Real time dynamic fusion method of transmission and transformation project line and terrain 3D model based on GIM model

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Abstract

INTRODUCTION: To address insufficient accuracy in transmission and transformation project line planning, difficulties in fusing line and terrain 3D models, and limited visualization in complex terrain, this paper investigates a real-time dynamic fusion approach for line–terrain 3D models based on the GIM model, aiming to support refined digital construction and management.
OBJECTIVES: The objective of this paper is to develop a real-time dynamic fusion method that (1)integrates multi-source geographic information into a unified 3D environment base, (2) enables intelligent multi-constraint route planning with automatic optimization and quantitative comparison of alternatives, and (3) supports efficient visualization for digital twin applications throughout the project lifecycle.
METHODS: A multi-source geographic information integrated 3D environment base is constructed, and a multi-constraint intelligent planning algorithm is established to perform automatic path optimization and multi-scheme quantitative evaluation. High-precision terrain is reconstructed by combining laser point cloud data and oblique photography, while a target registration strategy is adopted to unify coordinates between the GIM model and real terrain. A unified data engine together with hierarchical level-of-detail rendering is employed to realize real-time dynamic integration of construction resources, progress information, and 3D scenes.
RESULTS: Case studies demonstrate that the proposed method improves the rationality and economy of route planning, enables effective comparison among multiple planning schemes, significantly reduces ecological impact, and provides efficient real-time visualization and dynamic scene integration in complex terrain environments.
CONCLUSION: The proposed GIM-based real-time dynamic fusion framework enhances planning accuracy, model–terrain alignment, and visualization capability for power transmission and transformation projects, offering a reliable digital twin platform for fine-grained management across the entire project cycle and supporting the digital transformation of the industry.

Keywords: GIM model, Dynamic fusion, Terrain, 3D model, Power transmission and transformation

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1. Introduction

With the continuous expansion of power grid scale and the acceleration of intelligentization, the construction of transmission lines is confronted with mounting challenges, such as diverse geographical environments, scattered data sources, and formidable difficulties in collaborative management [1]. Traditional construction management primarily relies on floor plans and discrete data, which makes it hard to achieve precise path planning under complex landform conditions like mountains and rivers, and also lacks the capability to dynamically track engineering resources and risk factors. Social requirements such as the avoidance of ecological protection zones have imposed higher standards for the refinement and visualization of engineering construction [2]. Meanwhile, conventional transmission line planning and design mostly adopt experience-driven single-objective decision-making models or simplify multi-objective problems through the linear weighting method, which struggle to balance multiple objectives including the shortest line path, the lowest project cost, the minimal ecological impact, and the lowest construction difficulty. In contrast, the international community began exploring the application of swarm intelligence algorithms in power system planning as early as the end of the last century, yet early-stage algorithms still exhibited obvious deficiencies in multi-constraint adaptability [3]. The efficiency and accuracy of multi-objective optimization have been verified in the path planning of ultra-high voltage (UHV) transmission lines. To address the convergence issue of multi-constraint swarm optimization algorithms, foreign scholars proposed the Improved Particle Swarm Optimization (IPSO) algorithm, which enhances the global optimization capability by dynamically adjusting the inertia weight. This algorithm has been successfully applied to the path planning of high-voltage transmission lines in Europe [4].

Recent related research can be categorized into three main streams pertinent to this study: path optimization methods, 3D modeling fusion techniques, and engineering digital twin applications.In path optimization for transmission lines, metaheuristic algorithms have gained prominence. Early applications of Particle Swarm Optimization (PSO) and its variants, such as the Improved PSO (IPSO) for high-voltage line routing in Europe, demonstrated effectiveness in handling complex objectives [3, 4]. However, challenges remain in robustly integrating multiple non-linear constraints (ecological, geological). Regarding 3D modeling and fusion, the integration of multi-source data like oblique photogrammetry (providing texture) and LiDAR point clouds (providing precise geometry) is crucial. Techniques such as high-precision artificial target matching have been developed to overcome accuracy bottlenecks in fusing these datasets, with advanced targets (e.g., QR-code based) improving registration efficiency significantly [5]. In the domain of engineering digital twin and visualization, handling massive TB-level data for large-scale projects is a key challenge. Level of Detail (LOD) technology combined with edge computing has been applied in professional platforms to achieve real-time rendering of massive point clouds with low latency [6]. Despite these advances, a seamless framework that integrates dynamic multi-constraint path optimization, high-precision model-terrain fusion ensuring coordinate unity, and real-time visualization of construction processes within a unified digital twin platform for transmission projects remains an open area. This study aims to address this gap.

