RESEARCH ARTICLE

Optimal strategy for landscape plant configuration by hybrid genetic algorithm

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As urbanization accelerates and the concept of ecological civilization gains prominence, landscape design has evolved from a singular focus on visual aesthetics to addressing the integrated demands of ecological performance, functionality, and artistry. However, traditional design methods remain limited by high subjectivity, low efficiency, and a lack of quantitative evaluation. This study proposed a plant configuration optimization strategy that integrated artificial neural network (ANN) with genetic algorithm (GA) to improve the scientific rigor and efficiency of landscape design. An ANN model was developed to predict the adaptability of various plant combinations to specific environmental conditions by integrating a GA, in which plant configuration schemes were encoded, fitness functions were formulated, and genetic operations were applied to iteratively refine solutions. The ANN rapidly evaluated the fitness of newly generated individuals, significantly enhancing computational efficiency, while the GA performed a global search for optimal configurations. The approach was validated in two representative landscape environments with type A characterized by large open spaces and type B defined by compact, densely structured areas. Results demonstrated that the ANN–GA model could adaptively adjust plant configurations to site-specific conditions. In type A landscapes, ground cover plants constituted 10.5% of the total area with five species, whereas in type B landscapes, the proportion increased to 20.4% with twelve species. Compared with differential evolution and multi-objective evolutionary algorithms, the ANN–GA model achieved higher composite scores in ecological, economic, and social benefits, excelling particularly in balancing spatial utilization with aesthetic layering. The integrated ANN–GA optimization strategy effectively balanced ecological benefits with aesthetic value, while markedly improving the scientific basis and efficiency of landscape design.

Keywords: hybrid genetic algorithm; landscape design; plant configuration; optimization strategy; artificial neural network.

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Introduction

With the rapid pace of urbanization and the growing emphasis on ecological civilization, landscape design has shifted from an exclusive focus on visual aesthetics to a more integrated approach that balances ecological benefits, functionality, and artistic expression. As a core component of landscape design, plant configuration directly influences the ecological stability, spatial hierarchy, and cultural expression of a site through its scientific rationale and design logic [1]. However, conventional design methods rely heavily on the designer's personal experience, which tends to be subjective, inefficient, and difficult to quantify [2]. When confronted with complex site conditions such as variations in terrain, light distribution, and interspecific competition, experience-based approaches often result in plant communities with poor adaptability, high maintenance requirements, and even ecological imbalance [3].

In recent years, intelligent algorithms have introduced new opportunities for optimizing plant configuration in landscape design. Genetic algorithm (GA) that simulates biological evolution can efficiently search for global optima in multi-objective optimization problems and has been applied successfully to optimize architectural forms and spatial layouts [4]. Neural network technology, in contrast, establishes nonlinear mapping relationships between input parameters and design outputs, greatly reducing computational complexity [5]. Additionally, artificial intelligence (AI)-driven frameworks for landscape design are becoming increasingly sophisticated with integrated algorithmic systems emerging that combine plant growth simulation, environmental factor analysis, and aesthetic evaluation. These innovations offer strong theoretical support for the intelligent and precise configuration of plant species [6]. Nevertheless, fully integrating algorithmic advantages with the dual ecological and artistic objectives of landscape design remains a challenge with three core issues. Technically, GA must conduct daylight simulations and ecological benefit assessments for each evolutionary individual, leading to exponential growth in computational demands. In addition, quantifying plant competition still relies on empirical formulas, which lack dynamic adaptability [7]. Theoretically, the synergistic mechanisms linking ecological benefits and artistic expression remain unclear. Most existing studies address these aspects separately, overlooking the dynamic coupling between aesthetic form and ecological function during plant community succession [8]. Practically, GA parameters such as crossover and mutation rates have a substantial impact on optimization results, yet adaptive parameter-tuning strategies tailored for plant configuration are still lacking [9].

