Hindawi
Security and Communication Networks
Volume 2023, Article ID 9786472, 1 page
https://doi.org/10.1155/2023/9786472

Retraction

Retracted: Multiobjective Algorithm for Urban Land Spatial Layout Optimization

Security and Communication Networks

Received 5 December 2023; Accepted 5 December 2023; Published 6 December 2023

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. He and X. Zhang, "Multiobjective Algorithm for Urban Land Spatial Layout Optimization," *Security and Communication Networks*, vol. 2022, Article ID 3764215, 6 pages, 2022.

Hindawi
Security and Communication Networks
Volume 2022, Article ID 3764215, 6 pages
https://doi.org/10.1155/2022/3764215

Research Article

Multiobjective Algorithm for Urban Land Spatial Layout Optimization

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Received 24 February 2022; Revised 27 March 2022; Accepted 2 April 2022; Published 28 April 2022

Academic Editor: C. Venkatesan

In order to explore a quantitative and multiobjective optimization method of land use spatial allocation, this paper proposes a multiobjective algorithm for urban land spatial layout optimization. In this paper, the optimal multiobjective particle swarm optimization (MSO) algorithm is used to construct the optimal land use allocation model, and the variation characteristics of the optimized land use allocation scheme in quantity structure and spatial layout are analyzed. The results show that the total running time of the MSO model and the ordinary genetic algorithm spatial optimal allocation model is 8.57 h and 3.31 h, respectively, and the running efficiency of the mosolua model is 61.38% higher than that of the ordinary genetic algorithm spatial optimal allocation model. The configuration was optimized by using the model of land use spatial pattern from the plaque compactness, adjacency, aggregation degree, environmental compatibility, and the overall degree of resource-saving and environmental friendliness than the ordinary genetic algorithm model of optimal configuration results, and the model of overall fitness model compared with the ordinary genetic algorithm improved by 12.57%.

1. Introduction

In the spatial planning of urban land, we often need to face the specific problems of how to generate, evaluate, and select the spatial allocation scheme of urban land use [1]. For a certain area, there are many feasible urban land spatial allocation schemes. For example, for a planning area with 200 planned plots, if there may be 10 land use types in each plot, the possible schemes will reach 10200, a very large number [2]. It is neither feasible nor realistic for us to find out these plans one by one. At present, planners can only generate and select candidate schemes according to qualitative methods and subjective judgment. This process is called a "black box" operation. The result is more or less subjective, and the number of schemes obtained is very small [3]. In practice, there may be better schemes that have not been found, so it is very necessary and urgent to seek effective quantitative methods. The spatial layout of urban land belongs to the problem of resource allocation, which has combinatorial challenges [4]. Due to the diversity of objectives of land use spatial optimal allocation, such as saving land resources as much as possible and minimizing environmental incompatibility, land use spatial optimal allocation is a multiobjective decision-making problem. How to find an objective, quantitative, and spatial optimal allocation method that can solve the multiobjective decision-making problem is very important for the research of land use spatial optimal allocation [5].

In the research of optimal land use allocation, early scholars tried to use the linear programming model, system dynamics model, and other methods to solve the optimal land use allocation scheme. However, due to the large-scale and nonlinear characteristics of the spatial optimization problem, it is difficult to deal with the model for a long time, form an approximate optimal solution set, and find the optimal land allocation scheme [6]. At present, more and more heuristic optimization algorithms are applied to land optimal allocation, such as the genetic algorithm (GA), simulated annealing algorithm (SA), ant colony algorithm (ACO), and particle swarm optimization (PSO) [7]. On the one hand, the efficient optimization ability of the heuristic algorithm, combined with the improvement of computer performance, provides more research ideas for the optimal allocation of land use. Milad and others proposed a novel fixture layout optimization method by combining multi-objective ant colony algorithm (m-ACO) and the finite element method. The proposed method simultaneously optimizes the fixture layout and the number of fixtures as a multiobjective problem. The approximation of the Pareto front is obtained by the proposed method. This method is used to optimize the fixture layout of automobile side stiffeners. The results show that this method effectively performs the optimization of automatic fixture layout [8]. Sun and others proposed an optimization model of traffic sensor layout. Considering the influence of traffic big data, a set of influencing factors for traffic sensor layout are established, including system cost, multisource data sharing, data demand, sensor failure, road infrastructure, and sensor type. The influence of these factors is considered in the traffic sensor layout optimization problem. The optimization problem is formulated in the form of a multiobjective programming model, including minimum system cost, maximum truncated flow, minimum path coverage, and original destination (OD) coverage constraints. The tolerant entry method based on genetic algorithm solves the model. The case study shows that the model reflects the impact of multisource data sharing and fault conditions and meets the original destination coverage constraints to realize the multiobjective optimization of traffic sensor layout [9].

