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Multi-Objective Layout Method of Landscape Sponge Facilities Based on SWMM-MOPSO

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Abstract: The layout of sponge facilities in landscape architecture requires consideration of multiple objectives, including balancing hydrology, cost, and ecology. Traditional experiential planning lacks precise quantitative analysis, making it difficult to achieve an optimal balance and limiting the scientific rigor and refinement of the planning process. To address this issue, a multi-objective layout model, SMA-LM, for landscape sponge facilities is proposed. SMA-LM integrates Storm Water Management Model (SWMM) for hydrological simulation, Multi-Objective Particle Swarm Optimization (MOPSO) for optimization, and Analytic Hierarchy Process (AHP) for decision-making. This study presents the first framework to couple the refined hydrological simulation of Storm Water Management Model (SWMM) with an improved MOPSO algorithm that utilizes an adaptive grid strategy, which is subsequently integrated with Analytic Hierarchy Process (AHP) for decision-making. The model performance test showed that the generation distance at the 100th iteration of the research model was 0.20, significantly lower than the comparative model's 0.29. The super volume of the 200th iteration was 380, the diversity index of the solution set was 0.18, and 80 non-dominated solutions were obtained after 1500 calls, demonstrating outstanding efficiency. In simulation applications, the ecological benefit index for urban park scenes could range from 0.65 to 0.92, and the landscape adaptability score could reach 3.2 or higher. The ecological benefit index for campus scenes also ranged from 0.63 to 0.90, and the maintenance convenience score ranged from 3.2 to 4.6, achieving multi-objective collaborative optimization. This study provides a scientific quantitative tool for the precise layout of sponge facilities in landscape architecture, effectively improving the comprehensive efficiency and scientific decision-making of planning schemes, and has important practical application value.

Keywords: Storm Water Management Model (SWMM); Multi-Objective Particle Swarm Optimization Algorithm (MOPSO); landscape architecture; sponge facilities; layout optimization.

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1. Introduction

As an important component of urban ecosystems, landscape architecture serves multiple functions such as providing recreational spaces, improving microclimates, and conserving water sources. Its sustainable development is increasingly receiving attention. In recent years, integrating sponge facilities into landscape planning has become an important trend in industry development (Sun, 2023). However, the layout planning of the Landscape Sponge Facility (LSF) is a complex system engineering that requires consideration of natural factors such as hydrology and topography, as well as multiple objectives such as landscape effect, construction cost, and ecological benefits. Traditional planning methods rely heavily on the experience and intuition of planners, lacking precise quantitative analysis of complex hydrological processes and making it difficult to comprehensively evaluate the performance of different layout schemes. Especially when balancing multiple objectives, it is often hard to find the optimum (Yang et al., 2023). This, to some extent, constrains the scientific and refined level of LSF planning. However, a significant gap remains in the existing literature regarding the integration of refined-hydrological models with meta-heuristic algorithms. On the one hand, although hydrological models are vital tools for water resource management, they are often simplified representations of complex systems. Previous studies indicate that these models can struggle to accurately capture hydrodynamic processes due to factors such as soil heterogeneity and climatic variations, especially when relying on limited gauge discharge data (Sahu et al., 2023). On the other hand, while recent meta-heuristic algorithms have shown capability in balancing exploration and exploitation, standard approaches often suffer from drawbacks such as premature convergence or instability when handling highdimensional objectives in complex facility layouts (Makhadmeh et al., 2023). Therefore, in-depth exploration of optimization methods for LSF layout has become a key research direction for improving planning efficiency. Bah et al. (2023) used a rainstorm runoff management model to evaluate the feasibility of flood control of the Low Impact Development (LID) strategy for the flood problem in the Conakry urban area. The measures in this strategy were significantly more effective at reducing runoff, node flooding, and overflow than individual measures, providing data support and a practical reference for the Multi-Objective Layout (MOL) of LSF. Feng et al. (2023) established a suitability index system for LID facilities in sponge cities and identified suitable areas and area limits for various facilities across different sub-basins. At the same time, a multilayer perceptron was used as an alternative model to capture the nonlinear relationship between facility deployment area and rainfall characteristics. This provided an optimization solution for LSF layout, and could effectively shorten the calculation time while reducing runoff and peak flow. Chikhi et al. (2024) focused on the construction of Chinese sponge cities and proposed an idealized sponge city strategic model by analyzing policies, evaluating various implementation scenarios, and comparing the effects of three pilot cities. This model emphasized that integrating drainage zones and properly designing LID facilities were key to successful construction. This method could simultaneously achieve multiple goals, such as conserving water resources and providing important theoretical support for LSF layout.

Storm Water Management Model (SWMM) is a dynamic rainfall-runoff simulation model widely used in urban hydrology, hydraulic simulation, water quality analysis and many other fields. It can accurately simulate the rainfall runoff process and quantify the control effect of LID facilities on runoff (Tansar et al., 2024). This model offers unique advantages for solving rainwater management problems due to its powerful hydrological and hydraulic simulation capabilities and its parameterized simulation function for sponge facilities. To maximize the use of SWMM to optimize urban runoff systems and improve water quality, Ramonha et al. (2024) evaluated the application of various rainwater modeling tools for planning and improving runoff systems, assessed modeling efficiency, and analyzed the impact of urban expansion. SWMM could effectively support green infrastructure practices, but its accuracy was affected by the quality of input data and calibration methods. Nazari et al. (2023) developed a new SWMM framework to identify the most cost-effective LID solution for urban flood risk. This framework used SWMM to simulate rainfall-runoff processes and optimized the model using an integrated urban rainwater treatment and analysis system. Finally, two multi-criteria decision models were used to rank the schemes. This new framework could select the optimal solution based on the weights of different indicators.

The Multi-Objective Particle Swarm Optimization Algorithm (MOPSO), a metaheuristic based on swarm intelligence, has been widely applied to Multi-Objective Optimization (MOO) problems, such as scheduling optimization, path planning, and engineering design. It achieves a balance between global search and local development by simulating the foraging behavior of bird flocks, and can efficiently handle multiple conflicting targets, thus demonstrating unique advantages in finding the optimal solution set and providing an effective approach to solving Logistics Scheduling and Facility Management with Multi-Objective Optimization (LSF-MOL) problems (Zhang et al., 2025). Zheng et al. (2023) proposed an improved binary MOPSO based on problem features for optimizing design change plans in product development. This method first constructed a multi-layer network that includes service performance and defined its impact, and established three objective optimization models that include service performance impact, change cost, and change time. The experiment verified the effectiveness of the proposed model and algorithm in solving complex product change optimization problems. To address the shortcomings of MOPSO in convergence and diversity, Shu et al. (2023) designed a MOPSO with a dynamic population size that adjusts it based on changes in the archive's resources. This algorithm exhibited unique advantages in solving different benchmark problems and provided an effective solution for MOO problems.