With the acceleration of urbanization and growing environmental awareness, research and practice in plant landscape resource allocation have attracted increasing attention. Ecological adaptability studies highlight the synergistic relationship between plants and their environment, emphasizing the prioritization of native species and the risk assessment of introduced species. Liu *et al*. stressed the need to establish plant adaptability models by integrating parameters such as climate, soil, and hydrology. Through statistical analysis and growth prediction, plant configurations could be optimized [10]. Tang *et al*. suggested that plant configuration should balance carbon sequestration, soil and water conservation, and pest and disease resistance, while also incorporating rare and endangered species to enhance scientific value [11]. Ehtesham and Sohanian demonstrated the application of remote sensing, geographic information system (GIS), and big data technologies in plant growth simulation and spatial planning [12]. Current applications of the GA in plant configuration optimization are primarily concentrated in ecological planning, agricultural planting optimization, and landscape design. Fakhrzad *et al*. systematically reviewed the potential of GA in solving complex optimization problems and suggested that its efficient search capabilities in industrial engineering could be applied to plant spatial layout challenges. The research combined binary and real number encoding to dynamically optimize plant growth density and light distribution, effectively improving both farmland crop yields and urban greening coverage [13]. Hu *et al*. developed a GA inspired by virus evolution theory, which enhanced nutrient allocation efficiency in greenhouse plant communities by dynamically adjusting crossover and mutation rates [14]. In the field of landscape design, Khare *et al*. integrated GA with GIS to build a multi-objective plant configuration model that accounted for topography, soil, and climate, significantly improving ecological adaptability [15]. However, existing research often treats ecological benefits and artistic expression as separate domains, lacking in-depth exploration of the dynamic coupling between ecological function and aesthetic form during plant community succession, which makes it difficult to achieve an organic integration of ecological value and artistic quality. Intelligent landscape design, an innovative approach integrating modern technology with artistic expression, has become an important development direction in landscape architecture. By incorporating intelligent algorithms such as the GA into the design process, designers can address complex problems more scientifically while achieving a balance between ecological, aesthetic, and functional requirements [16].

Plant configuration should not only pursue visual aesthetics but also enhance ecological benefits such as improving air quality, regulating the microclimate, and promoting biodiversity. However, evaluating ecological benefits often requires complex ecological process simulations and data analyses, which traditional methods struggle to quantify accurately. The introduction of scientific computational models enables more precise assessment of the impacts of different configuration schemes on the ecological environment, thereby achieving an organic integration of ecological and landscape benefits. The artificial neural network (ANN) as a powerful nonlinear mapping tool can simulate the input–output relationships of complex systems. This study aimed to address the limitations of traditional design methods including high subjectivity, low efficiency, and the difficulty of quantitative evaluation by advancing plant configuration toward greater scientific rigor, intelligence, and precision. The ANN was employed to learn the mapping relationships between plant configuration schemes and target functions such as aesthetic scores and ecological benefit indices. By training on a large dataset of sample configurations, the ANN was able to predict target function values for different schemes, providing a rapid and accurate evaluation method for guiding the search process of the subsequent GA that was applied to the plant configuration optimization process through encoding plant configuration schemes, designing fitness functions, and performing genetic operations to iteratively evolve toward optimal or near-optimal solutions. This study also examined the dynamic coupling between ecological benefits and artistic expression, and, for the first time, deeply integrated ANN with GA for plant configuration optimization in landscape design. The findings would expand the application boundaries of intelligent algorithms in landscape ecological planning and enrich the theoretical and methodological framework of landscape design.

