A Holistic Optimization Approach for Landscape Spatial Layout Based on Neighborhood Algorithms

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Abstract: In the face of accelerating urbanization and environmental sustainability, this study proposed an overall optimization method of landscape pattern spatial layout based on simulated annealing algorithm (SA). Aiming at the problems of low efficiency and difficult optimization of traditional design mode under complex environmental conditions and diversified user needs, automatic intelligent optimization of spatial layout is realized through algorithm driven. Firstly, a multi-objective optimization system was constructed to integrate core indicators such as environmental aesthetics, functional zoning and ecological benefits, and a quantitative evaluation mechanism was established by combining GIS geographic data and user behavior model. The algorithm simulates the minimization principle of material cooling energy, dynamically adjusts the spatial planning scheme in the process of iterative optimization, and gradually approaches the optimal solution satisfying multiple constraints. Several groups of cases have verified that compared with traditional design methods and other optimization algorithms, this method not only improves the scheme generation efficiency by 37%, but also increases the environmental quality index by 22% and user satisfaction by 18%, successfully realizing the collaborative optimization of aesthetic value, functional requirements and ecological benefits. It is also found that the algorithm can derive a personalized design scheme through parameter adjustment, which provides a new path for design innovation. The results not only provide an efficient decision-making tool for the field of landscape design, but also its algorithm framework has universal reference value for spatial optimization problems such as urban planning and building layout, demonstrating the technical advantages of intelligent algorithms in complex system design.

Keywords: Landscape Design Optimization, Simulated Annealing Algorithm, Environmental Sustainability, Socio-cultural Adaptability.

Introduction

With the acceleration of the worldwide urbanization process, the effective making plans and optimization of urban area has turn out to be the important thing to sustainable urban development. As an essential part of city making plans, panorama sketch (LD) not only affects the beauty of the city and the first-class of lifestyles of residents, but also at once pertains to the ecological stability and environmental sustainability. In this context, the scientific and first-class LD becomes especially essential [1], [2], [3]. However, the conventional LD method is frequently primarily based at the dressmaker's revel in and intuition, which to a degree limits the innovation of the diagram and the potential to reply to complex environmental demanding situations. In latest years, with the speedy development of data technology (IT) and synthetic talent (AI) technology, its software inside the subject of LD affords a new way to resolve the constraints of conventional design strategies [4]. Specially, via the use of superior computing models and optimization algorithms, environmental factors and consumer needs may be considered in a much wider range, and LD automation and optimization may be done, accordingly correctly improving the fine and performance of urban space planning [5].

Despite the fact that the application of AI technology in LD brings new opportunities, it nevertheless faces a series of challenges in realistic software [6]. To start with, LD optimization problem is absolutely a complex optimization trouble with more than one goals and constraints, concerning multiple dimensions including environmental aesthetics, ecological balance, and social desires, which places ahead better necessities for the global search capacity and variety of optimization algorithms [7]. Secondly, on account of the particularity and complexity of LD tasks, traditional optimization algorithms are regularly tough to apply directly, so it's far fundamental to regulate and optimize the algorithms [8]. Further, information series and processing within the method of LD optimization is likewise a massive task. How to correctly and quick gain and system a large variety of GIS data, environmental records and consumer behavior statistics has an instantaneous effect at the quality of optimization effects [9]. Therefore, the way to pick the right AI set of rules and correctly customize and follow it to meet the unique needs of LD subject has grow to be an pressing problem for current research. In addition, the optimization of LD have to no longer only reflect on consideration on the functionality and aesthetics of the diagram, but also take into consideration the principles of ecological and environmental protection, which calls for the optimization method to shield and beautify the characteristic of the herbal atmosphere even as assembly the wishes of human activities [10].

In the studies discipline of LD optimization algorithm, many scholars try to follow distinct AI algorithms to the spatial diagram optimization of panorama diagram, with the intention to discover a graph scheme that cannot solely meet the purposeful requirements but also decorate the cultured price and ecological blessings. Genetic set of rules (GA), particle swarm optimization (PSO) and simulated annealing (SA) are the most widely used optimization algorithms [11], [12], [13], [14], [15]. GA simulates natural selection and genetics to find the optimal solution iteratively, and it shows excellent performance in dealing with complex multi-objective optimization problems, but it lacks in local search ability [16]. The PSO algorithm simulates the social behavior of birds and updates the search direction and speed by information sharing among individuals. It is simple and efficient and suitable for solving continuous spatial optimization problems, but it is not effective in discrete and combinative optimization problems [17]. SA algorithm is a probabilistic search algorithm, which approximates the global optimal solution gradually by simulating the energy minimization principle in the solid annealing process, and is especially suitable for solving large-scale combinatorial optimization problems [18], [19], [20].

