Research on Tunnel Segment Layout Technology Based on Intelligent Optimization Methods (Post-Print)

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Abstract

Segment assembly, as a critical process in shield tunneling construction, holds significant importance for tunnel construction. Current layout techniques based on designers' experience and traditional mathematical formulas suffer from low accuracy and efficiency. To enhance the precision and efficiency of segment layout, this paper proposes a segment layout model based on assembly posture by integrating modern optimization methods. Drawing upon a subway shield tunnel section construction project, and employing the grid search method, this study investigates the improvement in segment layout effectiveness and model stability under various hyperparameters for both the simulated annealing method and the greedy-simulated annealing method. The results demonstrate that: 1) The simulated annealing method exhibits favorable optimization performance under appropriate conditions, achieving a 23% improvement in objective function value for the optimal solution compared to traditional methods. 2) The simulated annealing method exhibits dependence on the selection of initial solutions, which can be categorized into three types based on iteration characteristics: fluctuation-decreasing, fluctuation-stable, and stable. 3) In terms of model layout effectiveness: simulated annealing method > greedy-simulated annealing method > greedy algorithm (traditional method); however, based on observation of solution distribution, the greedy-simulated annealing method demonstrates superior stability compared to the simulated annealing method. The findings of this research can serve as a reference for segment layout design, enabling the selection of appropriate layout algorithms based on different conditions.

Full Text

Research on Tunnel Segment Layout Technology Based on Intelligent Optimization Methods

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Abstract

Segment assembly is a critical process in shield tunneling, where the accuracy and efficiency of segment layout design significantly impact construction quality. Traditional methods relying on manual experience and mathematical formulas suffer from low precision and inefficiency. To address these limitations, this study proposes an optimized segment layout model based on assembly posture, incorporating modern optimization techniques. Taking a metro shield tunneling project as a case study, we investigate the performance and stability of the Simulated Annealing (SA) method and the Greedy-Simulated Annealing (GSA) hybrid method under different hyperparameters using a grid search approach. The results demonstrate that: (1) The SA method achieves effective optimization under appropriate conditions, with the optimal solution improving the objective function value by 23% compared to traditional methods. (2) The SA method exhibits sensitivity to initial solutions, which can be categorized into three types based on convergence behavior: fluctuating-decreasing, fluctuating-stable, and stable. (3) In terms of layout optimization performance: SA > GSA > Greedy Algorithm (traditional method). However, the GSA method demonstrates superior stability over SA in terms of solution distribution. The findings provide a reference for segment layout design, enabling the selection of appropriate algorithms under varying conditions. This research contributes to enhancing the precision and efficiency of shield tunneling construction.

Keywords: Shield Tunnel; Segment Lining Layout; Mathematical Model; Simulated Annealing; Hyperparameter Search

Introduction

In tunnel construction, the ring-by-ring and block-by-block assembly of tunnel segments demands high precision control while involving substantial workload. Discussions on segment layout methods have long entered the research scope, and researchers have achieved fruitful results in recent years. Tunnel segment layout technology refers to the determination of each ring's assembly posture during tunnel design, based on the tunnel's design axis, proposed segment types, and within certain tolerance limits, through mathematical theory or design experience [1,2]. Current layout techniques primarily focus on algorithmic improvements, simplifications, and real-time correction technologies for segment layout.

Traditional layout algorithms are limited by computational capacity and time, making them suitable only for local layout scenarios with a small number of segment rings. Building upon existing research, this paper integrates segment layout technology with modern intelligent optimization algorithms to improve layout accuracy while reducing time complexity, making it applicable to global layout across multiple segment rings. Furthermore, parameter search analysis is conducted according to algorithm characteristics to compare the layout effects of different algorithms.

1. Tunnel Segment Layout Model Based on Assembly Posture

When considering the use of universal tapered segments to fit the tunnel axis, the typical approach employs piecewise polylines to approximate smooth curved alignments. Tunnel design axes are predominantly three-dimensional spatial curves, where straight sections are easy to design, but horizontal and vertical curve segments rely on the taper amount of universal tapered segment rings for fitting. Based on this concept, segment layout technology can be abstracted as shown in [Figure 1: see original paper]: starting from the initial plane, the assembly configuration of the next segment ring is determined based on the current reference plane αi (initially the initial plane, subsequently the forward face αi+1 of the previous segment ring), the coordinates of reference plane center Vi (xi, yi, zi), the direction vector ni = (nxi, nyi, nzi) corresponding to the reference plane center, and the tunnel design axis.