In summary, existing research has achieved some results using MOO algorithms to address the sponge city layout problem, although there are still limitations in model convergence, diversity, and computational efficiency. Furthermore, few studies combine optimization algorithms with detailed hydrological models. To overcome these challenges, we propose an LSF-MOL method that integrates SWMM and MOPSO. This method combines the hydrological and hydraulic simulation capabilities of SWMM with the optimization capabilities of MOPSO, aiming to significantly improve computational efficiency while ensuring model convergence and diversity, and to offer a scientific foundation for the planning and design of LSF. The innovation lies in constructing a coupled framework that combines the SWMM hydrological and hydraulic model with the MOPSO algorithm, achieving precise simulation and efficient optimization of sponge facility layout. Secondly, strategies such as adaptive population size and dynamic leader selection have been proposed, effectively enhancing the global search capability and diversity of MOPSO, providing new ideas and methods for LSF-MOL. This study has important academic value and practical significance in solving complex MOO problems in practice.

The main contributions of this paper are summarized as follows: (1) A coupled "simulation-optimization" framework is established by integrating SWMM and MOPSO, effectively bridging the gap between hydrological accuracy and optimization efficiency. (2) An improved MOPSO algorithm with adaptive grid and elite archive mechanisms is proposed to enhance the diversity and convergence of solutions. (3) A systematic decision-making strategy combining Pareto optimal sets with Analytic Hierarchy Process (AHP) is developed to quantify qualitative indicators such as landscape adaptability, providing a scientific tool for practical planning.

2. Methodology

2.1. Construction Of Landscape Hydrological Simulation Model Integrating SWMM

Accurate hydrological and hydraulic simulation is a prerequisite for evaluating the runoff-control effect of sponge facilities in landscape architecture. However, the terrain in landscape areas is complex, and the underlying surface properties across different plots vary. Traditional methods have difficulty accurately capturing this complex rainfall-runoff process (Li et al., 2025). Therefore, this study introduces SWMM, with its strong distributed hydrological and hydraulic simulation capabilities, to accurately model the rainfall-runoff process in scenic areas. Given the importance of sub-watershed division for the effective operation of the SWMM model, this study finely divides the target landscape area based on terrain data and land use types, as shown in Fig. 1.

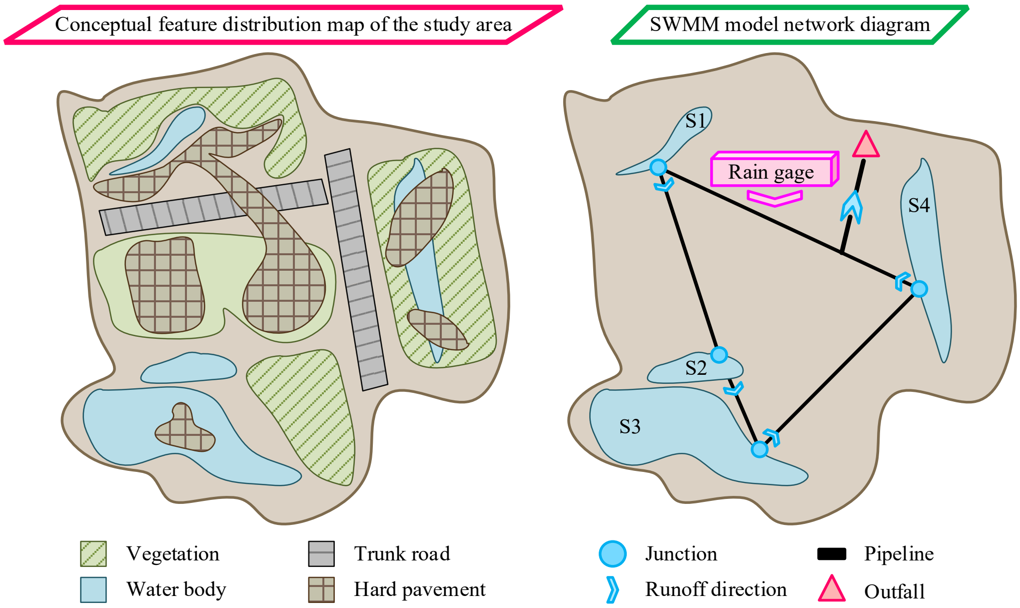


Fig. 1. SCA division of SWMM model in landscape architecture research area

In Fig. 1, based on a thorough analysis of the natural and social attributes of the study area, as well as a comprehensive consideration of terrain and confluence characteristics, this study first determines the drainage area (Fiorillo et al., 2023). Based on the distribution of drainage network main pipes and main roads, the number and spatial scale of Sub-Catchment Areas (SCAs) are strictly controlled to maintain a reasonable ratio of pipe segments and nodes to the number of SCAs. Within this framework and spatial scale, different types of underlying surfaces are classified into corresponding SCAs, laying a solid foundation for accurate simulation of rainfall runoff processes in various regions and evaluation of the effectiveness of sponge facilities in different SCAs. The formula for calculating the total catchment area of the research area is given by Eq. (1).

$$S_{\text{total}} = \sum_{n}^{i=1} S_i \tag{1}$$

In Eq. (1), S_{total} is the total catchment area of the landscape research area. S_i is the area of the i-th SCA. n is the total number of SCAs divided into the study area. i is the sub-watershed area number. The slope calculation of the sub-watershed area is shown in Eq. (2).

$$G_i = \frac{H_{max,i} - H_{min,i}}{L_i} \tag{2}$$

In Eq. (2), G_i is the average slope of the i-th SCA. $H_{max,i}$ and $H_{min,i}$ are the highest and lowest elevations within the i-th SCA. L_i is the horizontal distance of the main confluence path within the SCA. The formula for the Comprehensive Runoff Coefficient (CRC) of the sub-watershed area is shown in Eq. (3).

$$C_i = \sum_{m}^{j=1} f_{j,i} \cdot c_j \tag{3}$$

In Eq. (3), C_i is the CRC of the i-th SCA. $f_{j,i}$ is the proportion of the area of the j-th underlying surface type in the i-th SCA. c_j is the single runoff coefficient for the j-th type of underlying surface. m is the total number of underlying surface types within the SCA. j is the type of number of the underlying surface. After completing the scientific division of the SCA and the basic construction of the SWMM model, to further achieve accurate simulation of the LSF rainwater control effect, this study abstracts typical sponge facilities as the LID module of the SWMM model. The specific parameterized logic and configuration are shown in Fig. 2.

In Fig. 2, this study corresponds to the physical structure of sponge facilities, such as surface vegetation layer, surface soil layer, sand layer, gravel Water Storage Layer (WSL), and bottom drainage system, with their corresponding LID module parameters in the SWMM model. Among them, the surface layer is parameterized as water storage depth and surface roughness, while the soil layer is defined by thickness, porosity, hydraulic conductivity, and permeability (Jiang et al., 2023). The Infiltration Rate of the Soil Layer (SLIR) is shown in Eq. (4).