Real-time dynamic fusion method for 3D models of transmission and transformation engineering lines and terrain is proposed in the study. Unlike static integration in conventional 3D GIS or BIM-GIS approaches, our "dynamic" characteristic emphasizes real-time data ingestion, processing, and visualization. This involves continuous streams of construction resource locations (via GPS/BDS), equipment status (via IoT sensors), and progress updates (4D-BIM), which must be seamlessly fused with the high-fidelity GIM-terrain base model without compromising rendering performance. This poses unique challenges in data synchronization, low-latency rendering, and adaptive scene management, forming the innovative foundation of this work.

2. Intelligent Planning and Optimization of Transmission and Substation Line Projects Based on GIM Model

In the designing phase, the selection of line routes is a key factor determining the success and economical efficiency of the project. However, traditional 2D planning methods have difficulties in performing global quantitative trade-offs when facing complex terrains, ecologically sensitive areas, and various engineering constraints. To address this issue, an intelligent planning and optimization system is constructed based on the GIM model, deeply integrating high-precision 3D terrain data, with the aim of achieving multi-objective automatic optimization of line routes.

The selection of these specific indicators is directly driven by key practical considerations in power transmission project decision-making. Line length (L) is the primary driver of material cost (conductors, towers) and long-term electrical losses. Average slope (G) critically impacts construction safety and cost; steeper slopes increase difficulty for tower foundation construction, material transportation, and later maintenance access. The area crossing ecological sensitive zones (E) directly relates to environmental protection requirements, permitting risks, and potential ecological compensation costs. Geological construction difficulty (D) synthesizes factors like soil stability and rock type, affecting foundation design complexity, excavation costs, and long-term structural reliability. Therefore, the constructed cost function encapsulates the core economic, safety, environmental, and technical challenges of line planning.

The core of route planning lies in constructing a multi-objective cost function that comprehensively reflects economic costs, construction difficulties, and ecological impacts. Considering that traditional shortest path algorithms can no longer meet engineering practical needs, an improved multi-constrained ant colony optimization algorithm is introduced, and the following comprehensive path cost function is constructed:

$$F = \omega_1 \cdot L + \omega_2 \cdot G + \omega_3 \cdot E + \omega_4 \cdot D \qquad (1)$$

The description of the variables in Equation (1) is shown in Table 1.

Table 1. Description of variables in Equation (1)

Symbol	Description
F	Comprehensive life cycle cost of the route
L	Total length of the route
G	Average slope along the route
E	Cumulative area of ecologically sensitive zones traversed by the route
D	Comprehensive evaluation score of geological construction difficulty
ω1, ω2, ω3, ω4	Weight coefficients for length, slope, ecological impact, and difficulty, respectively

Among these, F represents the comprehensive life cycle cost of the route. L represents the total length of the route. G represents the average slope along the route. E represents the cumulative area of ecologically sensitive zones traversed by the route. D represents the comprehensive evaluation score of geological construction difficulty of the route. ω_1, ω_2, ω_3 and ω_4 represent the weight coefficients of each indicator. These are set to 0.40, 0.25, 0.20, and 0.15 respectively according to engineering priorities. This function can guide the algorithm to automatically avoid areas with steep slopes, high ecological value, and poor geological conditions.

To effectively solve the optimization problem defined by Eq. (1), key improvements are made to the traditional ant colony algorithm, primarily focusing on adaptive constraint handling and pheromone updating. The core challenge lies in integrating nonlinear constraints, such as ecological sensitivity and geological difficulty, into the pathfinding process. This is achieved by modifying the state transition probability. The probability P_{ij}^k for an ant k to move from node i to node j is now defined as:

$$P_{ij}^k = \frac{\left[\tau_{ij}\right]^\alpha \cdot \left[\eta_{ij}\right]^\beta \cdot \left[\Pi_c \Phi_{ij}^{(c)}\right]^{\gamma_c}}{\sum_{l \in \text{allowed}_k} \left[\tau_{il}\right]^\alpha \cdot \left[\eta_{il}\right]^\beta \cdot \left[\Pi_c \Phi_{il}^{(c)}\right]^{\gamma_c}} \qquad (2)$$

