.57	98.96	116.09
	Test	14.96	26.25	38.91	53.46	76.10	95.13	103.48
Error/%		22.46	84.69	104.14	110.59	109.82	104.03	112.19

The results of the flexibility optimization for different conditions under different volume constraints are shown in Table 4. 40% volume constraints, the overall geometric characteristics of the optimized nodes are similar to the optimization results under single condition, while the difference is that the optimized nodes under single condition have load sensitivity, i.e., there are some cases of large differences in the material stacking characteristics or even holes on the surface of the results under different conditions. The situation is improved after the multi-case compromise objective optimization, but there are some more obvious redundant structures.

The core area of the node under the 30% volume constraint shows clearer material separation between the upper and lower parts, and the surface thickness is more uniform and smooth compared to that in the single case, with no obvious redundant structures. The final flexibility for Case 3 is 9.18 $\times 10^5$ mm.

There are still more holes on the surface under the 20% volume constraint, and the surface of the material surrounding the holes is rough and non-uniform, because most of the material around the holes is in the state of "half-have, half-have-not" to be removed. The optimized results for the four conditions are 4.75 $\times 10^5$, 3.96 $\times 10^5$, 1.94 $\times 10^5$, 2.71 $\times 10^5$, and 2.71 $\times 10^5$, respectively.

Table 4: The flexibility of each condition is optimized by different volume constraints

Operating condition	40%		30%		20%	
	Initial flexibility	Final flexibility	Initial flexibility	Final flexibility	Initial flexibility	Final flexibility
1	3.62×10^5	1.52×10^5	6.35×10^5	2.37×10^5	1.47×10^5	4.75×10^5
2	2.98×10^5	1.30×10^5	5.32×10^5	2.04×10^5	1.23×10^5	3.96×10^5
3	1.64×10^5	5.65×10^5	2.79×10^5	9.18×10^5	6.24×10^5	1.94×10^5
4	2.55×10^5	8.73×10^5	4.36×10^5	1.46×10^5	9.73×10^5	2.71×10^5

IV. B. 2) Finite element analysis of optimized nodes

The average flexibility values of the original nodes with the optimized results under different volume constraints for each operating condition and the volumetric comparisons are shown in Table 5.

It is obvious that the optimized node with 20% volume constraint has the highest flexibility, i.e., the lowest stiffness for each condition. The optimized node with 40% volume constraint has the lowest flexibility, i.e., the highest stiffness, while the optimized node with 30% volume constraint has a similar volume to the original design node, and although the optimized node for Case 3 has a slightly higher flexibility than the original node, the flexibility values for the other three cases are lower than the original design node through the compromise planning, which means that for most of the cases the static stiffness of the optimized node has been increased to some extent for a given amount of material. The stiffness is improved to some extent.

So far, it can be concluded that the optimized results of the multi-case compromise with 30% volume constraints in the design region have better geometric topology characteristics and good load carrying capacity for the given initial design region. However, it is worth noting that the optimization results only represent the optimal conceptual expression under this particular combination of conditions, not the final design results, and subsequent optimization work such as shape optimization and size optimization is beyond the scope of this paper.

Table 5: Average flexibility and volume comparison

Node form	Mean flexibility/ $(N\cdot mm)$				Volume/ cm^3
	Operating condition 1	Operating condition 2	Operating condition 3	Operating condition 4	
Original design node	2.59×10^5	2.47×10^5	7.13×10^5	1.59×10^5	7450
40% volume constraint optimization node	1.52×10^5	1.30×10^5	5.65×10^5	8.73×10^5	10240
30% volume constraint optimization node	2.37×10^5	2.04×10^5	9.18×10^5	1.46×10^5	7652
20% volume constraint optimization node	4.75×10^5	3.96×10^5	1.94×10^5	2.71×10^5	5050

V. Conclusion

This study explores the application of topology optimization algorithms in landscape design and spatial layout planning through multi-scale model building and node topology optimization design. The study shows that the topology optimization technique can effectively improve the performance of spatial structures. The optimized node with 30% volume constraint shows clear features of material separation between the upper and lower parts and a uniform and smooth surface without obvious redundant structure under the multi-case trade-off optimization. Compared with the original node, this optimized node shows improved static stiffness under most working conditions with similar material usage (optimized node volume of 7652 cm³, original node volume of 7450 cm³), especially in Case 2, the optimized node flexibility value is reduced by 17.4%. Through the comparative analysis of different volume constraints, it is found that the optimized node under 20% volume constraint has the least amount of material, but the stiffness is obviously insufficient; while the optimized node under 40% volume constraint has the greatest stiffness, but the amount of material is too much, which is not in line with the requirements of lightweight design. The study also shows that the structure generated by topology optimization not only has good mechanical properties, but also presents the characteristics of bionic organic structure and the aesthetics of flowing space, which reflects the advantages of topology optimization in meeting the engineering needs and aesthetic value at the same time. These findings provide new design ideas and methods for landscape design and spatial layout planning, and are of great significance in promoting technological innovation in related fields. Future research can further explore the subsequent design work such as shape optimization and size optimization to obtain more perfect design solutions.

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