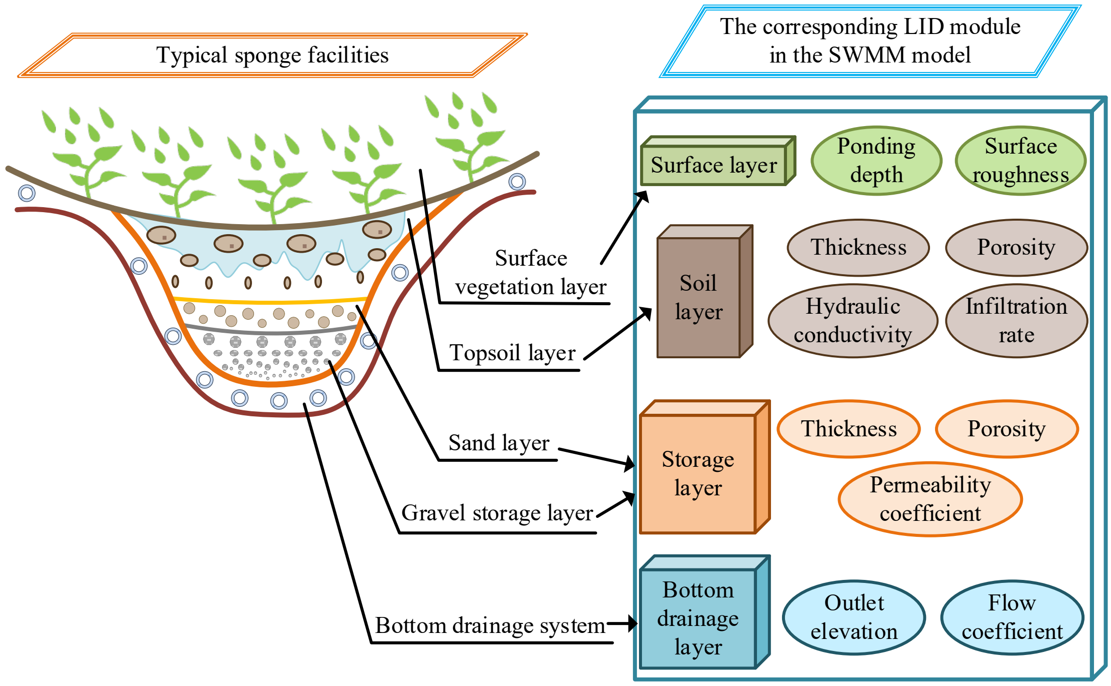


Fig. 2. Parameterization of typical sponge facilities in SWMM model

$$f_s = f_c + (f_0 - f_c) \cdot e^{-k_1 \cdot t} \tag{4}$$

In Eq. (4), f_s represents the instantaneous SLIR in the sponge facility. f_c is the stable iSLIR. f_0 is the initial infiltration rate. k_1 is the infiltration attenuation coefficient. t is the duration of rainfall. The thickness, porosity, and permeability coefficient of the WSL need to be set, while the bottom drainage system is characterized by the elevation of the drainage outlet and the flow coefficient. The Water Storage Capacity (WSC) of the WSL is shown in Eq. (5).

$$V_s = A_s \cdot d_s \cdot n_s \tag{5}$$

In Eq. (5), V_s is the maximum WSC of the sponge facility WSL. A_s is the horizontal projection area of the WSL. d_s is the thickness of the WSL. n_s is the porosity of the WSL. This formula quantifies the water storage potential using WSL's structural parameters and is directly related to the LID module's "maximum water storage depth" parameter in the SWMM model. The flow rate of the bottom drainage system is shown in Eq. (6).

$$q_d = c_d \cdot A_d \cdot \sqrt{2g \cdot \Delta h} \tag{6}$$

In Eq. (6), q_d represents the instantaneous drainage flow rate of the sponge facility's bottom drainage system. c_d is the flow coefficient of the drainage outlet. A_d is the effective discharge area of the drainage outlet. g is the acceleration due to gravity. Δh The head difference between upstream and downstream of the drainage outlet is the difference between the reservoir water level and the drainage outlet elevation. Using the above method, the physical characteristics of different types of sponge facilities can be accurately converted into model-identifiable parameters, laying a solid foundation for subsequent accurate hydrological simulation and MOO.

2.2. Design of MOO Model and Collaborative Strategy Based on MOPSO

After constructing and calibrating the SWMM hydrological model for sponge facility parameterization, this study introduces MOPSO to address the challenge that single-objective optimization or traditional planning methods struggle to effectively solve the complex system engineering problem of LSF layout. A dynamic closed-loop collaborative optimization framework is constructed by combining the precise simulation capability of SWMM with the efficient global MOO capability of MOPSO. The core logic and technical implementation are shown in Fig. 3.

In Fig. 3, the framework revolves around closed-loop iteration as its core logic. Firstly, MOPSO generates an initial sponge facility layout scheme via particle position encoding and converts it into the LID module parameters for the SWMM model (Abdalla et al., 2024). Subsequently, SWMM simulates the output of objective function values such as total runoff, construction cost, and ecological benefits based on the SCA division and facility parameterization results, and feeds them back to MOPSO. MOPSO updates particle velocity and position based on feedback values, generates a new scheme, and repeats the above process until the iteration termination condition is met. The fitness function is shown in Eq. (7).