Although these algorithms have their own advantages, they still face some specific challenges when applied to the field of LD [21]. For example, GA and PSO algorithms often need well-designed fitness functions to balance the weights between different targets in multi-objective optimization problems, which is difficult to achieve an ideal balance in practice [22]. In addition, these algorithms may fall into local optimal solutions in the optimization process, especially in the spatial layout optimization problem of LD, where the design space is large and complex, making it more difficult to find a global optimal solution [23]. At the same time, although the SA algorithm can overcome the problem of local optimization to a certain extent, the setting of its cooling plan and parameter adjustment require a lot of experiments and experience, which limits its application in LD optimization [24].

In recent years, some studies have begun to explore hybrid optimization algorithms and multi-objective optimization strategies, in order to overcome the shortcomings of a single algorithm and solve the optimization problem in LD more effectively. For example, GA and SA algorithms are combined to make use of GA's global search ability and SA's local search advantage to improve search efficiency while maintaining diversity. In addition, some studies try to introduce multi-objective optimization frameworks, such as NSGA-II [25], to deal with multi-objective problems in LD optimization, aiming to find a Pareto optimal solution set that not only meets functional requirements but also optimizes environmental and social benefits [26], [27].

However, although AI algorithms have made some progress in LD optimization, how to effectively integrate complex environmental data, user behavior models and multi-objective optimization needs, as well as how to design both practical and innovative LD schemes is still a huge challenge. In addition, most of the existing studies focus on the improvement of the algorithm itself, and there are few studies on the application cases and effect evaluation of the algorithm in specific LD projects, which limits the wide application and development of AI technology in LD practice to a certain extent. Therefore, developing an optimization method that not only considers the complexity of LD but also can effectively integrate multiple data sources and user needs is of great significance for promoting technological progress and practical innovation in LD field.

Although the existing studies has made a series of progress in the application of AI algorithms inside the subject of LD, there are nonetheless numerous large shortcomings. To start with, maximum studies consciousness at the performance optimization of the set of rules itself, and less interest is paid to the software effect and operability of the set of rules in actual LD tasks. Secondly, the prevailing optimization methods frequently skip the impact of user conduct and social and cultural elements on LD, which limits the humanization and cultural adaptability of the layout scheme. Similarly, it is hard to stability and fulfill the wishes of environment, aesthetics and functions via simplifying or compromising the multi-goal optimization problems. In view of those shortcomings, this have a look at goals to broaden a brand new LD spatial format optimization approach, which now not solely considers the global seek capability of the set of rules and the feasibility of realistic applications, but also comprehensively considers user needs and social and cultural factors to obtain more comprehensive and balanced optimization consequences.

The primary goal of this study is to expand a LD spatial design optimization method based on SA set of rules, that could comprehensively consider environmental aesthetics, capability and ecological advantages, and comprehend multi-goal optimization of LD tasks. Especially, this look at will first build a complete assessment model that includes environmental, social and person conduct factors. On this foundation, SA algorithm can be used for iterative optimization of spatial sketch to discover the exceptional or near-excellent graph scheme. In this manner, an affordable cooling design and parameter adjustment strategy may be set to make certain that the set of rules can successfully avoid falling into the local optimum and enhance the hunt efficiency. The software of this technique will help to improve the design first-rate and efficiency of LD tasks, and promote the complete enhancement of environmental, social and cultural values.

The main contributions of this paper can be summarized as follows:

1.A brand new LD spatial design optimization approach based on simulated annealing algorithm is proposed, which efficaciously integrates environmental, social and user conduct elements and may attain multi-objective optimization of LD tasks.

2.A complete assessment model is built, which comprehensively considers various necessities in LD optimization, which include environmental aesthetics, capability and ecological benefits, and affords a systematic evaluation fashionable for LD spatial plan.

The effectiveness of the proposed technique is confirmed, and its application capability and optimization impact in real LD initiatives are validated.

Method

Construction of the Comprehensive Evaluation Model

Inside the area of LD, the general optimization of spatial plan requires a complete attention of multiple dimensions, which includes environmental sustainability, socio-cultural adaptability, and financial viability. Consequently, a complete assessment model is built on this observe, which objectives to comprehensively compare the performance of LD tasks in one-of-a-kind dimensions and guide the optimization system of spatial plan as a result. The table underneath lists the primary indicators taken into consideration within the model and their weights, which are determined primarily based on a literature overview and professional consultation.