This study will improve and optimize based on the multiobjective algorithm and apply it to the land use optimization allocation study in the study area. In terms of model construction, the research first clarified the goal of land use optimization allocation, namely, land suitability maximization, land agglomeration maximization, and ecological value maximization, and further clarified the model constraints to form a multitarget planning model. In terms of the optimization algorithm, the model improves the algorithm with optimization strategies such as variant operators and dynamic crowding distance when the particle group algorithm converges prematurely and easily reaches the local optimization.

2. Research Methods

2.1. Construction of the Land Use Multiobjective Algorithm Optimization Model. The multiobjective optimization model of land use constructed in this paper takes the multiobjective particle swarm optimization (MOPSO) as the algorithm basis, objective function, constraints, and decision support as the basic elements, takes the maximization of land suitability, ecological service value, and land agglomeration as the optimization objectives of the model, and obtains the optimal land allocation scheme of each objective based on the Pareto optimization principle.

2.1.1. Multiobjective Particle Swarm Optimization

Definition 1. MOPSO defines a multiobjective optimization problem composed of n decision variables, m objective functions, p inequality constraints, and q equality constraints, which can be described as shown in the following formula:

$$\begin{cases} \min F(x) = \min\left(f_1(x), \ldots, f_m(x)\right), \\ g_j(x) \le 0, \quad j = 1, \ldots, p, \\ h_j(x) = 0, \quad j = 1, \ldots, p, \end{cases} \tag{1}$$

where $F(x)$ is the objective function and the decision variable is $x = (x_1, \ldots, x_n)$; $f_i(x)(i = 1, \ldots, m)$ is the ith objective function of the model; $g_j(x)$ is the jth inequality constraint; and $h_j(x)$ is the jth equality constraint.

Storage definition of Pareto optimal solution 1 (Pareto domination): for any two solutions A and B in the feasible solution set of the model, when the following conditions are true, solution A can be regarded as superior to solution B, as shown in the following formula:

$$\begin{gathered} \{\forall i \in (1, \ldots, m)\colon f_i(a) \le f_i(b)\} \cup, \\ \left\{\exists j \in (1, \ldots, m)\colon f_j(a) < f_i(b)\right\}. \end{gathered} \tag{2}$$

Definition 2. (Pareto optimal solution). When there is no feasible solution dominating x' in the dominating solution set x_p, the solution x' is called Pareto optimal solution and all optimal solutions constitute Pareto frontier in the following formula:

$$\exists x \in x_p\colon x > x'. \tag{3}$$

Each iteration of the model algorithm can get a group of nondominated solutions, and there is no dominant relationship between these solutions, so it is difficult to determine which solution is superior to other solutions. In order to select the learning samples of particle swarm optimization and store them in the external file, the nondominated solutions are usually sorted first. For the elite particles (learning samples) stored in the external file, their quality will directly affect the execution efficiency of the algorithm [9]. Therefore, in order to make the distribution of nondominated solutions as uniform as possible and minimize the distance from the real Pareto front, this study obtains the density information of nondominated solutions in the external file through analysis and calculation, which can be used as the basis to measure the advantages and disadvantages of nondominated solutions and store elite particles [10].

Definition 3 The construction of an adaptive grid and the scale limitation of external files manage the external files by constructing the adaptive grid. The three-dimensional search space is evenly divided into grids with the same interval. The particle density is estimated by counting the number of particles in each grid, and the fitness function is designed according to the particle density information. We obtain

$$d_i = \frac{\max f_i(x) - \max f_i(x)}{k_i}, \tag{4}$$

where d_i is the grid width of the i-dimensional target of each grid; $x \in D$ and X is the decision variable; D is the decision space; and k_i is the partition fraction of the i-dimensional target space [11]. In terms of scale control of external archives, this study adopts the calculation method based on dynamic crowding distance to eliminate the particles with a small crowding distance from the external archives, so that the whole nondominated solution can be evenly distributed in the search space, so as to avoid falling into local optimization during model calculation, and to improve the diversity of solutions and the execution efficiency of the algorithm [11, 12].