In actual engineering, universal tapered segment rings often have multiple connection types at segment joints (denoted as m). The assembly posture of segment rings multiplied by m/2π represents the angle between the reference line corresponding to the key block of the previous segment ring's forward face and the reference line 0 corresponding to the key block of the current segment ring's reference plane, with counterclockwise defined as positive. As shown in Figure 2: see original paper and (b), the outer ring represents the current segment ring's reference plane, while the inner ring represents the previous segment ring's forward face. The two planes are tightly pressed together, but different assembly positions create corresponding angles, which constitute the angle between lines li and li-1.

Based on the current ring's assembly information (Vi, ni, ni+1, ϕi) and the tunnel design axis, the next segment ring's assembly information Si+1 = (Vi+1, ni+1, ni+2, ϕi+1) can be determined through fundamental mathematical calculations and optimization algorithms. According to the current segment information, Vi+1 and ni+1 can be directly obtained; the optimal assembly posture can be selected through enumeration of all possible assembly configurations; and ni+2 can be determined through geometric relationships after ϕi+1 is established. In practical engineering applications, calculations can be performed ring-by-ring to determine segment assembly information.

2. Segment Layout Optimization Algorithms

2.1 Greedy Algorithm

The greedy algorithm, also known as the greedy strategy, is a common approach for solving optimization problems. Its principle involves selecting at each decision step the choice that optimizes the target variable. The entire decision-making process considers only whether each current decision is locally optimal, without regard for global optimality—that is, without considering the impact of current decisions on subsequent ones.

Current shield tunnel segment layout techniques employ the greedy algorithm concept: based on the current segment ring position, the layout position and method for the next ring (or next two rings) are determined through exhaustive search. The greedy algorithm is suitable for scenarios requiring rapid results but suffers from insufficient accuracy. While local optimums may be adequate for exploring multi-ring or entire tunnel layout methods, global exhaustive search would create a computational catastrophe of geometric proportions, necessitating the introduction of intelligent algorithms to improve computational efficiency.

2.2 Simulated Annealing Method

Simulated Annealing (SA) is a stochastic optimization algorithm based on the physical process of metal solid annealing. Its essence is that solid particles have high internal energy, strong activity, and greater instability at high temperatures. As temperature decreases, internal particle energy reduces, activity weakens, and the system tends toward stability. Based on this principle, the algorithm conducts a certain number of Metropolis trials at each temperature, accepting new states with lower energy; otherwise, it accepts higher-energy states with a certain probability.

This probability typically relates to the energy difference between new and current states—larger energy differences yield higher acceptance probabilities. This optimization approach avoids becoming trapped in local minima and attempts to find global optimal solutions.

2.3 Improved Mathematical Model Based on Simulated Annealing

Simulated annealing is a powerful optimization algorithm that can escape local optima even when the objective function deviates from minimal values. However, existing theory suggests that SA application is overly dependent on initial solution selection, posing significant challenges for hyperparameter optimization and initial solution choice. For shield tunnel segment layout problems, segment assembly postures must be specific discrete values constrained by tunnel axial connections, which differs from SA's typical approach of applying micro-perturbations to continuous variables. This requires targeted modifications to make SA applicable to practical engineering problems.

In this engineering problem, segment assembly information can be calculated through progressive mathematical transmission theory. That is, with the initial plane and initial center point determined, only the assembly posture of each ring needs to be established to determine the complete segment layout.

Forming a sequence of each segment ring's assembly posture {$ $1, $ $2, $ $3, …} as independent variables, the optimization objective uses the sum of squared perpendicular distances from segment ring centers to the tunnel design axis as the fitting target:

The objective function is: min $\Sigma(||Vi - Hi||^2 + ||Vi+1 - Hi+1||^2)$

where: - Vi is the center point of the current segment ring's reference plane - Hi is the closest point on the tunnel design axis to Vi - Vi+1 is the center point of the current segment ring's forward face - Hi+1 is the closest point on the tunnel design axis to Vi+1

Based on requirements for staggered segment joints during actual assembly, control conditions are added. Different numbers of longitudinal joint connection bolts and different shield tunnel universal segment ring divisions create varying condition differences; in this problem, only the simple case ϕi $\neq$ 0 is considered.