Materials and methods

ANN principle and its application in landscape design

The diversity of plant community layout styles offers greater flexibility and creativity in design solutions. This study explored how to achieve the integration of technological intelligence and artistic expression [17]. In the intelligent design process, the diversity of plant community layout styles was fully considered. Different styles not only influenced the overall visual appeal of the landscape but also affected ecosystem stability and functionality. Naturalistic layouts mimicked plant distribution patterns in nature, emphasizing randomness and spatial layering, and were suitable for park green spaces or wetland restoration projects. In this style, careful species selection and combination were essential to avoid excessive signs of human intervention while maintaining community structural stability [18]. Formal layouts, in contrast, emphasized symmetry and geometric order, and were often applied in courtyards and squares that required a solemn or ceremonial atmosphere. In such layouts, precise calculations of plant spacing and arrangement were critical to ensuring a harmonious and unified visual effect. This study considered four typical plant community layout styles, which included naturalistic scattered layouts that mimicked natural vegetation distribution with relatively large spacing between individuals as plant spacing ≥ twice the crown diameter and was suitable for open urban parks and suburban green spaces, often creating sparse woodland or flower-dotted grassland landscapes; clustered dense layout that combined trees, shrubs, and groundcovers in a ratio of 3:2:5 to form multi-layered communities with ≥ 80% canopy coverage, which was compact and suitable for small street green spaces or residential courtyards, enabling rapid canopy closure; formal symmetrical layout that arranged uniform-sized trees like *Ginkgo biloba* and *Koelreuteria paniculata* in a grid pattern along a central axis with equal row and column spacing commonly 5 m × 5 m, which emphasized formality and was often used in municipal squares and memorial sites; linear tree array layout that the trees were planted in single or double rows along roads or waterways with spacing set at 1.2 times the crown diameter to balance shading and directional guidance, which was frequently applied along urban main roads and waterfront promenades. Landscape greening is a core component of national ecological civilization development and plays a crucial role in advancing urban ecological sustainability [19]. By integrating Internet of Things (IoT) technology into modern ecological gardens, it is possible to establish a big smart garden data platform that intelligently connects people with nature, enabling mutual perception, understanding, and interaction between humans and the natural environment. The basic framework of the smart garden management platform showed that GIS-based open garden information management enabled comprehensive oversight of urban garden resources. Through hierarchical permission settings, the platform supported garden planning and management, recorded current and historical green space data, and facilitated plant species management and biodiversity conservation [20]. The system relied on a network of sensor nodes, combined with wired and wireless communication technologies deployed throughout urban gardens (Figure 1). This infrastructure enabled intelligent sensing, irrigation control, early warning, and analytical functions, thereby achieving refined cultivation, visualized management, and data-driven decision-making.

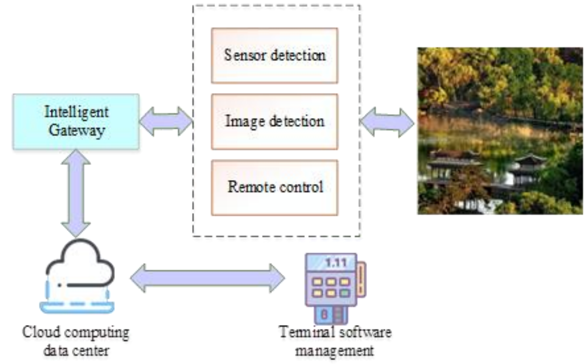

Figure 1. Smart garden management platform.

ANN is a computational model inspired by the human nervous system, in which information is processed and transmitted through interconnected neurons. The most widely used ANN architecture is the three-layer structure, consisting of an input layer, a hidden layer, and an output layer. The input layer receives the relevant data, while the hidden layer processes and transforms these signals, determining the form of the output, and the output layer delivers the results. The number of input nodes in the input layer is determined by the number of input variables, while the number of output nodes varies according to specific software implementations and processing objectives (Figure 2).

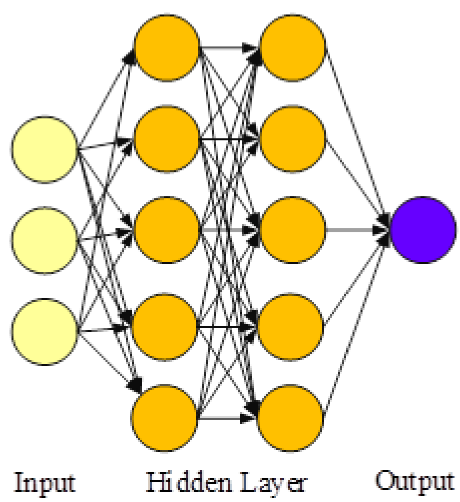

Figure 2. ANN structure.

Through iterative training with sample data, the network continuously adjusted its weights to minimize prediction errors [21]. If the error after each training session remained large, the process continued until the predefined termination condition was satisfied. Input nodes were not connected to any preceding nodes, whereas other nodes received the outputs of preceding layers as their inputs to complete further training [22]. Each node operated through an adder and an activation function. Let *X* denote the input value of a node and *y* as the output signal of the output node. The adder function of node *j* could be expressed as below.

$$U_f = \sum_{i=1}^{n} w_{ij} x_i + \theta_j \tag{1}$$

where w_{ij} was the network weight between the upper node i and the node j in two adjacent layers. θ was node deviation. n was the number of nodes in the upper layer. x_i was the output of node i. In the network, the activation function was also relatively important and could be expressed as follows.