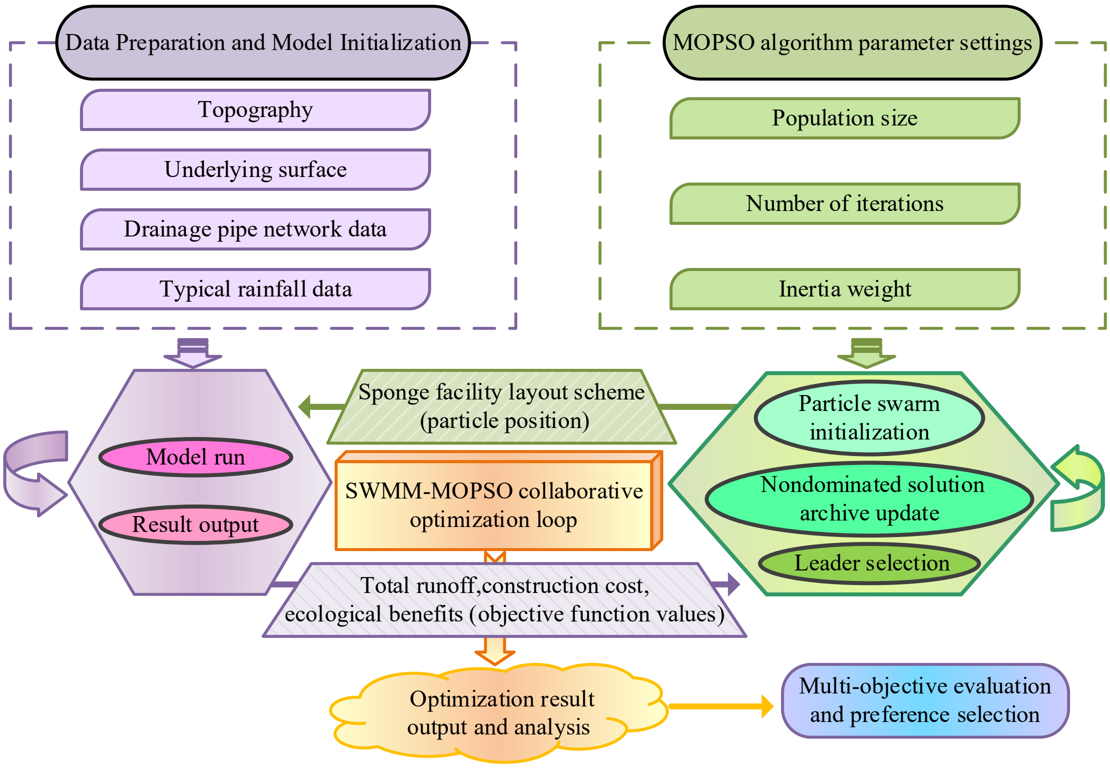


Fig. 3. SWMM-MOPSO collaborative optimization framework

$$F = w_1 \cdot \frac{Q_t}{Q_{max_2} \frac{C_t}{C_{max_3}\left(1-\frac{E_t}{E_{max}}()\right)}} \tag{7}$$

In Eq. (7), F is the fitness value of the particle. w_1, w_2, and w_3 are target weights, reflecting the importance of runoff control, cost control, and ecological benefits. Q_t and Q_{max} are the total runoff of the current plan and the maximum possible runoff of the study area. C_t and C_{max} represent the construction cost and the maximum possible cost of the current plan. E_t and E_{max} are the ecological benefits and theoretical maximum ecological benefits of the current plan. The smaller the fitness value, the better the overall performance of the scheme. The termination condition formula for iteration is shown in Eq. (8).

$$\Delta F = \left|\frac{F_{\text{avg},k+1} - F_{\text{avg},k}}{F_{\text{avg},k}}\right| \leq \varepsilon \tag{8}$$

In Eq. (8), ΔF is the average fitness change rate of two consecutive iterations. $F_{\text{avg},k+1}$ and $F_{\text{avg},k}$ are the population average fitness for the $k+1$-th and k-th iterations. ε is the convergence threshold. When $\Delta F \leq \varepsilon$ or the iterations reach the preset maximum value, the optimization process terminates, and the solution set is the optimal layout scheme set. This framework achieves a dynamic balance between hydrological simulation accuracy and optimization efficiency, and the specific improvement mechanism of the MOPSO algorithm is shown in Fig. 4.

Fig. 4 is a refinement of the optimization core mechanism in the SWMM-MOPSO collaborative framework. The process begins with particle swarm initialization, where each particle encodes a corresponding sponge facility layout plan. At the same time, it combines the runoff, cost, and ecological benefit data generated by SWMM to calculate particle fitness and dynamically stores Non-Dominated Solutions (NDSs) in elite archives (Li et al., 2023). Adaptive grids partition the target space, prioritizing the selection of leaders from sparse grids to balance convergence and solution diversity (Boyar et al., 2023). The formula for grid congestion is shown in Eq. (9).

$$c_g = \frac{n_g}{vol_g} \tag{9}$$

In Eq. (9), c_g is the crowding degree of the g-th grid in the target space. n_g is the number of sponge facility layout schemes (non-dominated solutions) included in the g-th grid. vol_g is the volume of the grid in the 3D target space (total runoff, construction cost, ecological benefits). The lower the crowding level, the sparser the distribution of solutions in the region, and priority should be given to preserving them to enhance solution set diversity. The probability formula for leader selection is given by Eq. (10).

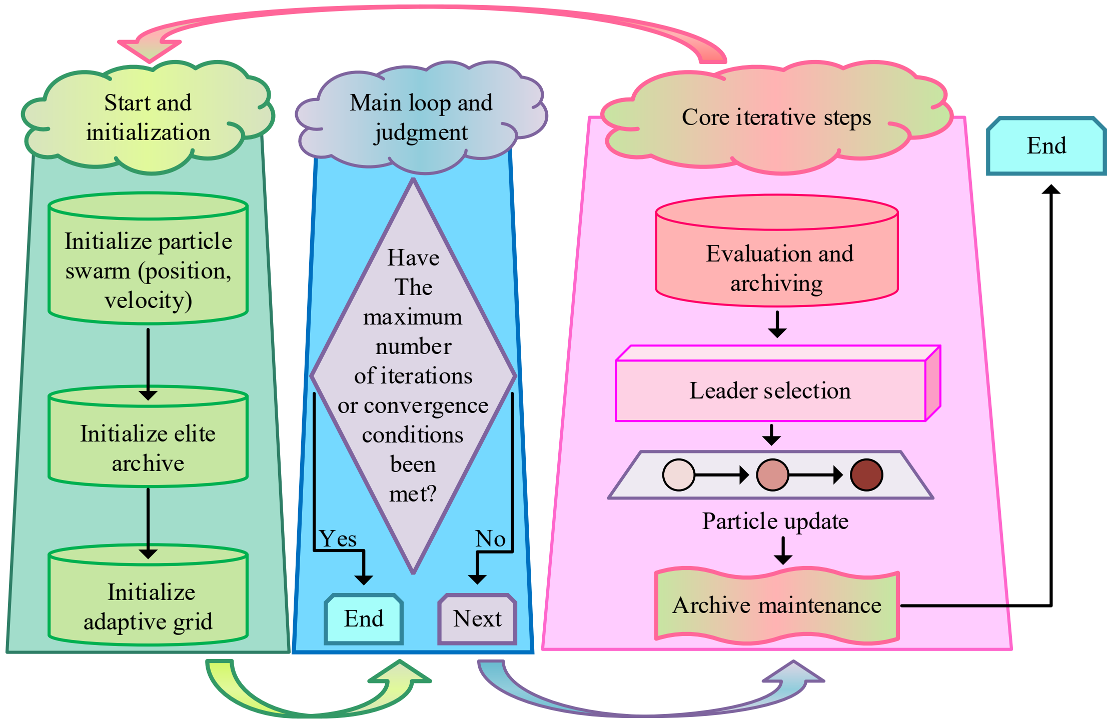


Fig. 4. Improved MOPSO algorithm process

$$c_g = \frac{n_g}{vol_g} c_g g n_g g vol_g p_g = \frac{1/c_g}{\sum_{g=1}^{m} 1/c_g} \tag{10}$$

In Eq. (10), p_g represents the probability of selecting a leader from the g-th grid. m is the total number of grids in the target space. This formula uses *inverse* -crowding weighting to increase the probability of selecting solutions in sparse grids, balancing the convergence and diversity. Subsequently, the population size is dynamically adjusted based on the archive size to avoid redundant calculations. Finally, after multiple iterations until convergence, the distribution characteristics of the Pareto optimal solution set output by the algorithm will be further presented in Fig. 5.