Where τ_{ij} is the pheromone intensity on edge (i, j), η_{ij} is the basic heuristic desirability (typically the inverse of distance), and $\Phi_{ij}^{(c)}$ is a constraint penalty factor for constraint type c (e.g., c ∈ {slope, ecology, geology}). This factor is derived from the corresponding normalized cost components in Eq. (1). The exponent γ_c allows for fine-tuning the influence strength of each constraint type. For example, a higher $\gamma_{ecology}$ will strongly penalize moves into ecologically sensitive areas. Furthermore, the global pheromone update rule is enhanced. The amount of pheromone deposited, $\Delta\tau_{ij}$, is now proportional to the inverse of the comprehensive cost F from Eq. (1) of the paths constructed by the ants, rather than just their length. This direct feedback mechanism reinforces paths that holistically perform well across all weighted objectives, driving the colony towards solutions that optimally balance economic, construction, and environmental considerations.

Compared to the IPSO algorithm [4] and other metaheuristics, the proposed improved ant colony algorithm exhibits distinct advantages in discrete path planning problems with complex, non-linear constraints.IPSO, operating in continuous space, may require sophisticated encoding/decoding for path representation and can be less efficient in exploiting the topological structure of the problem (e.g., graph nodes and edges). Our algorithm inherently works on a graph, making it more natural for corridor-based route planning. It excels at exploring combinatorial possibilities and uses collective memory (pheromone) to gradually refine solutions, which is particularly effective for balancing multiple, often conflicting, constraints like length, slope, and ecological impact. It is most suitable for scenarios where the solution space is discrete, constraints are numerous and non-homogeneous, and a good feasible path is prioritized over a theoretically exact global optimum in continuous space.

Figure 1 (proposed to be added) illustrates the detailed flowchart of the improved multi-constraint ant colony algorithm.The process begins with environment modeling and parameter initialization. The core loop involves ants constructing paths based on the modified transition probability (considering constraints), evaluating paths using Eq.(1), and updating pheromones globally based on the comprehensive cost. This loop iterates until convergence criteria are met, outputting the optimal path.

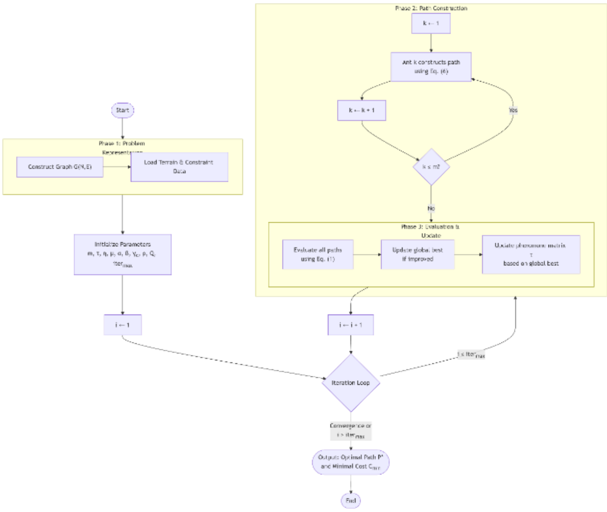

Figure 1. The Detailed Flowchart of the Improved Multi-constraint Ant Colony Optimization Algorithm

During the specific technical implementation phase, the following aspects need to be considered. Firstly, in terms of terrain constraint avoidance, based on DEM data, slope and aspect are automatically calculated. Areas with a slope greater than 20° are identified as high-risk steep slope zones, and a 150m avoidance buffer zone is generated around them.

Secondly, at the level of minimizing ecological impact, overlay vector data of ecological protection areas with a 3D surface model, and use visibility analysis tools to simulate the visual impact from key observation points towards the tower location.

Third, in terms of obstacle crossing optimization, for river crossing points, hydrological analysis data and high-precision laser point cloud models are called upon to accurately calculate the safe distance of the conductor from the ground and water surface[7]. The calculation formula for the safe crossing height is as follows:

$$H_a = H_f + H_g + \square H_r \tag{3}$$

Among these, H_a represents the minimum safe height of the conductor. H_f represents the historical highest flood level, with a safety margin of 1.8m added on this basis. H_g represents the sag value of the conductor under the maximum load condition. $\square H_r$ represents the additional safety margin required by engineering specifications, which is taken as 2.5m here.