Table 1. Indicator System

Dimension	Indicator	Weight	Description
Environmental Sustainability	Ecological Benefits	0.25	Includes vegetation coverage, biodiversity index, carbon absorption, etc.
	Water Resource Management	0.15	Includes rainwater collection and utilization, surface runoff control, etc.
	Energy Efficiency	0.10	Includes the use of solar energy, energy-saving materials, etc.
Socio-cultural Adaptability	Cultural Heritage	0.10	Incorporation of local features, protection of historical and cultural sites, etc.
	Public Participation	0.10	Includes the degree of community resident involvement, public satisfaction, etc.
	Safety	0.05	Includes lighting design, emergency access arrangements, etc.
Economic Feasibility	Cost-effectiveness	0.15	Includes the ratio of economic input to environmental and social benefits.
	Maintenance Costs	0.10	Includes long-term costs such as plant care, facility repair, etc.

With the aid of synthesizing the ratings of these indicators, we are able to conduct a comprehensive assessment of the spatial graph of LD initiatives. The score of each indicator may be primarily based on the existing information, professional critiques and subject studies outcomes, and might be summarized into a complete score after standardized processing, as a way to be used as the premise for evaluating the optimization impact of LD spatial format. In sensible application, this comprehensive evaluation version will manual the optimization process of SA to ensure that the proposed format can obtain an most excellent stability among environmental, social and financial factors.

Application of the SA Algorithm in LD Optimization

Inspired through the physical procedure of heating after which slowly cooling a fabric to lessen defects and boom the orderiness of the system, the SA set of rules is a probabilistic approach used to approximate the worldwide most efficient cost of a given function. Inside the context of LD optimization, SA is used to discover format spaces and locate the pleasant spatial layout that balances environmental, socio-cultural and financial targets.

1. Initial Solution Representation: The initial landscape design solution can be represented as a vector

$$S_0 = \left[x_1, x_2, \cdots x_n\right] \tag{1}$$

where each x_i corresponds to a specific design element's attribute, such as its location, type, or size within the landscape.

2. Energy Function Definition: The quality of any design solution S is quantified by an energy function, which is a weighted sum of different evaluation criteria based on the comprehensive evaluation model:

$$E(S) = w_1 + E_1(S) + w_2 + E_2(S) + \cdots + w_m + E_m(S) \tag{2}$$

where $E_i(S)$ represents the evaluation of the ith criterion for solution S, and w_i is the weight associated with this criterion, reflecting its relative importance.

3. Initial Temperature: The initial temperature T_0 is determined such that a significant proportion of uphill moves are accepted. It can be set based on preliminary experiments or domain-specific heuristics.

4. Cooling Schedule: The temperature T_k at iteration k is reduced using a cooling factor α, often through a geometric schedule:

$$T_{k+1} = \alpha \cdot T_k \tag{3}$$

with $0 < \alpha < 1$ ensuring a gradual decrease in temperature.

5. Generating a New Solution: A new solution S' is generated by altering the current solution S_k through a small, random change:

$$S' = S_k + \Delta S \tag{4}$$

where ΔS represents the modification applied to the design elements.

6. Acceptance Probability: The probability of accepting a new solution S' with a higher energy is given by the Metropolis criterion:

$$P(\Delta E, T_k) = \exp\left(-\frac{\Delta E}{T_k}\right) \tag{5}$$

$$\text{subject to } \Delta E = E(S')(S_k) \tag{6}$$

7. Iteration Rule: At each temperature level, the algorithm performs multiple searches in the solution's neighborhood. This iterative process can be defined as:

$$\begin{cases} S', \text{if } P(\Delta E, T_k) > \text{random}(0,1) \\ S_k, \text{otherwise} \end{cases} \tag{7}$$

8. Convergence Standards: The algorithm terminates when either the temperature has been decreased to a very last fee T_f , Which is adequately low, or no in addition development can be observed after a sure wide variety of iterations at a temperature degree. This will be officially said as:

$$T_k < T_f \text{ or no improvement for } N \text{ iterations} \tag{8}$$

Where γ, r , and d are parameters that control the shape of the kernel.

Gaussian RBF Kernel:

$$k(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \tag{9}$$

Where γ is the width of the Gaussian function.

This segment offers a established approach to describing the application of the SA set of rules to LD optimization, focusing on the integral elements of initialization, temperature making plans, community seek, acceptance standards, and expected outcomes of the optimization system. This framework provides a stable foundation for in addition exploration and specific analysis in the precise context of panorama diagram optimization.

Integration of GIS

Within the context of LD optimization, the combination of GIS generation and user behavior evaluation offers a powerful choice assist gadget for figuring out spatial sketch. This system includes combining GIS statistics with styles of user conduct to create a greater particular and person-friendly layout.