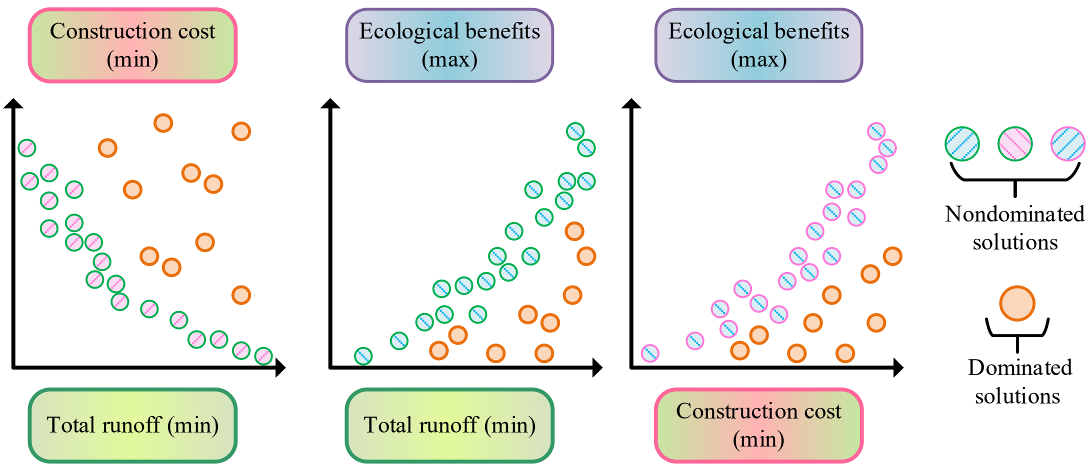


Fig. 5. Pareto front and solution set distribution

Fig. 5 visually presents the trade-off relationship between total runoff, construction cost, and ecological benefits in the LSF layout. The solution set is presented in 2D coordinate form in the figure, with each point representing a layout scheme. The points on the front curve are NDSs, which means that it is impossible to improve one target without harming other targets (Li et al., 2024). For example, low-cost solutions often have limited runoff control effects, while solutions with outstanding ecological benefits may be accompanied by higher construction investment. This distribution feature clearly reveals the conflict mechanism between multiple objectives, providing a visual decision-making basis for subsequent scheme optimization based on the AHP.

2.3. Multi-Objective Evaluation and Scheme Optimization Strategy Based on AHP

Through the SWMM-MOPSO collaborative optimization framework, multiple balancing schemes for LSF layout have been obtained. However, these NDSs need to be further screened based on preferences in planning practice, and a single quantitative model is difficult to integrate the comprehensive balance of quantitative and qualitative indicators. Therefore, this study introduces the AHP to establish a multi-objective evaluation and scheme optimization strategy, as shown in Fig. 6.

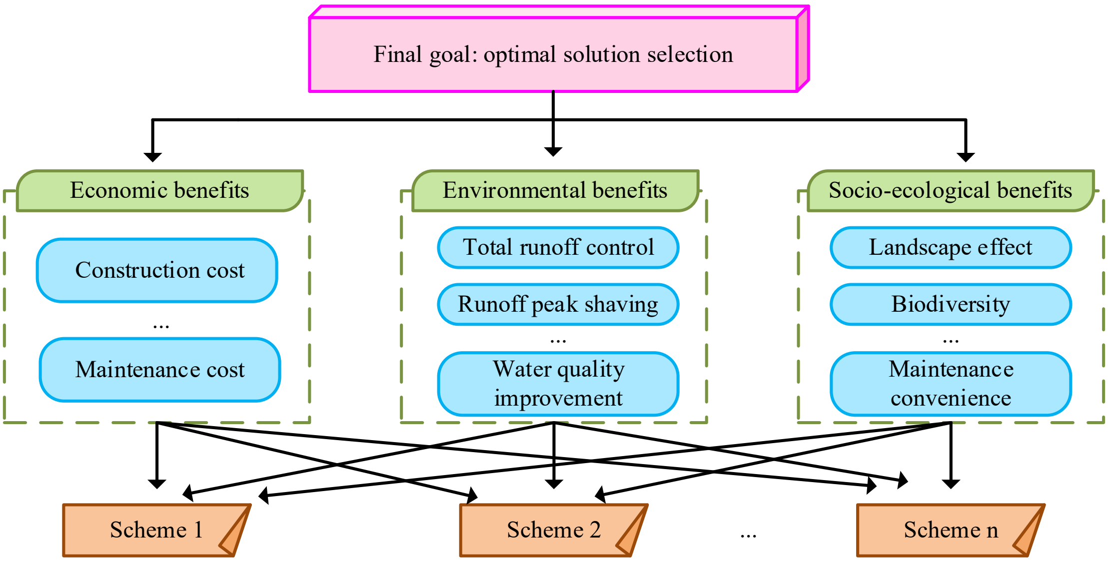


Fig. 6. Framework of multi-objective evaluation index system fusion AHP model for sponge facility layout scheme

In Fig. 6, this framework is the core tool for transitioning from a Pareto-optimal solution set to the final decision. The framework aims to select the optimal sponge facility layout plan as the objective layer, with a criterion layer and an indicator layer below. The criterion layer integrates quantitative and qualitative dimensions, covering hydrological efficiency, economic rationality, ecological value, and landscape adaptability. The indicator layer refines the specific quantification or descriptive indicators of each criterion. Specifically, qualitative indicators such as landscape adaptability are quantified using a fuzzy scoring method based on expert evaluation. A 1-to-5 scoring scale is used, where 5 indicates excellent coordination with the existing landscape texture, and 1 indicates poor adaptability. These scores are then normalized and incorporated into the Judgment Matrix (JM) of the AHP model to ensure their compatibility with quantitative hydrological data. At the same time, the framework is embedded with the core logic of AHP, which transforms experts preferences for various indicators into a quantifiable decision-making basis through hierarchical structure construction, JM assignment, weight calculation, and consistency testing, providing systematic support for scheme optimization (Tavana et al., 2023). Among them, the consistency index is calculated as given by Eq. (11).

$$\mathrm{CI} = \frac{\lambda_{max}}{n-1} \tag{11}$$

In Eq. (11), CI is a consistency indicator used to test the logical consistency of the JM. λ_{max} is the maximum eigenvalue of the JM. n is the total number of indicators. The consistency ratio formula is shown in Eq. (12).