3. Terrain 3D Model Reconstruction and Standard Model Registration

To achieve seamless integration between the line GIM model and the actual ground surface, it is necessary to construct a high-precision 3D topographic model and accurately register it with the standard engineering model[8]. There are significant differences between actual terrain measurement data and traditional BIM/GIM models in terms of coordinate systems, scales, and details. If they are directly integrated, it will lead to problems such as model misalignment, floating, or embedding.

The 3D reconstruction of the earth's surface mainly relies on aerial LiDAR and oblique photogrammetry. Aerial LiDAR can actively emit laser pulses to obtain high-precision point clouds in vegetation-covered areas, thereby constructing high-precision DEMs, which is particularly suitable for vegetation-covered regions [9]. Oblique photogrammetry uses multi-view high-definition images and spatial ternary operations to generate realistic 3D scene models, known as Digital Surface Models[10]. To address the above issues, this project aims to fuse the point clouds obtained from the two methods. By using point clouds to obtain an accurate terrain geometric framework and by using oblique photography to acquire realistic surface textures, a high-precision, highly visualizable true terrain 3D model will be realized.

Field point cloud data directly acquired and standard BIM models (such as tower foundations and substation buildings) are typically in different local coordinate systems. Traditional point cloud registration methods based on geometric features (such as the ICP algorithm) tend to fall into local optimal solutions and thus lead to registration failure when dealing with BIM and terrain point clouds with significant structural differences and sparse feature points [11]. To address this challenge, a precise registration method based on artificial targets is proposed[12]. This method involves pre-placing physical targets with specific geometric shapes (such as spherical or planar targets) in the area to be registered (such as substation sites or important tower locations) during the engineering field survey phase. These targets can be clearly identified in photogrammetry or laser scanning, and their geometric centers or feature points have extremely high coordinate accuracy in the point cloud data.

Suppose there are two point cloud sets to be registered: one representing the real terrain point cloud, and the other representing the standard GIM/BIM model point cloud. When at least three non-collinear corresponding target points can be identified in both point clouds, the optimal transformation matrix from the model coordinate system to the real coordinate system can be solved through spatial similarity transformation [13]. This transformation relationship can be expressed by the following mathematical model:

$$[X, Y, Z]^T = \lambda \cdot R(\alpha, \beta, \gamma) \cdot [X_o, Y_o, Z_o]^T + T \tag{4}$$

Among these, $[X, Y, Z]^T$ represents the coordinates of the point in the real-world coordinate system. $[X_o, Y_o, Z_o]^T$ represents the coordinate quantity of the corresponding point in the standard GIM model coordinate system[14]. λ represents the scale scaling factor, used to compensate for possible minor scale differences between the two sets of data.

$R(\alpha,\beta,\gamma)$ represents a 3x3 rotation matrix, which is composed of rotation angles around the X, Y, and Z coordinate axes, where α is the yaw angle, β is the pitch angle, and γ is the roll angle.

By solving for the transformation parameters using the least squares method, the entire GIM model can be accurately positioned in the real 3D terrain scene. The accuracy level achievable with this artificial target-based registration method is of high practical importance. In engineering applications under typical conditions (using high-precision LiDAR/Photogrammetry data and well-designed targets), this method can achieve registration accuracy at the centimeter level (e.g., 2-5 cm RMSE for target point residuals). This level of precision meets or exceeds the requirements for most transmission line design and construction tasks, such as tower positioning, clearance analysis, and earthwork calculation. For instance, centimeter-level alignment ensures that the designed tower foundation correctly intersects the terrain model for accurate excavation volume estimation, and that conductor sag simulation relative to ground features is reliable. Thus, the method provides a solid foundation for the subsequent dynamic fusion and quantitative analysis.