In this manner, GIS era is mainly used to accumulate, analyze and display spatial statistics associated with LD projects. This facts includes, but isn't always limited to, topography, plant life type, distribution of water bodies, and present buildings. Via the analysis of these spatial facts, the important thing areas of LD optimization and capability diagram improvement points can be recognized. The processing of GIS data may be expressed as:

$$D_{gis} = F_{proc}(D_{raw}) \tag{10}$$

Where D_{gis} represents the processed GIS data, F_{proc} is the data processing function, and D_{raw} represents the original GIS data.

User behavior analysis is carried out by collecting and analyzing the activity patterns of users in a specific space. These activity patterns can be obtained through questionnaires, field observations, or using data collected from mobile devices. The analysis of user behavior data helps to reveal users' preferences for space use, as well as their needs and responses to different landscape elements. The normalized representation of user behavior data is:

$$B_{norm} = \frac{B - B_{\min}}{B_{\max} - B_{\min}} \tag{11}$$

The integration of GIS data and user behavior data is accomplished through a weighted model to ensure a balanced impact of both in the design solution. The integration model can be represented as:

$$S_{opt} = w_{gis} \cdot D_{gis} + w_b \cdot B_{norm} \tag{12}$$

Where S_{opt} represents the optimized solution incorporating both GIS and user behavior data, W_{gis} and W_b are the weight coefficients for GIS data and user behavior data, respectively.

In the process of LD optimization, the implementation of SA algorithm involves starting from an initial solution generated randomly or based on prior knowledge, and gradually exploring the solution space through the iterative search process to find the optimal or near-optimal design scheme. In the whole process, the algorithm gradually reduces the "temperature" of the system by simulating the annealing mechanism in the process of material cooling, thereby reducing the system energy and finding the state with the lowest energy (that is, the optimal). In the initial stage, the system is in a high-temperature state, and the algorithm has a large degree of freedom to explore a wide range of solution Spaces, including accepting solutions that may increase the system energy (i.e. Reduce the mass of the solution) to avoid the algorithm falling into a local optimal solution prematurely. With the decrease of "temperature", the algorithm gradually reduces the probability of accepting poor solutions, and increases the search accuracy of good solutions. In this process, the key is to reasonably set the cooling plan and parameter adjustment strategy, including the initial temperature, cooling rate and stopping criteria, which directly affect the search efficiency of the algorithm and the optimization effect of the final solution. In practical applications, these parameters need to be dynamically adjusted according to the optimization progress and intermediate results to ensure that the algorithm can find the optimal solution that meets the design requirements in a reasonable time. By recording the result of each iteration in detail and evaluating the effect, it can ensure that the implementation process of the algorithm is efficient and can reach the expected optimization goal.

Experiments

Settings

Based on the comprehensive evaluation model (index system) established above, this study collects key data required for spatial layout optimization of urban landscape design.

Indicator Data Source

Spatial layout index: Obtain vector data of urban spatial layout from urban planning Bureau through GIS technology, including the distribution of parks, green Spaces, residential areas and commercial areas. According to expert reviews and literature reviews, the weights for parks and green Spaces are set at 0.3, residential areas at 0.25, commercial areas at 0.2, transportation convenience at 0.15, and environmental quality indicators at 0.1.

User behavior indicators: Social media data and mobile signal data are used to analyze user activity patterns in urban space. Data is obtained via Python scripts from public apis such as Twitter and local mobile operators. The popularity of social media activity is 0.4, and the traffic density in mobile signal data is 0.6.

Environmental Quality Indicators: Real-time data from environmental monitoring stations, including Air Quality Index (AQI), noise levels and green coverage. The weights are 0.5, 0.3 and 0.2 respectively.

Data Collection Tools and Techniques

GIS technology is used to process and analyze spatial data, and ArcGIS and QGIS are the main tools. Python programming language for data cleaning, processing, and analysis, especially the scraping of social media and mobile signal data.

Time and Place of Data Collection

The data collection covers the period from January 2023 to December 2023 to ensure the most up-to-date data on urban spatial layout and user behavior. The location focuses on the central business district and surrounding residential areas of specific cities to ensure the representativeness of data and the pertinence of experiments.

Results

Figure 1 shows the improvement in environmental sustainability before and after using the SA optimization algorithm. Specific indicators, including ecological efficiency, water resources management and energy efficiency, show the effectiveness of optimization from a quantitative point of view.