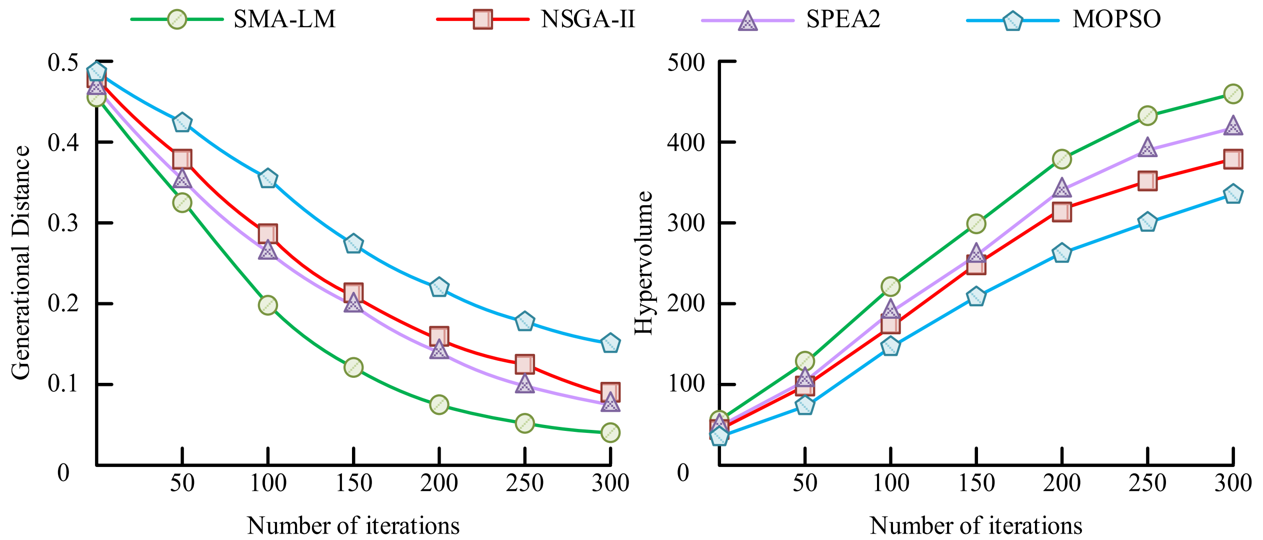
$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{12}$$

In Eq. (12), CR is the consistency ratio. RI is a random consistency indicator. When $CR < 0.1$The JM passes the consistency test; otherwise, the relative importance assignment between indicators needs to be readjusted. The research model is based on SWMM hydrological simulation and combined with improved MOPSO for MOL optimization of sponge facilities. It then uses AHP to select optimal solutions from the Pareto set, forming a dynamic collaborative framework of “simulation-optimization-decision” that balances runoff, cost, and ecological benefits. This study names the LSF-MOL model based on SWMM-MOPSO-AHP as SMA-LM.

3. Results

3.1. SMA-LM Model Performance Testing

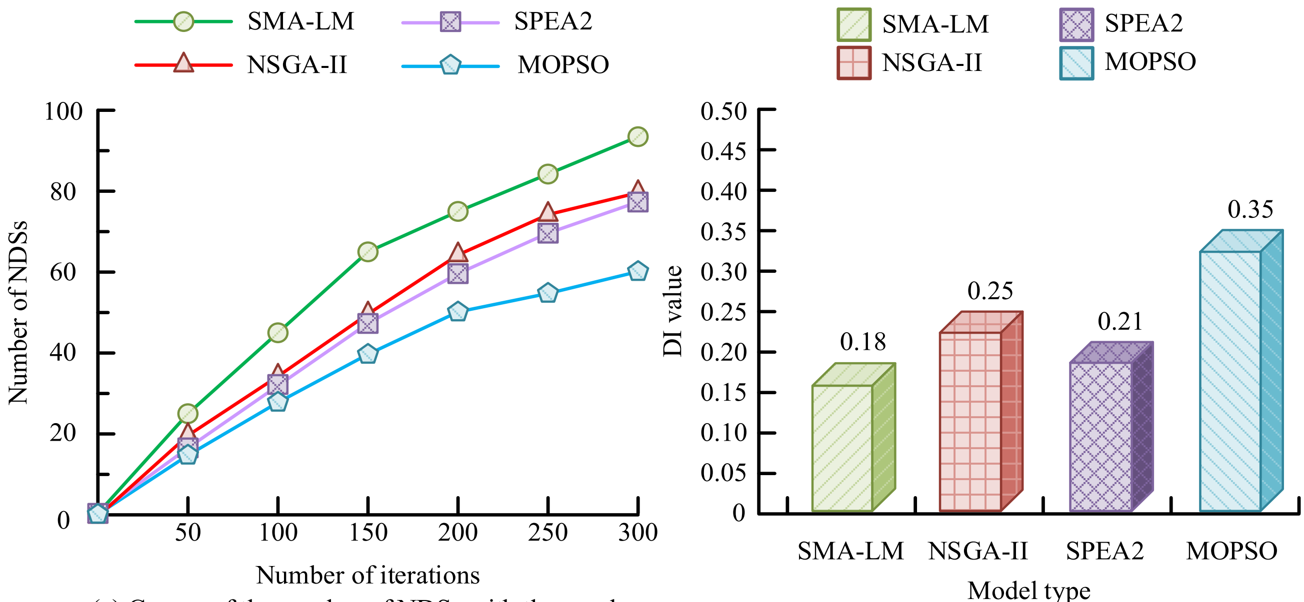
To verify the effectiveness and superiority of the SMA-LM model in solving LSF layout problems, this study selects three representative MOO algorithms (all based on SWMM models) for comparison: Non-dominated Sorting Genetic Algorithm II (NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA2), and the original MOPSO without elite archives and adaptive grid mechanism. The experimental data are sourced from the SWMM standard test dataset provided by the US Environmental Protection Agency (EPA), which is utilized for hydrological simulation and LID performance evaluation. This study converts its preprocessing into an input file that SWMM can directly call. This study first verifies the significant advantage of the research model in convergence performance, as shown in Fig. 7.



(a) Curves of convergence rate with the number of iterations for each model
(b) Curves of hypervolume with the number of iterations for each model

Fig. 7. Comparison of convergence performance of various models

In Fig. 7(a), at the beginning of iteration, the Generative Distance (GD) of each model is relatively high. However, the SMA-LM curve decreases most rapidly, with its GD dropping to 0.20 at the 100th iteration, significantly lower than NSGA-II's 0.29, SPEA2's 0.27, and the original MOPSO's 0.35. When the algorithm finally converges, the GD value of SMA-LM remains stable at 0.04, far superior to other comparative algorithms, indicating that it has the fastest convergence speed and the highest convergence accuracy. Furthermore, a t-test is conducted to verify the statistical significance of the performance differences between SMA-LM and the comparative algorithms. The results indicate that SMA-LM's improvement in the GD metric is statistically significant compared to NSGA-II and SPEA2 ($p < 0.05$), confirming that the superior convergence is not due to random chance. In Fig. 7(b), on the Hypervolume (HV) index, the SMA-LM curve maintains a leading position from the beginning and climbs at the fastest speed. At the 200th iteration, its HV reaches 380, indicating that the research model effectively balances solution-set diversity while converging to the optimal frontier. This study further validates SMA-LM's superiority in improving solution set diversity, as shown in Fig. 8.