$$y_j = f\left(U_j\right) \tag{2}$$

where y_j was the activation function value. U_f was the input value in the activation function. Sigmoid function was the most commonly used activation function in ANN and was expressed below.

$$f\left(U_j\right) = \frac{1}{1+e^{-U_j}} \tag{3}$$

The operational principles of ANNs were also applicable to landscape ecological planning. In this study, landscape planning elements such as patches, corridors, and roads exhibited complex interrelationships with ecological patterns. The overall system could be regarded as a mapping composed of numerous nonlinear functions [23]. The black-box characteristics of ANNs could be leveraged to interpret these relationships with the specific application model (Figure 3). Given the substantial human intervention inherent in landscape ecological design, achieving complete accuracy was not feasible. As a method that simulated human cognition, behavior, and decision-making, ANNs could facilitate the intelligent advancement of landscape design and planning.

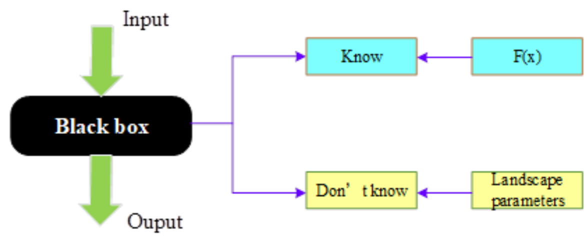

Figure 3. Application model of landscape design based on ANN.

Plant configuration based on genetic algorithm

The primary steps of GA included encoding, population initialization, selection, crossover, and mutation [24]. These steps replicated genetic and evolutionary mechanisms, enabling the algorithm to identify global optimal or near-optimal solutions in complex search spaces. In plant configuration optimization, GA evaluated alternative schemes through a fitness function, which typically incorporated multiple criteria such as plant growth requirements, seasonal variation, species diversity, and economic benefits [25]. Through successive iterations, GA identified plant combinations and layout plans that best satisfied the design objectives. Integrating ANN with GA combined their respective strengths. ANN was used to model and predict plant growth patterns, while GA refined configuration schemes. This synergy not only enhanced optimization efficiency but also improved the reliability of results. Initially, ANN could filter candidate plant combinations, excluding clearly unsuitable options. GA then further optimized the remaining schemes to achieve more precise and targeted solutions. The characteristics of plant species and environmental settings were critical to achieving

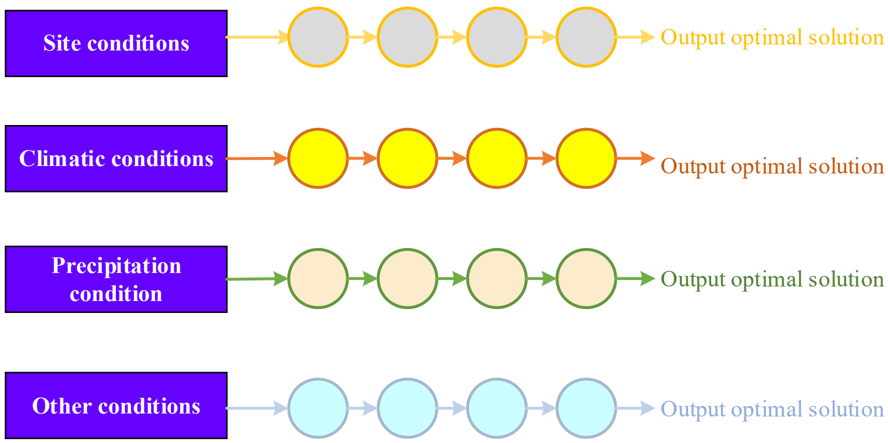

Figure 4. Parameter operation model of ANN hidden layer.

optimal results. Additional factors such as site conditions, climate, and precipitation were also considered. Within the backpropagation (BP) neural network framework, a professional evaluation system or expert judgment was applied to iteratively refine parameters until the optimal configuration was obtained (Figure 4). Given the vast number of possible plant pairings and the need to account for multiple influencing factors, enumerating all potential plant configurations using computational algorithms was infeasible. Therefore, specific constraints were necessary to limit the range of feasible plant pairing schemes. In landscape design, practical experience regarding spatial utilization in different environments provided valuable guidance for establishing such constraints. This study adopted plant landscape configuration formulas developed by Japanese researchers for various spatial contexts. These equations primarily referred to the height of plants (H_1) and (H_2) and the distance between plants (L).