Definition 4 In mutation operator, when the historical optimal position of the particle swarm has not changed for a long time, the speed update change is small, and the convergence speed of the particle swarm is too fast, it is easy to fall into the local optimum [13]. In order to solve this problem, a mutation operator is added in the iterative process of the algorithm to expand the search range, improve the uniformity of particle distribution, and avoid falling into local optimization. The mutation operator used in this study is similar to the method in the genetic algorithm. When the particle swarm gathers, while retaining the historical optimal position, the particle swarm is evenly divided into three subsets according to quantity and scale, and some particle structures are mutated to varying degrees. The defined algorithm is shown in Algorithm 1.

2.1.2. Construction of the Objective Function. According to the current situation of land spatial layout to be optimized, insufficient cultivated land resources, low land use intensity, and deteriorating ecological environment in Wujin District, the following objective functions are formulated: (1) Ecological service value function is the direct or indirect quantitative value provided by the ecosystem to human activities. This value can reflect the impact of the spatial allocation results of excavated land on the ecological environment of the study area [14, 15]. When the value of ecological services is maximized, it means that the regional ecological environment has reached its best state. In order to facilitate the estimation of ecological service value, it is necessary to establish a matching relationship between the classification of land use status and ecosystem land. According to the classification system of ecosystem by Xie Gaodi and others, secondary or tertiary land of land use status with a small area and similar ecological service value should be combined into the category of ecosystem land [16]. For example, farmland ecosystem land includes not only subland types such as dry land and irrigated land but also grassland with the same ecological service function; forest ecosystem land includes forest land and garden land; industrial ecosystem land includes industrial and mining storage land and transportation land; and residential ecosystem land includes commercial land, residential land, public management and public service land, and special land. The calculation formula is shown in the following formula:

$$f_{\mathrm{Eco}} = \sum_{i=1}^{N} A_i^* VC_i. \tag{5}$$

Here, f_{Eco} is the total ecological benefit of the land unit in the study area; A_i is the area of the ith land type in the study area; and VC_i is the ecological service value corresponding to type I land use.

2.2. Optimal Allocation of the Multiobjective Land Use Space

2.2.1. Initialization of the Land Use Grid. Since the main research object of this paper is the spatial optimal allocation of urban land use, the focus of native land use classification is urban land. According to the importance of urban land function, the developed land in the study area is classified into three types: residential land, commercial land, and industrial land; in addition, in order to simplify the complexity of land use classification and improve the running speed of the program, the undeveloped land is classified into undeveloped land and nonconstruction land (mainly mountains, water bodies, green space, urban planning protection land, etc.). Therefore, by sorting and merging the existing land use data, the land use in the study area is divided into five types, residential land, commercial land, industrial land, undeveloped land, and nonconstruction land, and the land use grid is divided into $30\,\mathrm{m} \times 30\,\mathrm{m}$ [17, 18].

2.2.2. Generation of the Initial Feasible Solution. In this study, the model adopts 3 × 3, the critical value B of the number of developed land units in the neighborhood is taken as 3. According to the model setting, each land use grid can only allocate one land use type and accommodate one agent. According to the current population situation of the study area from 1993 to 2005, the study area is obtained by using the gray GM (1,1) prediction model.

The demand quantity of residential land, commercial land, and industrial land in 2010 is 69.42, 45.85, and 30.39 km^2, respectively. According to the demand quantity, the quantity of resident agents, industrial enterprise agents, and commercial enterprise agents in 2010 is determined in proportion. Here, an agent only reflects the proportional relationship and does not represent one person or one enterprise. In this paper, the actual meaning is the average number of people or enterprises accommodated in a $30\,\mathrm{m} \times 30\,\mathrm{m}$ grid. Next, these agents are allocated to the 2005 land use grid according to their types, and the remaining agents to be allocated are allocated to the undeveloped land use grid in the study area by the Monte Carlo method. The land use types of these grids change with the types of agents distributed on them. This step produces the parent individual of the model, that is, the initial solution of the model.