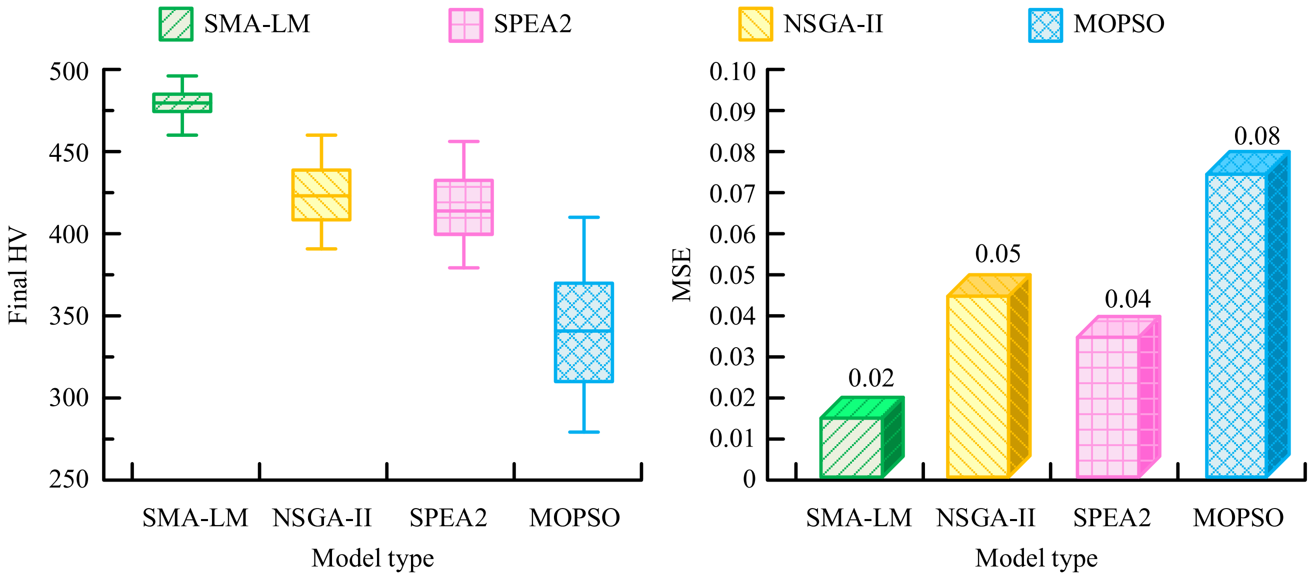


(a) Curves of the number of NDSs with the number of iterations for each model
(b) Comparison of diversity metrics for Pareto solution sets of each model

Fig. 8. Comparison of solution set diversity and distribution performance among various models

In Fig. 8(a), the dynamic curve of the number of NDSs in SMA-LM maintains the fastest growth rate from the beginning. At the final iteration, the number of NDSs in its elite archive reaches 92, far exceeding NSGA-II's 80 and the original MOPSO's 60. This demonstrates the effectiveness of the "elite archive" mechanism in the research model's multi-objective search process, which can continuously and effectively discover and retain high-quality non-dominated solutions. In Fig.

8(b), the Diversity Indicator (DI) value of SMA-LM's Pareto solution set is only 0.18, significantly lower than NSGA-II's 0.25, SPEA2's 0.21, and the original MOPSO's 0.35. This indicates that while maintaining excellent convergence of the Pareto front, the improved MOPSO can generate a more uniform and diverse solution set. This study further validates the superiority of SMA-LM for solving complex MOO problems, as shown in Fig. 9.

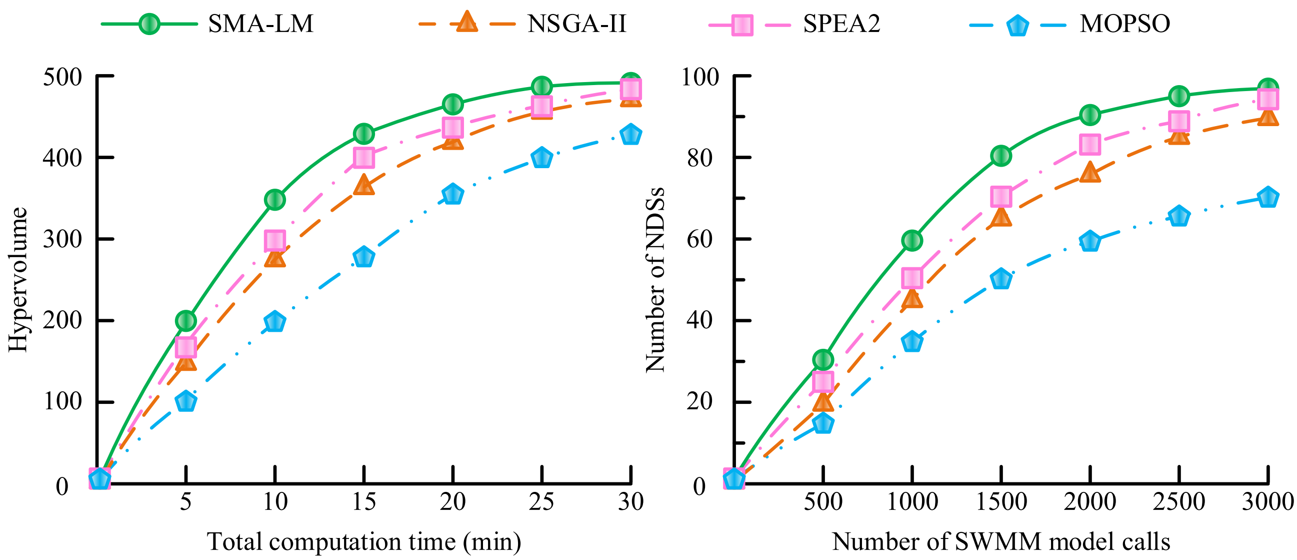


(a) Comparison of final HV for each model

(b) Comparison of final MSE for each model

Fig. 9. Comparison of optimization accuracy and algorithm stability of various models

In Fig. 9(a), the final median HV of SMA-LM is as high as 480, much higher than the original MOPSO's 340. The height of its enclosure (i.e., quartile range) is only 10, and the fluctuation range of the upper and lower limits is only 35, which is much smaller than the original MOPSO's 60 and 130. This indicates that the elite archive and adaptive grid mechanism can effectively prevent the algorithm from getting stuck in local optima and reduce the volatility of the results. In Fig. 9(b), the Mean Squared Error (MSE) of SMA-LM is only 0.02, significantly better than NSGA-II's 0.05, SPEA2's 0.04, and the original MOPSO's 0.08, demonstrating the high accuracy of the research model in approaching the optimal frontier. The collaborative framework efficiency of each model is shown in Fig. 10.



(a) Curves of HV with total computation time for each model

(b) Curves of the number of NDSs with the number of SWMM model calls for each model

Fig. 10. Comparison of collaborative framework efficiency among various models

In Fig. 10(a), the slope of the SMA-LM curve is the steepest, with HV reaching 430 at 15 minutes, far exceeding NSGA-II's 370 and the original MOPSO's 280, indicating the maximum performance improvement achieved per unit time. In Fig. 10(b), the curve of SMA-LM tends to saturate at the fastest speed, finding 80 NDSs with only 1,500 calls, while the original

MOPSO only reaches 50 solutions with 1,500 calls. This strongly demonstrates that the research model achieves higher efficiency in using computing resources and shorter optimization cycles when solving multi-objective problems.