The specific SA process is shown in [Figure 3: see original paper], where: - X is the number of solution updates at current temperature - x is the maximum number of solution updates at current temperature - Y is the number of consecutive non-updated solutions at current temperature - y is the maximum number of consecutive non-updated solutions at current temperature - T is the current SA temperature - t is the minimum acceptable temperature - k is the probability of accepting non-optimal solution replacement

The SA stopping condition is: temperature T $<$ t.

2.4 Greedy-Simulated Annealing Algorithm

During SA model establishment, generating new solutions from initial solutions applies perturbations to random independent variables ϕi. However, in this model, ϕi represents the position change of the current segment ring relative to the previous ring. Therefore, when ϕi is perturbed to ϕi', the subsequent ϕi+1 in the original solution must change accordingly. Due to three-dimensional spatial connection transmission effects, this cannot be directly propagated, as illustrated in [Figure 4: see original paper].

Considering the poor interpretability of the SA method, we propose the following improved approach: maintain the initial perturbation unchanged, and determine ϕi+1, ϕi+2, ϕi+3,… using the greedy algorithm to form a new solution. From the perspective of solution variation, this can rapidly perturb the original solution to generate new solutions. Moreover, since all nodes after the perturbation point are generated according to the greedy algorithm, the new solution maintains substantial consistency with the original solution in format, satisfying SA's micro-perturbation characteristics while resolving the issue that nodes after perturbation points become meaningless in the original SA method, as shown in [Figure 5: see original paper].

3. Hyperparameter Analysis

3.1 Engineering Background

Based on a metro shield tunnel construction project, we investigated how different model hyperparameters affect fitting performance. The shield interval comprises a spatial curve with a horizontal curve radius of 500m and a longitudinal gradient of approximately 30‰. Segment specifications include: inner diameter 5400mm, thickness 300mm, ring width 1500mm, 6 blocks per ring, and 10 longitudinal assembly positions. Fifty segment rings from the curve section were selected as the research object, with the objective function value of these 50 rings serving as the evaluation metric.

Hyperparameter selection for the SA model (x, y, k) employed grid search. The SA model considered 10 randomly generated initial solutions for subsequent calculations. Given that parameters x and y relate to iteration counts, while x and k relate to annealing acceptance probability, preliminary experiments were conducted to explore inter-parameter relationships before investigating relationships between initial solutions and hyperparameters.

The hyperparameter iteration ranges for this experiment were: - x: 10 to 100, step size 10 - y: 10 to 100, step size 10 - k: 10 to 300, step size 10

3.2 Analysis of Iteration Count Hyperparameters

Parameters x and y are iteration-related hyperparameters in SA that directly affect algorithm effectiveness. Across all SA methods, a three-dimensional coordinate system was established with hyperparameter values x and y as axes and objective function value as the z-axis, as shown in [Figure 6: see original paper]. Observation reveals that the overall objective function value decreases with increasing x and y, rapidly at first, but showing significant fluctuation when x and y exceed 50. At this point, iteration steps have reached the marginal range of the SA algorithm, and further increasing iteration steps yields limited improvement in solution quality. Additionally, increasing x proves more beneficial for objective function reduction, while increasing y shows some but less pronounced effect.

In [Figure 7: see original paper], the red plane represents the 95th percentile of all objective function solutions, showing that nearly all 95th percentile points distribute in regions where x and y (or either) exceed 50. For subsequent analysis, we designate the larger of x and y as the iteration count.

3.3 Analysis of Iteration Probability Hyperparameters

Parameters x and k are hyperparameters related to solution replacement probability. Due to existing formulas, relationships can be established directly based on formulas and expected SA iteration behavior.

The iteration probability is: p = exp(-ΔE/T/k)

When k = 300 and iterating to 100 generations (x = 100): T = 100 × 0.95^1.77

When Δ = 10: p = exp(-10/1.77)   0.003

The product result p = 0.003 at iteration's end indicates that with x = 100 and Δ = 10, setting k = 300 already satisfies the requirement of maintaining substantial stability at iteration's end.