2.2.3. Determination of the Agent Structure and Decision Parameters. In this paper, three types of agents are mainly defined: resident agents, commercial enterprise agents, and industrial enterprise agents. Different types of agents have different decision variables and decision parameters. In this paper, the main decision-making behavior of the resident agent is to select the appropriate location as the residence,

Sub_sizes = [ABC] For particle swarm subset a, there is no variation;
If Uniform mutation operator>0 Particle swarm subset B performs uniform mutation according to the value of uniform mutation operator;
end.
Nonuniform mutation operator=(1-Current iteration/maximum iteration)(5 * Number of decision variables) * Number of particles in subset C;
If Nonuniform mutation operator>0.
Particle swarm subset C performs nonuniform mutation according to the value of nonuniform mutation operator;
end.

Algorithm 1

Table 1: Development cost standard of land use conversion.

Land type	Industrial land	Residential land	Commercial land
Industrial land	—	0.20	0.20
Residential land	0.90	—	0.90
Commercial land	0.45	0.45	—
Undeveloped land	1.80	1.80	1.80

Table 2: Environmental compatibility between adjacent land use types.

Land type	Nonconstruction land	Commercial land	Residential land	Industrial land
Undeveloped land	1.0	1.0	1.0	1.0
Nonconstruction land	1.0	1.0	0.5	0.0
Residential land	1.0	1.0	0.7	0.0
Commercial land	0.5	0.7	1.0	0.2
Industrial land	0.0	0.0	0.2	1.0

while the main decision-making behavior of the enterprise agent is to select the appropriate location as the land for enterprise development [17, 18]. After consulting relevant industry experts, the decision variables such as slope, land value, environmental value, planning completeness, traffic accessibility, and industrial agglomeration are given for agent selection. The decision variables selected by different types of agents are different, and their decision parameters are also different.

In the above calculation process, the function value of the agent to the target (1) is obtained by calculating the distance between the land use grid where the agent is located and the nearest developed land use grid. The function value of the agent is obtained by calculating the development cost of land use conversion. The development cost standard of land use conversion is shown in Table 1.

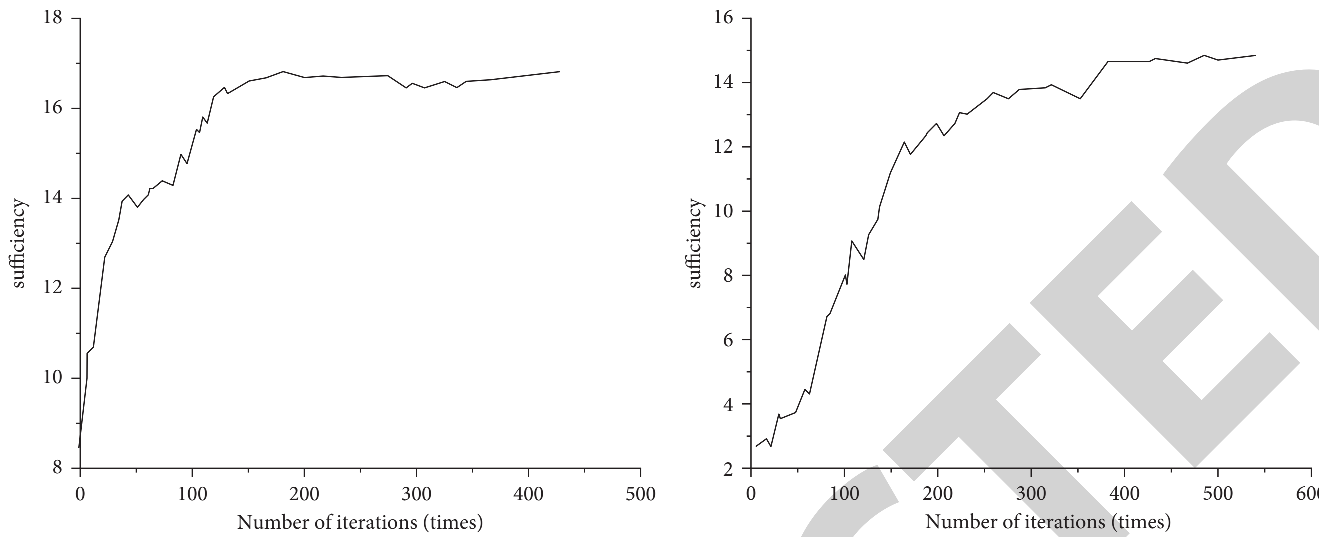
By calculating the sum of the compatibility between the land use objectives expected by other agents in the 3×3 neighborhood of the agent and the land use objectives expected by the agent [19]. Zhang et al. developed a multiagent spatial optimization model for land use configuration. The model is applied to solve the multitarget spatial optimization allocation of land use in the core area of the Changsha-Zhuzhou-Xiangtan urban agglomeration in China. The results show that the MOSO model performs better than GA for solving complex multiobjective space optimization configuration problems and is a promising way to generate land use schemes [20].