$$L > (H_1 + H_2) \tag{4}$$

It was established that, when equation (4) was satisfied, the configuration was suitable for single-plant landscape environments.

$$(H_1 + H_2) > L > (H_1 + H_2)/2 \tag{5}$$

When equation (5) was satisfied, the configuration was suitable for environments dominated by tree-lined plants.

$$(H_1 + H_2)/2 > L > H_1 + H_2/4 \tag{6}$$

When equation (6) was satisfied, the layout was appropriate for open spaces and could accommodate sun-loving plants.

$$(H_1 + H_2)/4 > L > H_1 + H_2/8 \tag{7}$$

When equation (7) was met, the design fitted tourist activity areas with sparse tree coverage.

$$(H_1 + H_2/8) > L > (H_1 + H_2)/16 \tag{8}$$

When the density condition expressed in equation (8) was moderate, the configuration was suitable for environments combining herbaceous and woody plants.

$$(H_1 + H_2)/16 > L \tag{9}$$

When equation (9) held, shade-tolerant herbs should predominate. Plant configuration plans were encoded as chromosomes to form the initial population for the GA. Each chromosome consisted of multiple genes with each gene representing a plant's spatial location or quantity parameter. The initial population might be generated randomly or constructed based on empirical design rules. Subsequently, genetic operations were applied to iteratively improve population quality through the steps of selection for superior individuals from the current population based on fitness values to serve as parents for the next generation, crossover by exchanging gene segments between pairs of parent chromosomes to produce offspring with combined traits, mutation randomly to alter gene values with a defined probability to maintain genetic diversity within the population. After each iteration, the ANN model evaluated the newly generated individuals and returned their fitness values to the GA. This closed-loop interaction enhanced both the efficiency and accuracy of the optimization process.

Determination of model adaptability

This study primarily used MATLAB software (https://www.mathworks.com/) to construct the ANN model and employed TensorFlow (https://www.tensorflow.org/) for training, validation, and evaluation of the landscape greening model. The processed dataset included plant species, specifications, attributes, spatial coordinates to facilitate subsequent analysis and practical application. To validate the performance of the plant configuration model, publicly available data from a landscape design website (www.zhulong.com/sitemap/index-prof.html) were used for testing. The dataset contained detailed information on each plant's species, specifications, and attributes. Data collection spanned from January 1, 2023 to December 31, 2023. Initially, 1,260 plant configuration cases were recorded. After data cleaning, 1,173 valid samples remained. Plant attributes included species name, growth height (m), crown diameter (m), ecological habit (e.g., sun-loving, shade-tolerant, drought-resistant), and phenological characteristics of flowering period and leaf color phase. Environmental parameters encompassed site area (m^2), slope (°), daily sunlight duration (hours/day), soil type (sandy loam, clay loam, loam), and annual precipitation (mm).

Data processed by the ANN were compiled using processing software and AutoCAD (https://www.autodesk.com/). Plant parameters were imported into site plan diagrams to automate the generation of overall layout simulations. During operation, the system initially determined the locations for plant configurations and then progressively expanded the layout outward from these points. Key parameters considered included land area, green space coverage, building plot ratio, planting area range, and grid cell size. To evaluate the adaptability of the plant configuration model, simulations were conducted in two distinct garden environments, which included type A garden characterized by spacious and open areas, and type B garden, featured as compact and densely structured. To further assess the performance of the proposed ANN-GA-based plant configuration optimization model, advanced optimization algorithms including differential evolution (DE) and non-dominated sorting genetic algorithm II (NSGA-II) (https://deap.readthedocs.io) were employed as benchmark controls. Model performance was evaluated based on objective function values across three dimensions of ecological benefits, economic benefits, and social benefits.

Results and discussion

Application of the ANN-GA plant configuration model

The results demonstrated that the proposed system could flexibly adjust plant configuration plans based on garden terrain and area characteristics. In the larger type A garden, groundcover plants accounted for 10.5% of the total area, comprising five species. In contrast, in the smaller type B garden, the proportion of groundcover plants increased to 20.4% with the number of species rising to twelve (Figure 5). These findings highlighted the model's adaptability to varying environmental conditions, particularly its ability to optimize plant configurations by increasing groundcover coverage in limited spaces.