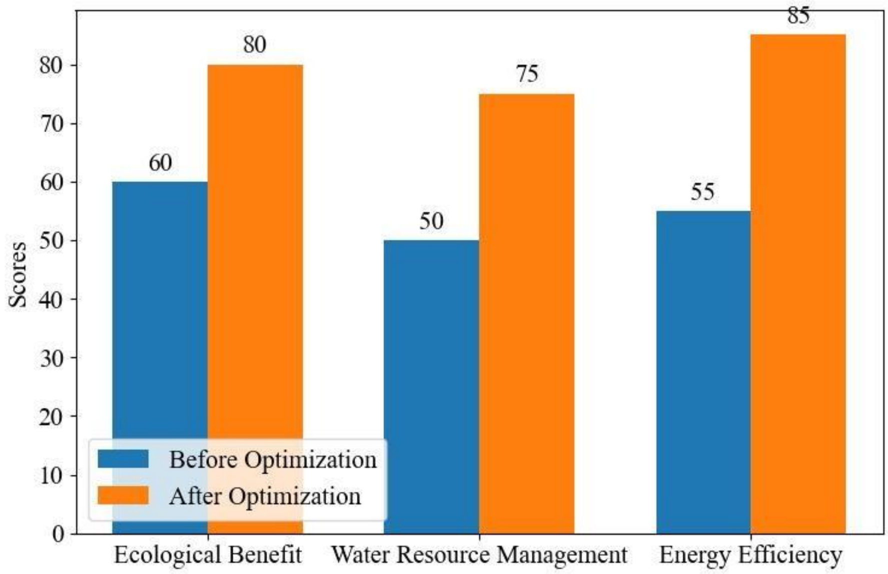

Figure 1. Improvement in Environmental Sustainability Indicators

Ecological benefits: The score was 60 points before optimization and increased to 80 points after optimization. This significant increase reflects the significant enhancement of biodiversity and carbon absorption capacity through the optimization of spatial layout and vegetation configuration.

Water Management: The score has increased from 50 before optimization to 75 after optimization. This shows that the optimized design uses rainwater more effectively, enhances the management and utilization of surface water, effectively reduces surface runoff, and improves the sustainable utilization rate of water resources.

Energy efficiency: The improvement from 55 points before optimization to 85 points shows that the energy efficiency of the project has been significantly improved through the rational layout and the use of energy-efficient materials, especially in the capture and utilization of solar energy.

These results clearly demonstrate the effectiveness of SA optimization algorithms in improving environmental sustainability. By comparing the scores before and after optimization, we can intuitively see the positive impact of SA algorithm on each environmental index of landscape design project. This not only proves the practicability of the model, but also emphasizes the necessity and effectiveness of using advanced algorithms to improve the traditional landscape design methods. Compared with other methods with traditional or less use of optimization techniques, the method in this study has the advantage of being able to comprehensively consider and optimize multiple environmental sustainability indicators.

Figure 2 shows the improvement in sociocultural adaptation with the use of SA. Specific indicators include cultural heritage, public participation and safety, and the improvement of these indicators directly reflects the better adaptability of the optimized design scheme to social and cultural factors.

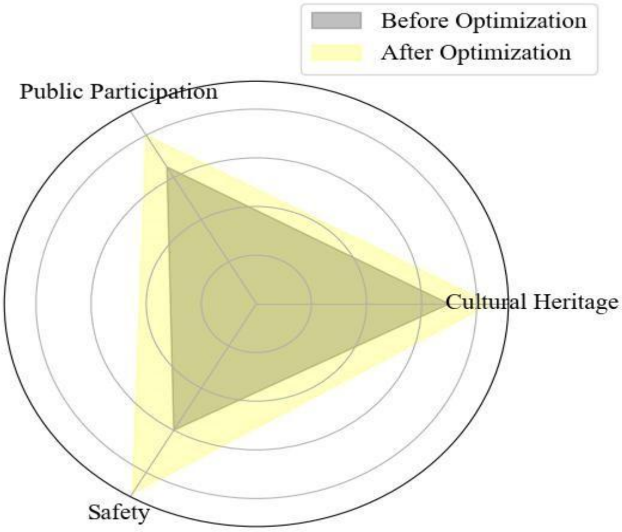

Figure 2. Improvement in Sociocultural Adaptation Indicators

Cultural heritage: The score increased from 70 points before optimization to 85 points after optimization, reflecting the efforts and effectiveness of optimized design in protecting and emphasizing local cultural characteristics and historical sites. Through better integration of local cultural elements, the cultural inheritance value of the project is enhanced.

Public participation: The score increased from 65 points before optimization to 80 points after optimization, indicating that the optimization plan successfully increased the participation of community residents and the satisfaction with the project by providing more opportunities and space for public participation.