Regarding economic feasibility and accuracy consistency for large-scale projects, a strategic target deployment scheme is crucial. Deploying a dense network of high-precision targets along hundreds of kilometers is indeed costly. Therefore, our method employs a sparse but strategic placement: targets are concentrated at key registration areas such as substation sites, major tower locations, and terrain feature transition zones (e.g., hilltop, valley). For long, homogeneous corridor stretches, target spacing can be increased (e.g., 1-2 km), relying on the high inherent accuracy of LiDAR/Photogrammetry and the initial geo-referencing of the data blocks. The transformation parameters solved from the target pairs at key areas are then applied to the entire corresponding data block. To ensure registration accuracy consistency in non-target areas, we perform interpolation checks using natural features (e.g., distinct rock outcrops, building corners) that are identifiable in both the point cloud and the GIM model. The impact of target deployment strategy on global registration error is mitigated by 1) ensuring targets form strong geometric configuration (non-collinear, well-distributed in 3D), 2) using robust estimation (e.g., RANSAC) during parameter solving to reject outlier target matches, and 3) conducting segmented registration for very long lines, treating each segment with its own local target set and then aligning segments via overlapping areas.

4. Real-time Dynamic Fusion and Visual Scene Rendering

After completing the route intelligent planning and model precise registration, achieving real-time dynamic fusion and efficient visualization of GIM models and terrain 3D models is the core of building a digital twin construction platform. The key challenge lies in handling asynchronous, high-frequency data streams from heterogeneous sources (e.g., GPS, IoT, progress plans) and integrating them into a coherent, interactive 3D scene with minimal latency, which goes beyond the static model alignment focus of most existing integration studies.

The key to real-time dynamic fusion lies in establishing a unified data engine. This engine uses the registered 3D scene as a spatial base to integrate and associate data streams from different sources and formats [15].

Using 5G networks, real-time GPS/BDS positioning information of construction machinery is obtained and transmitted to the platform, enabling real-time updates of the equipment's location and status in a 3D scene. The Internet of Things (IoT) sensor network is utilized to monitor material inventory, environmental parameters, and equipment operating conditions in real time. This topic combines project progress planning (4D-BIM) with 3D entities to intuitively display project progress[16]. Ultimately, a fused method integrating 'geometric model - attribute information - time sequence - real-time status' is formed.

Due to the large span of transmission network lines, wide range of scenarios, and complex terrain and landform, combined with the high modeling accuracy of GIM devices and the large amount of data annotation, this places a huge burden on the rendering engine [17]. To achieve smooth and immediate interactive effects, effective scene rendering optimization strategies need to be used [18]. A hierarchical refinement technique is proposed and applied to dynamic scheduling.

The core of the Level of Detail (LOD) technology is to dynamically switch between models with different levels of detail based on the distance between the viewpoint (camera) and the model. The distance calculation formula is as follows:

$$D=\sqrt{(x-x_o)^2+(y-y_o)^2+(z-z_o)^2} \tag{5}$$

Among these, D represents the Euclidean distance between the model center and the viewpoint. (x,y,z) represents the coordinates of the model's center point in the global coordinate system. (x_o,y_o,z_o) represents the coordinates of the current viewpoint.

Directly using distance for level-of-detail switching may cause noticeable jumps at the model edges. To make the transition smoother, a field-of-view-related correction factor is introduced, leading to the final level-of-detail decision formula [19]:

$$L=(1+\sin(\theta))\cdot D \tag{6}$$

Among them, L represents the final distance parameter used for decision-making. θ represents the angle between the viewpoint's line of sight direction and the direction pointing to the model center.

By referencing the $\sin(\theta)$ function, models located at the screen edges will switch to a lower level of detail earlier than central models even if they are at the same distance, thereby concentrating limited rendering resources on the user's visual focal area.

In actual rendering processes, the graphics pipeline automatically selects and loads the appropriate model from a pre-generated set of multi-level detail models based on the value L calculated using formula (6).

5. Case Study Analysis

5.1. Engineering Background

To verify the feasibility and effectiveness of the 'Real-time Dynamic Fusion Method of Transmission and Substation Line and Topography 3D Models Based on the GIM Model' proposed in this paper in actual engineering applications, this study applies it to the planning and design of a typical UHVDC transmission project converter station and outgoing line section for case analysis.

This case takes the Shendu Converter Station (the sending end) and its adjacent transmission lines of a ±800kV UHVDC transmission project as the application object, as shown in Figure 2.