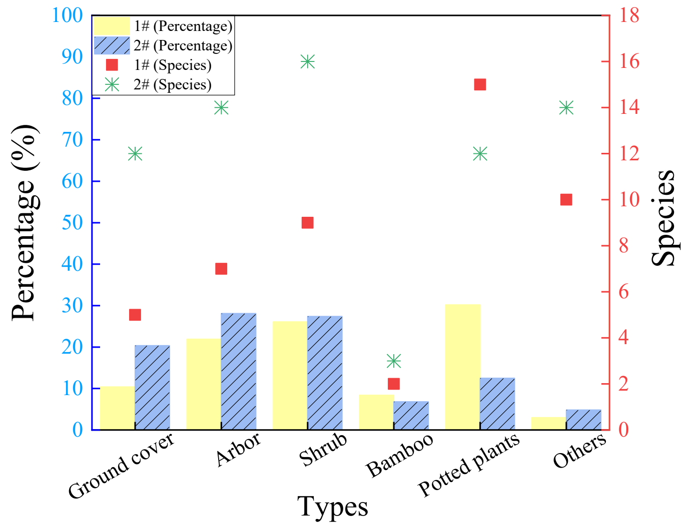

Figure 5. Plant configuration results of gardens with different areas.

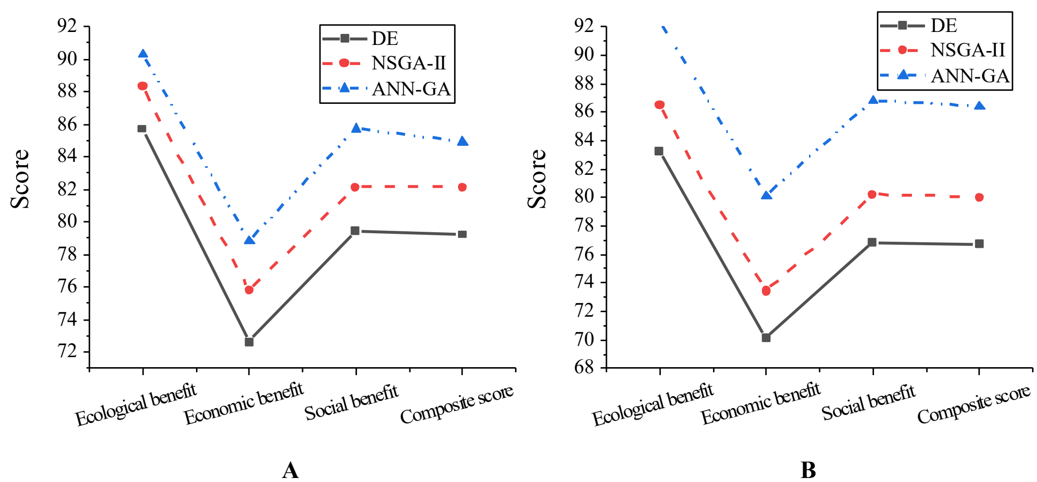

Figure 6. The accuracy of garden optimization for different models. **A.** Type A gardens. **B.** Type B gardens.

Optimization accuracy of the ANN-GA plant configuration model

The optimization accuracy of different models applied to type A and type B gardens demonstrated that the integrated ANN-GA model achieved significantly higher comprehensive scores compared to other methods in both garden environments with pronounced advantages observed in social and economic benefit metrics (Figure 6).

This study proposed a plant configuration optimization model that integrated ANN and GA to landscape design, demonstrating superior performance in addressing complex multi-objective problems. Compared to traditional methods and other optimization algorithms, the proposed model significantly improved optimization accuracy with particularly notable advantages in social and economic benefits. In smaller spaces, the model maximized spatial utilization by adjusting the proportion of groundcover plants, while, in open areas, it emphasized the integration of ecological diversity and aesthetic hierarchy. By combining insights from AI, ecology, and design art, this study highlighted the vital role of modern technology in overcoming traditional design challenges and opened new avenues for innovative landscape design development. Although significant progress had been achieved, there remained considerable potential for further research. Future studies could explore the integration of deep learning techniques to enhance the predictive accuracy of the ANN model or incorporate reinforcement learning methods to dynamically optimize GA parameter settings. Furthermore, with ongoing advancements in the IoT and big data technologies, future plant configuration optimization models are expected to enable more precise real-time monitoring and dynamic adjustments, thereby better supporting the requirements of smart garden construction.

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