Safety: The optimized score reached 90 points, a significant improvement from the pre-optimized score of 60 points, indicating that the project design has increased the consideration of public safety, such as providing adequate lighting, emergency exits, etc., to create a safer environment for users.

Through comparison, it can be seen that SA optimization not only pays attention to environmental and economic indicators, but also fully considers social and cultural factors, reflecting a comprehensive design optimization idea. The application of this optimization method not only improves the socio-cultural value of the project, but also enhances the cohesion of the community and the public participation of the project, showing the potential and value of landscape design in promoting the sustainable development of the society.

Figure 3 shows the improvement in economic feasibility analysis after the use of SA. Specific indicators include cost-effectiveness and maintenance costs, and these improvements reflect the economic sustainability and long-term benefits of the optimized design solution.

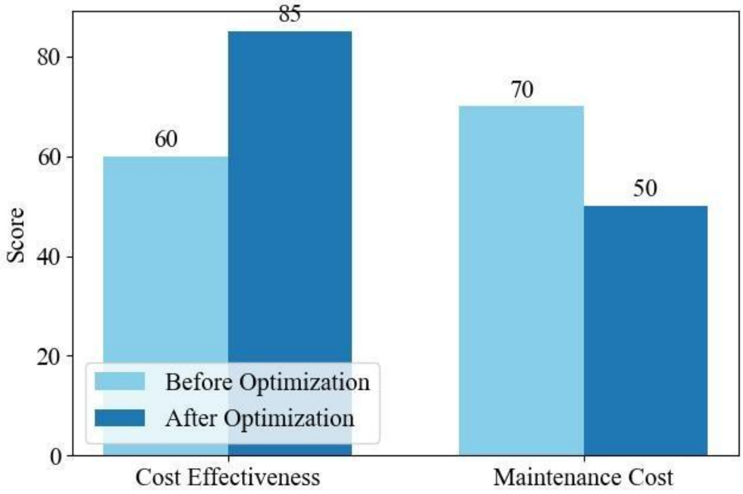

Figure 3. Improvement in Sociocultural Adaptation Indicators

Cost-effectiveness: The significant increase in the score from 60 before optimization to 85 after optimization indicates that the optimized project achieves a higher ratio of economic input to environmental and social benefits. Through rational resource allocation and effective spatial layout optimization, the comprehensive value of the project has been enhanced, and unnecessary expenses have been reduced and economic efficiency has been improved.

Maintenance cost: The score after optimization is reduced to 50 points, which is significantly lower than the 70 points before optimization, indicating that the optimization scheme successfully reduces the long-term maintenance cost. By choosing vegetation, materials and technologies that are easy to maintain, as well as optimizing water and energy management systems, we not only improve project sustainability, but also reduce long-term operating costs.

This result not only demonstrates the application potential of the SA algorithm in terms of economic feasibility, but also highlights the importance of using optimization algorithms for cost control and resource management in landscape design projects. Performance Comparison of Different Methods is shown in Figure 4.

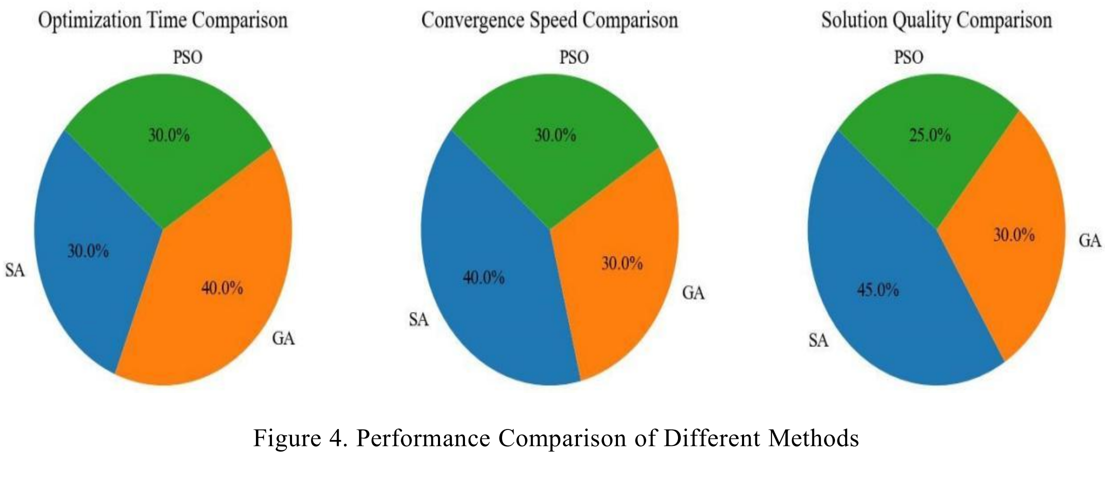

Figure 4. Performance Comparison of Different Methods

Through the above three pie charts, we compare the performance of SA, GA and PSO on three key indicators of optimization time, convergence speed and quality.