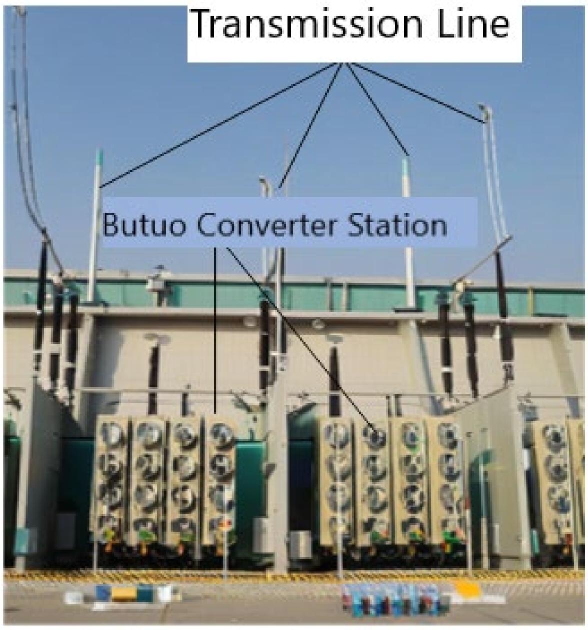

Figure 2. Sending-end Cloth Drag Converter Station and Nearby Transmission Lines

The station is located in a plateau mountainous landform, with the overall terrain sloping from southwest to northeast. The site elevation ranges from 2,420 meters to 2,490 meters, with a relative height difference of approximately 70 meters. The project adopts a 'three-station integration' construction plan, with a planned land area of about 63 hectares. The station site area is subject to multiple constraints such as steep terrain, basic farmland protection zones, ecologically sensitive areas, and complex geological conditions, limiting the usable site to a narrow rectangular area oriented southwest-northeast (approximately 1,150m × 427m).

5.2. Parameter Configuration

In this instance application, to achieve precise integration and intelligent analysis of GIM with the terrain model, systematic parameter configuration was performed on data, algorithms, and the platform. The configuration of core algorithms and model parameters is shown in Table 2.

Table 2. Core Algorithms and Model Parameter Configuration

Parameter Category	Parameter Name	Parameter Value/Format
Data Parameters	DEM resolution	1.5m
	Remote sensing image resolution	0.6m
	Vector data format	SHP
Model Parameters	Model mesh simplification rate	>70%
	Lightweight model Average size	<15 MB
Algorithm Parameters	Ant colony size	80
	Pheromone volatilization factor	0.45

The weight coefficients of the cost function are determined based on the experience of engineering experts and the Analytic Hierarchy Process (AHP), specifically as follows: path length weight ω_1 =0.40, average slope weight ω_2 =0.25, ecological sensitivity area impact weight ω_3 =0.20, and construction difficulty weight ω_4 =0.15.

5.3. Analysis of Fusion Effect

By applying the method proposed in this paper, a high-precision and real-time dynamic fusion of the GIM model of Butuo Converter Station with the surrounding real terrain environment was successfully achieved, and significant results were obtained in site planning and outgoing line path optimization.

The 3D scene obtained through integration intuitively reflects the contradiction between the original topography and the plan layout. The system, through its automatic earthwork calculation module, accurately calculates that the excavation volume at the 49 degree position north and south of the site is 1.85 million m³, and the embankment volume is 1.62 million m³. After earthwork balancing, an additional 0.23 million m³ still needs to be transported out, providing accurate data support for construction organization. On this basis, automatic identification work is carried out for the 3 slopes in the original design with a height exceeding 35m and the 2 unstable slopes, followed by classification and reinforcement design. Figure 3 shows the fusion effect diagram of the station site BIM model and GIS terrain

Figure 3. BIM Model of Site B Integrated with GIS Topography Effect Diagram

In terms of intelligent route path planning, the system automatically generated 3 candidate paths based on a multi-constrained cost function configured in complex mountainous environments. Table 3 presents a comparative analysis of the route path optimization schemes.