3.2. Analysis of the simulation application effect of SMA-LM model

To verify the practical applicability of SMA-LM, particularly its optimization of sponge facility layout in complex terrain and artificial intervention areas, this study selects two representative scenarios for simulation experiments. The data for Experiment 1 are selected from the hydrological dataset of Beijing Olympic Forest Park, sourced from the National Earth System Science Data Center, which includes rainfall data from 2018 to 2022, 1:2000 topographic data, and land use type maps. The data source for Experiment 2 is the green space dataset for Zhejiang University Zijingang Campus, obtained from the Zhejiang University Open Data Platform, which includes rainfall data from 2019 to 2023, campus topographic maps, and vector maps of building and green space distributions. This study divides two types of datasets into SCAs, extracts underlying surface parameters, and standardizes rainfall time series to adapt to the SWMM model's input format. Experiment 1 sets up two application scenarios: urban parks and campus green spaces, generating 10 Pareto optimal solutions. The simulation application results of urban parks are listed in Table 1.

Table 1. Simulation results of SMA-LM model for optimizing sponge facility layout in urban parks

Scheme No.	Total runoff reduction rate (%)	Construction cost (10,000 yuan)	Ecological benefit index	Landscape adaptability score	Rainstorm peak flow reduction rate (%)
S1	42.3	185	0.72	4.2	38.5
S2	51.6	230	0.81	3.8	45.2
S3	35.8	150	0.65	4.5	32.1
S4	58.2	275	0.89	3.5	52.7
S5	48.5	210	0.78	4.0	43.3
S6	62.1	310	0.92	3.2	57.9
S7	39.7	170	0.69	4.3	36.8
S8	55.3	250	0.85	3.7	49.6
S9	45.6	195	0.75	4.1	40.2
S10	59.8	290	0.90	3.4	55.4

In Table 1, the 10 Pareto-optimal solutions exhibit significant multi-objective trade-offs. With the construction cost increasing from 1.5 to 3.1 million yuan, the reduction rate of total runoff increases from 35.8% to 62.1%, and the reduction rate of rainstorm peak flow increases from 32.1% to 57.9%. The ecological benefit index increases from 0.65 to 0.92, while the landscape adaptability score decreases from 4.5 to 3.2. This indicates that SMA-LM can effectively balance runoff control, construction costs, ecological benefits, and landscape adaptability under complex terrain and diverse underlying surface conditions in urban parks, verifying its practical application value as an MOO. Table 2 shows the simulation application results of campus green spaces.

In Table 2, the 10 Pareto-optimal solutions exhibit a clear trade-off pattern across the objectives. As the unit area cost increases from 150 yuan/m^2 to 280 yuan/m^2, the annual runoff total control rate increases from 58.5% to 82.6%, and the ecological benefit index increases from 0.63 to 0.90. The utilization rate of rainwater resources has increased from 28.1% to 47.9%, while the facility maintenance convenience store has decreased from 4.6 to 3.2. This confirms that SMA-LM can effectively balance runoff control, cost, ecological benefits, and maintenance convenience in areas with high levels of artificial intervention on campus.

4. Discussion

4.1. Mechanism of Algorithm Superiority

The superior performance of SMA-LM, as evidenced by the convergence and diversity metrics, can be attributed to the integration of the elite archive and adaptive grid mechanisms. Unlike traditional MOPSO (Zhang et al., 2025), the adaptive grid strategy ensures a more uniform distribution of solutions along the Pareto front by dynamically penalizing crowded regions. This mechanism effectively prevents the algorithm from becoming trapped in local optima, which explains why SMA-LM outperforms NSGA-II and SPEA2 in HV and DI. Furthermore, the integration with SWMM ensures that the optimization process is driven by realistic hydrological responses rather than simplified proxies. As demonstrated in recent studies, distributed numerical simulations are essential for accurately capturing the complex interactions among rainfall, runoff and underlying surfaces in sponge city construction (Li et al., 2025).

Table 2. Simulation application data of SMA-LM for optimizing the layout of sponge facilities in campus green spaces

Scheme No.	Annual total runoff control rate (%)	Cost per unit area (yuan/m2)	Ecological benefit index	Facility maintenance convenience score	Rainwater resource utilization rate (%)
C1	65.2	185	0.70	4.3	32.5
C2	72.8	220	0.78	3.9	38.2
C3	58.5	150	0.63	4.6	28.1
C4	78.3	255	0.85	3.5	43.7
C5	69.4	200	0.75	4.1	35.6
C6	82.6	280	0.90	3.2	47.9
C7	62.1	170	0.67	4.4	30.3
C8	75.5	235	0.81	3.7	40.5
C9	67.8	190	0.73	4.2	33.8
C10	80.1	265	0.87	3.4	45.3

4.2. Practical Implications for Urban Planners

In practice, the proposed SMA-LM model represents a paradigm shift for urban planners. Traditionally, balancing cost and ecological benefits relies heavily on subjective experience. The SMA-LM model provides planners with a set of visualized NDSs (as shown in Fig. 5), allowing for informed trade-offs. For instance, in the urban park scenario, planners can explicitly quantify that a 10% increase in investment yields a 15% improvement in runoff control. This quantitative support significantly reduces the uncertainty in decision-making and enhances the scientific basis of landscape planning.

5. Conclusion and Recommendations

In response to the difficulties of balancing multiple objectives in LSF layout and the lack of precise quantitative analysis in traditional methods, this study developed an MOL model based on SWMM-MOPSO-AHP, namely SMA-LM. This model integrated the refined hydrological simulation capability of SWMM with the efficient MOO function of improved MOPSO to construct a dynamic collaborative optimization framework. It combined AHP to complete scheme optimization, ultimately forming a complete closed loop of "simulation-optimization-decision". In performance verification, the SMA-LM model had high convergence accuracy, with a final GD value of 0.04, far superior to NSGA-II's 0.29. Its solution set had strong diversity, with 92 NDSs, surpassing NSGA-II's 80. At the same time, its efficiency advantage was evident, with an HV of 430 within 15 minutes, a median HV of 480, and an MSE of only 0.02, resulting in both stability and accuracy. In the simulation test, the runoff reduction rate in the urban park scene ranged from 35.8% to 62.1%, the construction cost was controlled within 1.5 million to 3.1 million yuan, and the rainstorm peak flow reduction rate ranged from 32.1% to 57.9%. In the campus green space scene, the annual runoff control rate ranged from 58.5% to 82.6%, and the utilization rate of rainwater resources ranged from 28.1% to 47.9%. The research model achieved multi-objective balance in two typical scenarios. In summary, this paper demonstrates the effectiveness of SMA-LM in enhancing the scientific rigor and efficiency of LSF layout. The shortcomings lie in insufficient validation of the model's adaptability to extreme rainfall scenarios and the need to strengthen its universality across different types of gardens. Subsequent research will expand the simulation of extreme climate scenarios to enhance the adaptability to diverse garden scenes.

Author Contributions

Jian Du contributed to conceptualization, methodology, software, draft preparation and manuscript editing. Jinling Zhong contributed to methodology, analysis, data collection, draft preparation and manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

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