3.4 Analysis of Initial Solution Hyperparameters

The initial solution is the most critical parameter in SA. As an intelligent optimization search method, SA is highly sensitive to initial solutions, where a good initial solution may yield better final results. This study employed 10 initial solutions for exploration.

The distribution of objective function values for these 10 solutions under different hyperparameters is shown in [Figure 7: see original paper]. The tenth solution is the greedy algorithm solution, represented by a red dashed line due to its invariance across hyperparameters. The greedy algorithm's objective function value is 727.9. Except for initial solution 1, all other initial solutions show objective function values below the greedy algorithm's solution, with the minimum reaching 556.8. Eighty percent of initial solutions outperform the greedy algorithm, optimizing the objective function value by 23%.

All initial solution distributions exhibit long-tailed, spindle-shaped patterns. The long tail indicates large initial objective function values, representing rapid reduction during early iterations. The spindle shape indicates that SA gradually reduces objective function values, with fluctuations at local optima causing solution accumulation in certain ranges. The pointed tip shows that SA explores some superior solutions during iteration with certain probabilities, appearing as pointed shapes due to small quantities. Initial solution 1 falls into a local optimum that cannot be escaped within the current hyperparameter search range.

Further exploration of the relationship between initial solutions and iteration counts is shown in [Figure 8: see original paper]. Based on objective function variation trends with iteration counts, three categories emerge: (1) Fluctuating-decreasing class: represented by initial solutions 2, 4, 5, showing gradual decrease with fluctuations as iteration count increases, reaching lower objective function values; (2) Fluctuating-stable class: represented by initial solutions 3, 6, 7, 8, 9, showing fluctuations around the initial solution's objective function value as iteration steps increase—these have relatively low initial objective function values but haven't fully converged to lower values due to insufficient total iteration steps; (3) Stable class: represented by initial solutions 1 and 10 (SA solution), showing no fluctuation with increasing iteration steps.

After identifying initial solution characteristics, we further examine the objective function fluctuation patterns of optimal solutions across all iterations. As shown in [Figure 9: see original paper], objective function values alternate between peaks and valleys during iteration, rapidly decreasing from peaks to valleys, then jumping from valleys to peaks after stabilization, exhibiting a "jumping descent" pattern. Overall, valley-corresponding objective function values gradually decrease, demonstrating SA's effectiveness in gradually escaping local optima to find newer, better local optima until final stabilization at a certain objective function value. The traditional greedy algorithm's optimal objective function value is 727.9, while SA's optimal solution reaches 556.8, representing a 23% improvement over the greedy algorithm.

3.5 Comparative Analysis of Models

Comparative analysis of greedy algorithm, SA method, and GSA method reveals their respective objective function value distributions. As shown in Figure 10: see original paper and (b), the horizontal axis represents objective function values, while the vertical axis shows the cumulative proportion of solutions exceeding the horizontal axis value.

As shown in Figure 10: see original paper, from the solution distribution perspective: all GSA solutions distribute in the 600–1200 range, while only 80% of SA solutions distribute in this range. GSA demonstrates superior stability compared to SA.

As shown in Figure 10: see original paper, the traditional greedy algorithm's objective function value is 727.9. Approximately 12% of SA solutions fall below 727.9, while about 5% of GSA solutions achieve this. SA's minimum value is 556.8, 23% lower than the greedy algorithm, while GSA's minimum is 658.2, 10% lower than the greedy algorithm. SA produces better solutions than GSA.

Based on comparative analysis of SA and GSA, we conclude: (1) SA demonstrates good optimization performance under appropriate conditions, with segment layout effects superior to traditional methods in 80% of initial solutions, optimizing the objective function value by 23% compared to traditional methods. (2) SA exhibits initial solution dependency, with different initial solutions categorized into three types based on iteration characteristics: fluctuating-decreasing, fluctuating-stable, and stable. Fluctuating-decreasing solutions are most effective for substantial objective function reduction, comprising approximately 30% of all solutions. (3) This paper proposes the highly interpretable, low initial-dependency GSA method, which optimizes the objective function value by 10% compared to traditional methods. Layout performance ranking: SA > GSA > traditional method. GSA shows more concentrated solution distribution and stronger algorithmic stability. Traditional methods, limited by computational capacity, can only perform local layout before superposition. Our algorithms achieve higher-precision, higher-efficiency global layout in practical applications, with high model stability ensuring consistently high-quality output.

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