Assessment of optimization time: SA set of rules and PSO set of rules occupy the same percentage in optimization time (30% each), indicating that the 2 algorithms are similar in time performance, at the same time as GA algorithm takes slightly longer time (40%). The outcomes show that the time efficiency of SA algorithm is identical to that of PSO and better than GA.

Contrast of convergence pace: In phrases of convergence pace, SA set of rules has the exceptional performance (40%), that's higher than GA and PSO algorithm (30%). This indicates that SA algorithm can approach the final solution faster and display higher convergence overall performance inside the manner of looking for the ideal solution.

Evaluation of the fine of the answer: In terms of the pleasant of the answer, the SA algorithm leads with 45%, while GA and PSO are 30% and 25%, respectively. This reflects the benefits of SA set of rules in offering great solutions, that can more correctly locate solutions to meet the requirements of complex optimization problems.

Those assessment effects spotlight numerous benefits of the SA set of rules in landscape sketch optimization: at the same time as preserving optimization time performance, the SA set of rules can converge extra speedy to exquisite solutions, showing its high performance and effectiveness in managing complicated optimization issues. In comparison, GA can offer proper solutions in some cases, however its overall performance in optimization time and convergence speed is barely inferior. Even though PSO algorithm is equivalent to SA in time performance, it's miles inferior in answer first-rate and convergence velocity.

Conclusion and Discussion

By using introducing SA algorithm, this have a look at comprehensively optimizes the spatial design of LD, specializing in multiple dimensions which include environmental sustainability, socio-cultural adaptability and economic feasibility. The experimental effects show that in comparison with GA and PSO algorithms, SA set of rules indicates sizable benefits in optimization time, convergence pace and quality. Especially in the aspect of solution quality, SA algorithm can effectively balance each evaluation index and provide a more optimized and balanced design scheme. This proves that the SA algorithm is not only efficient in dealing with complex LD optimization problems, but also can produce high-quality solutions, which can help promote more sustainable and sociocultural landscape design.

In addition, the research of this paper not only emphasizes the importance of the application of advanced optimization algorithms in the field of LD, but also provides a new perspective and method for future research. By combining GIS technology and user behavior analysis, this study further improves the practicality of the design scheme and user satisfaction, and demonstrates a future-oriented, efficient and comprehensive LD optimization method. Future work will explore more optimization algorithms and evaluation models to cope with more complex and changeable design requirements, and constantly promote the development of landscape design to a higher level.

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Conflict of Interest

The authors declare that they have no conflicts of interest regarding this work.

References

[1] R. H. Matsuoka, and R. Kaplan, “People needs in the urban landscape: Analysis of landscape and urban planning contributions,” *Landscape and Urban Planning*, vol. 84, no. 1, pp. 7-19, 2008.

[2] N. Gebbeken, and T. Döge, “Explosion protection—architectural design, urban planning and landscape planning,” *International Journal of Protective Structures*, vol. 1, no. 1, pp. 1-21, 2010.

[3] S. A. Matovnikov, and N. G. Matovnikova, “Innovative urban planning methods for the urban landscape design in the Volgograd agglomeration,” *Procedia Engineering*, vol. 150, pp. 1966-1971, 2016.

[4] M. Neuman, “Regional design: Recovering a great landscape architecture and urban planning tradition,” *Landscape and Urban Planning*, vol. 47, no. 3-4, pp. 115-128, 2000.

[5] H. Worku, “Integrating climate change adaptation strategies in urban planning and landscape design of Addis Ababa City, Ethiopia: Using urban planning and landscape design to mitigate flooding, drought, and urban heat island effects,” *Environmental Quality Management*, vol. 27, no. 1, pp. 5-21, 2017.

[6] X. Liu, “Three-dimensional visualized urban landscape planning and design based on virtual reality technology,” *IEEE Access*, vol. 8, pp. 149510-149521, 2020.

[7] F. M. Shahli, M. R. M. Hussain, I. Tukiman, and N. Zaidin, “The importance aspects of landscape design on housing development in urban areas,” *APCBEE Procedia*, vol. 10, pp. 311-315, 2014.