The environmental compatibility between different land use types is shown in Table 2.

3. Result Analysis

In order to further verify the feasibility of the model, based on the same objective function, the land use allocation results obtained by using the model and the spatial optimal allocation model using an ordinary genetic algorithm and the convergence performance of the two models are compared (Figure 1). According to D_{MPF}, d_{MEN}, IA, and IE, the land use allocation results obtained by using the spatial optimal allocation model of the general genetic algorithm are evaluated (Tables 3 and 4).

From Figure 1, it can be found that when the spatial optimal allocation of land use in the same study area is carried out, the general fitness of the model when the spatial optimal allocation model of the general genetic algorithm and the mosolua model are used to obtain the final results of the spatial optimal allocation of land use is 14.88 and 16.75, respectively. The overall fitness of the mosolua model is improved by 12.57% compared with the spatial optimal allocation model of the ordinary genetic algorithm. Comparing Table 4 with Table 3, it can also be found that D_{MPF} and d_{MEN} of all kinds of land in Table 4 are higher than those optimized in Table 3, while IA and IE are lower than those optimized in Table 4, reflecting that the overall resource conservation and environmental friendliness of the land use



(a) (b)

Figure 1: Convergence comparison between the mosolua model and the general genetic algorithm spatial optimal allocation model. (a) Convergence curve of spatial optimal allocation model of general genetic algorithm. (b) Convergence curve of the mosolua model.

Table 3: Evaluation results of land use spatial pattern before and after optimization.

Parameter	Before optimization			After optimization		
	Residential land	Industrial land	Commercial land	Residential land	Industrial land	Commercial land
D_{MPF}	1.120	1.436	1.260	1.002	1.345	1.101
d_{MEN}	140.123	169.240	145.631	132.510	145.554	138.536
IA	65.345	38.211	57.268	70.216	45.110	66.475
IE	0.600	0.666	0.607	0.770	0.634	0.649

Table 4: Evaluation of land use allocation results based on the spatial optimal allocation model of the general genetic algorithm.

Land type	$\mathrm{D_{MPF}}$	$\mathrm{d_{MEN}}$	I_A	I_E
Residential land	1.005	130.567	64.803	0.567
Industrial land	1.213	146.53	38.226	0.572
Commercial land	1.026	140.23	58.321	0.623

allocation results obtained based on the mosolua model are significantly better than those obtained based on the spatial optimal allocation model of ordinary genetic algorithm. In addition, for the same research area, based on the same objective function, in order to obtain the optimal configuration results, the total actual operation time of the mosolua model and the general genetic algorithm spatial optimal configuration model is 8.57 h and 3.31 h, respectively. The operation efficiency of the mosolua model is 61.38% higher than that of the general genetic algorithm spatial optimal configuration model.

4. Conclusion

Under multiobjective constraints, combined with the reality of urban land use spatial optimal allocation, this paper constructs a multiobjective algorithm applied to urban land use spatial optimal allocation. The application results show that the algorithm can not only obtain reasonable and feasible optimal configuration results but also have good operation efficiency.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The study was supported by the "Natural Science Foundation of Hubei Province (Grant No. 2019CFB355)" and the Think-Tank Project of Jingzhou (Grant No. Jzsk-yk2139).

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