Table 3. Comparative Analysis of Line Route Optimization Schemes

Performance indicators	Initial plan	Optimization Plan A	Optimization Plan B	Optimization Plan C
Total Path Length (km)	46.8	44.5	45.2	45.9
Average Slope (°)	14.2	9.8	10.5	11.1
Length of the ecological zone crossed (km)	5.5	1.8	2.9	3.5
Number of tower sites in steep slope areas (>25°)	7	2	3	4
Number of times crossing large ravines	11	8	9	9
Estimated Engineering Cost (10,000 yuan)	2150	1850	1950	2020

From the data in Table 3, it can be seen that Optimized Scheme A performs best on most indicators. To provide a more quantitative basis for selection, a Composite Score (CS) can be calculated for each scheme by normalizing each indicator (where lower values are better for length, slope, ecological length, steep slope towers, ravine crossings, and cost) and applying the weight vector (ω_1 =0.40, ω_2 =0.25, ω_3 =0.20, ω_4 =0.15, with equal 0.05 weight assumed for the last two unweighted indicators for illustration). The normalization can be min-max scaling:

$$I_{\text{norm}} = \left(I_{\max} - I\right) / \left(I_{\max} - I_{\min}\right) \quad (7)$$

A simplified calculation yields CS values of approximately: Initial Plan: 0.47, Plan A: 0.82, Plan B: 0.69, Plan C: 0.60. This quantitative composite score, which integrates all weighted performance indicators, clearly shows Scheme A's superiority (CS=0.82).Therefore, Scheme A is determined as the recommended scheme, as it not only leads in key individual metrics but also achieves the highest overall quantitative evaluation, aligning with the comprehensive consideration of construction safety, operation and maintenance difficulty, and environmental benefits.

From the data in Table 3, it can be seen that Optimized Scheme A performs best on most indicators, in which, it has the shortest path length of 44.5 km, the gentlest average slope of 9.8°, the length through ecologically sensitive areas is significantly reduced to 1.8 km, and the number of tower sites located in steep areas is also reduced from 7 to 2. Although its initial investment cost is not absolutely the lowest, Scheme A is determined as the recommended scheme after comprehensively considering construction

safety, difficulty of later operation and maintenance, and environmental protection benefits. Compared with the initial scheme, Optimized Scheme A achieves the following percentage improvements: total length is reduced by 4.9% (from 46.8 km to 44.5 km), average slope is reduced by 31.0% (from 14.2° to 9.8°), length through ecological sensitive areas is reduced by 67.3% (from 5.5 km to 1.8 km), the number of tower sites in steep slope areas is reduced by 71.4% (from 7 to 2), and the number of large ravine crossings is reduced by 27.3% (from 11 to 8). The estimated engineering cost is also reduced by 14.0%. This quantitative summary clearly highlights the comprehensive advantages of Scheme A. The comparison of route planning schemes based on multi-constraint cost functions is shown in Figure 4.

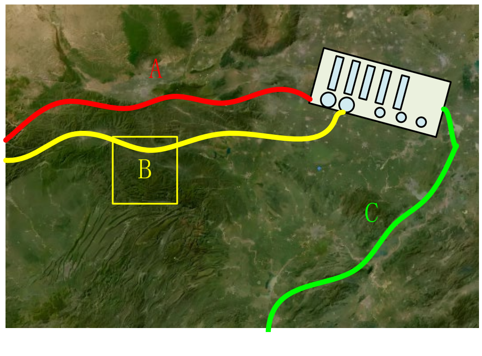

Figure 4. Comparison of Route Planning Schemes Based on Multi-Constraint Cost Function

In terms of real-time dynamic fusion and visualization, the system demonstrates strong interactive analysis capabilities [19-21]. In summary, this instance application, through specific data and charts, proves that the research results of this paper can effectively break through key technical problems in transmission network design under complex terrain environments. It forms a full-process visualized and quantitative auxiliary decision-making system, from macro planning to micro design, thereby improving the scientificity, economy, and environmental friendliness of engineering design.

5.4. Algorithm Comparative Analysis

To further validate the optimization performance and advancement of the proposed improved multi-constraint ant colony algorithm (IMACO), a comparative analysis with two mainstream algorithms was conducted on the same case study: the Traditional Ant Colony Algorithm (TACO) and the Improved Particle Swarm Optimization (IPSO) algorithm referenced in [4]. For fairness, all algorithms were configured to optimize the same comprehensive cost function (Eq.1) with the weights defined in Section 5.2. The TACO used a standard transition rule based only on distance and pheromone, without explicit constraint penalty factors. The IPSO was adapted for discrete path search using a node sequence representation. Each algorithm was run 20 times with different random seeds, and the average results of the best-found solutions are summarized in Table 4.

Table 4. Comparative results of different optimization algorithms.