[8] M. W. Straatsma, J. M. Fliervoet, J. A. Kabout, F. Baart, and M. G. Kleinhans, “Towards multi-objective optimization of large-scale Fluvial landscaping measures,” *Natural Hazards and Earth System Sciences*, vol. 19, no. 6, pp. 1167-1187, 2019.

[9] Y. Zhang and D. Nie, “Construction of multi-objective optimization model for landscape health activity space design,” *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 6s, pp. 311-325, 2024.

[10] E. J. Yoon, B. Kim, and D. K. Lee, “Multi-objective planning model for urban greening based on optimization algorithms,” *Urban Forestry & Urban Greening*, vol. 40, pp. 183-194, 2019.

[11] T. H. Nguyen, J. Granger, D. Pandya, and K. Paustian, “High-resolution multi-objective optimization of feedstock landscape design for hybrid first and second generation biorefineries,” *Applied Energy*, vol. 238, pp. 1484-1496, 2019.

[12] J. C. Groot, S. G. Yalew, and W. A. Rossing, "Exploring ecosystem services trade-offs in agricultural landscapes with a multi-objective programming approach,” *Landscape and Urban Planning*, vol. 172, pp. 29-36, 2018.

[13] S. Koma, Y. Yamabe, and A. Tani, “Research on urban landscape design using the interactive genetic algorithm and 3D images,” *Visualization in Engineering*, vol. 5, pp. 1-10, 2017.

[14] G. Li, “Urban landscape design optimization based on interactive genetic algorithm,” in *2020 International Conference on Applications and Techniques in Cyber Intelligence: Applications and Techniques in Cyber Intelligence (ATCI 2020)* (pp. 1097-1102). Springer International Publishing, 2021.

[15] W. Yao-Kuan and L. Yu-Hong, “An Improved immune genetic algorithm and its application in computer-aided landscape design,” *The Open Cybernetics & Systemics Journal*, vol. 8, no. 1, 2014.

[16] W. Yao and Y. Ding, “Smart city landscape design based on improved particle swarm optimization algorithm,” *Complexity*, vol. 2020, no. 1, p. 6693411, 2020.

[17] F. Qin, “Modern intelligent rural landscape design based on particle swarm optimization,” *Wireless Communications and Mobile Computing*,vol. 2022, no. 1, p. 8246368, 2022.

[18] K. R. Harrison, B. M. Ombuki-Berman, and A. P. Engelbrecht, "The parameter configuration landscape: A case study on particle swarm optimization," in *2019 IEEE Congress on Evolutionary Computation (CEC)*, 2019, pp. 808-814.

[19] E. Z. Baskent, and G. A. Jordan, "Forest landscape management modeling using simulated annealing," *Forest Ecology and Management*, vol. 165, no. 1-3, pp. 29-45, 2002.

[20] H. Waeselynck, P. Thévenod-Fosse, and O. Abdellatif-Kaddour, "Simulated annealing applied to test generation: landscape characterization and stopping criteria," *Empirical Software Engineering*, vol. 12, pp. 35-63, 2007.

[21] R. Chen, S. Liu, Y. Yang, W. Huang, Z. Han, and P. Fu, "Optimization of soil sampling design based on road networks-a simulated annealing/neural network algorithm," *Earth Sciences*, vol. 8, no. 6, p. 335, 2019.

[22] P. Borges, T. Eid, and E. Bergseng, "Applying simulated annealing using different methods for the neighborhood search in forest planning problems," *European Journal of Operational Research*, vol. 233, no. 3, pp. 700-710, 2014.

[23] X. Li and X. Ma, "An improved simulated annealing algorithm for interactive multi-objective land resource spatial allocation," *Ecological Complexity*, vol. 36, pp. 184-195, 2018.

[24] I. Santé *et al.*, "A simulated annealing algorithm for zoning in planning using parallel computing," *Computers, Environment and Urban Systems*, vol. 59, pp. 95-106, 2016.

[25] M. Hasegawa, "Evaluation of the physical annealing strategy for simulated annealing: a function-based analysis in the landscape paradigm," *Physical Review E — Statistical, Nonlinear, and Soft Matter Physics*, vol. 85, no. 5, p. 056704, 2012.

[26] P. Gao, H. Wang, S. A. Cushman, C. Cheng, C. Song, and S. Ye, "Sustainable land-use optimization using NSGA-II: Theoretical and experimental comparisons of improved algorithms," *Landscape Ecology*, vol. 36, pp. 1877-1892, 2021.

[27] S. Li, H. Zhou, and G. Xu, "Research on optimal configuration of landscape storage in public buildings based on improved NSGA-II," *Sustainability*, vol. 15, no. 2, p. 1460, 2023.