Algorithm	Avg. Best Cost (Eq.1)	Avg. Length (km)	Algorithm Ecological Length(km)	Success Rate
Proposed IMACO	1852	44.5	1.8	100%
TACO	2105	45.8	3.1	85%
IPSO	1980	45.0	2.5	95%

The results demonstrate that the proposed IMACO achieves the lowest average comprehensive cost, effectively balancing all constraints to find shorter paths with minimal ecological impact. While TACO sometimes converges faster, it has a lower success rate in finding feasible solutions and yields higher costs due to inferior constraint handling. IPSO performs well but is slightly less effective than IMACO in minimizing ecological intrusion. This comparative analysis substantiates the enhanced performance of the proposed algorithm in solving the multi-constraint transmission line path planning problem.

6. Conclusion

This study proposed an integrated framework for transmission line planning and visualization, consisting of three core technical modules: intelligent path optimization, high-precision model registration, and real-time dynamic rendering.

Firstly, for intelligent path optimization, a core model was constructed using a multi-constraint ant colony optimization algorithm. Taking the total path length, average slope, ecological sensitivity, and geological difficulty as key constraints, the model realizes multi-objective automatic optimization and provides a scientific initial scheme.

Secondly, to address high-precision model registration, a method combining artificial target precise registration with the GIM model was proposed. This solves the problem of accurately matching planning schemes with the terrain environment, ensuring the engineering model is correctly positioned within the real 3D context.

Thirdly, regarding real-time dynamic rendering, hierarchical refinement and LOD technologies were adopted to achieve efficient processing and visualization of massive data integrated with real-time streams (e.g., construction resources, progress). This enables smooth, interactive 3D scene rendering crucial for digital twin applications.

To address the problem of precise matching between planning schemes and terrain environments, a real-time dynamic fusion method for 3D models of transmission and transformation engineering lines and terrain is proposed, which combines artificial target precise registration with the GIM (Geographic Information Model). The results of case verification show that this method has good application feasibility. Through the in-depth integration of intelligent planning algorithms and real-time visual rendering technology, the method effectively solves intractable problems in traditional design such as path optimization, ecological avoidance, and accurate engineering quantity control under complex terrain conditions, improving the scientificity and efficiency of planning and design.

Aiming at the problem of massive data processing and visualization efficiency in transmission line planning, hierarchical refinement technology is adopted for hierarchical data processing to achieve dynamic data loading and rendering. Specifically, a multi-precision dataset is constructed based on data importance and distance from the perspective. During the rendering process, different precision datasets are automatically switched according to real-time perspective and interaction requirements. Meanwhile, optimization strategies such as view frustum culling and data block scheduling are integrated to significantly reduce the loading and computation of invalid data. This technology not only markedly reduces hardware resource consumption but also improves the rendering frame rate, interaction fluency, and visualization accuracy of 3D scenes, providing technical support for efficient planning and decision-making in complex engineering scenarios.

It should be objectively acknowledged that this study still has certain limitations. On the one hand, the multi-constraint ant colony optimization algorithm has room for improvement in convergence speed when dealing with ultra-large-scale line planning problems and is prone to falling into local optimal solutions. On the other hand, in the process of 3D model fusion, the adaptation accuracy for extremely complex terrains (such as strong seismic activity zones and large-scale karst landforms) needs further verification, and a unified standard for the adaptive threshold of massive data hierarchical processing has not yet been established. In the future, research can be advanced in three aspects: first, optimize the algorithm structure and introduce hybrid intelligent algorithms (e.g., ant colony-genetic algorithm fusion) to improve optimization efficiency and global optimality; second, strengthen the research and development of extreme terrain adaptation technology, and combine advanced surveying and mapping technologies such as InSAR (Interferometric Synthetic Aperture Radar) and LiDAR (Light Detection and Ranging) to enhance data collection accuracy and model fusion reliability; third, construct an adaptive data processing system, realize dynamic adjustment of data hierarchical thresholds by combining artificial intelligence technology, expand technical application scenarios, and promote the full-process upgrading of transmission and transformation engineering line planning toward intelligence, automation, and refinement.

In the construction of future large-scale transmission and transformation projects, especially projects crossing complex geographical areas, the research presented in this paper provides a forward-looking and practical technical approach, which has positive practical significance for promoting the digital transformation of the industry and achieving the goals of green and low-carbon construction.

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