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Research paper

Optimal allocation of urban land space based on NSGA2

Yi Guo[1], Chaoqin Bai[2], Peiwen Zhao[3]

Abstract: Urban land spatial optimization is one of the important issues in urban planning and land resource management. As the speed advancement of urbanization and the continuous increase of population, the rational use of land resources has become the key to sustainable urban development. Based on this, the study adopts the optimization goals of maximizing gross domestic product (GDP), reducing aerosol optical thickness and non-point source pollution (NPSP) load, and reducing land use change costs and incongruity. Three constraints are set simultaneously, including minimum construction land, water body, and cultivated land area. In addition, a fast non dominated sorting genetic algorithm (NSGA2) with elite strategy is used to address it. The outcomes denoted that the iterative distance of the proposed algorithm on the Bin and Cohen functions was only 0.048%, which was 0.522% lower than that of the NSGA2. Meanwhile, the reverse iteration distance value of this algorithm was only 4.14%, which was 22.76% lower than the adaptive weighted genetic algorithm. In addition, the algorithm's Spacing value was only 4.28%, and the hypervolume index value was as high as 78.66%. This indicated that the research method had a good optimization effect on the optimal allocation (OA) of land space in urban agglomerations, providing scientific decision-making support for sustainable urban development.

Keywords: land space, multi-objective optimization, NSGA2, optimize configuration, urban agglomerations

[1]LEP., PhD, School of Human Settlements and Civil Engineering, Xi'an Jiaotong University, Xi'an 710000, China, e-mail: guoyi2200@126.com, ORCID: 0009-0009-2192-1080
[2]A.P., School of Civil Engineering and Architecture, Henan University of Science and Technology, Luoyang 471000, China, e-mail: bcq1980@163.com, ORCID: 0009-0001-6521-7791
[3]S.A., MS., First Affiliated Hospital, Henan University of Science and Technology, Luoyang 471000, China, e-mail: zhaopeiwen127@163.com, ORCID: 0009-0009-6697-2308

1. Introduction

Since the 21st century, significant achievements have been made globally in economic development and urban construction. Land, as a scarce and non renewable resource, provides limited space for humans to engage in various production activities, and the limited land area often cannot meet the needs of human economic development for land resources. The past economic development and urban construction were mostly achieved through excessive consumption of land resources. The land use model is relatively extensive, with the rapid expansion of construction land, a significant reduction in arable land and water area, and a high energy consumption and emissions growth model, resulting in a reduction in natural resources, ecosystem degradation, environmental pollution, and many other problems. This indicates that the previous approach of "exchanging resources and environment for economic growth" is unsustainable. Therefore, adopting a more scientific and reasonable land use model to improve the efficiency of urban land use and achieve the goal of optimizing the allocation of urban land use is an important means to promote the sustainable use of urban land resources and the fundamental way to solve the contradiction between economic development and ecological protection. Meanwhile, the rational allocation of urban land can effectively improve land use efficiency and promote sustainable urban development [1]. However, due to the limitations of land resources and the complexity of urban development, the optimization of urban land spatial allocation is a certain challenge. In existing research, many scholars have utilized various methods and models to study the OA of urban land space, such as linear programming, integer programming, genetic algorithms, etc. However, these methods have some limitations in solving the issue of OA of urban land space, such as slow convergence speed and insufficient diversity of solutions [2,3]. To overcome these problems, the study first designs a multi-objective system and constraint conditions for land spatial optimization, setting optimization goals such as maximizing GDP, reducing aerosol optical thickness and NPSP load, and setting minimum construction land, water body, and cultivated land areas as constraint conditions. Subsequently, the study employed the Fast NSGA2 based on elite strategy for multi-objective optimization (MOO) of urban land spatial allocation. By transforming the problem of optimizing urban land spatial allocation into a MOO problem, and mainly focusing on general existing urban expansion and new urban planning, the research aims to find a set of optimal solutions to achieve the rational use and spatial allocation of these urban lands, providing reference for urban expansion and planning. The main content of the study includes four parts. The first part summarizes relevant research results and methods, including urban land use planning, optimization allocation methods, etc. The second part introduces the application of NSGA2 to the optimization of urban land spatial allocation. The third part proves the performance and feasibility of the proposed method through experiments and simulations. The fourth part summarizes the main research results and provides prospects for future research directions.

2. Related works

The rational allocation and management of land resources are of great significance in contemporary times. Strauch and other scholars have proposed a constrained MOO tool for land use allocation problems. This tool can integrate user specific spatial models, consider multiple competitive needs. The results indicated that the repair mechanism was more effective than the penalty mechanism [4]. Masoumi and other researchers found that urban spatial planning changes frequently, so they proposed a two-step approach. The first step was to use MOO technology to obtain the optimal arrangement for surrounding land use. The second step was to use clustering analysis to provide appropriate solutions for decision-makers. The optimization results showed that this method could achieve better results than existing land use [5]. Researchers such as Cai proposed a point of interest (POI)-based visualization method for identifying and analyzing land use features around urban rail transit stations. The results indicated that this method could effectively identify and analyze the land use situation of urban rail transit stations [6].

At present, the NSGA2 is widely used in solving various MOO problems. Scholars such as Civira proposed a new method based on MOO and genetic algorithm to address the impact of sensor location on performance in monitoring systems for civil buildings and infrastructure. The findings denoted that this method could maintain the optimal performance of sensor configuration after disasters, and was particularly suitable for complex masonry buildings in high seismic risk areas [7]. Deng and other researchers proposed a two-stage gene selection method that combined eXtreme gradient boosting (XGBoost) and NSGA-2 algorithms to address the challenge of gene selection in microarray gene expression data. The results indicated that XGBoost-NSGA2 outperformed other algorithms in evaluation indicators such as accuracy, F-value, precision, and recall [8]. Priya's team proposed a rule-based fuzzy classification method to predict sowing fuzziness in order to explore the impact of planting schedules on yield in agricultural production. The results indicated that this method could accurately predict sowing ambiguity [9].

In summary, numerous researchers both domestically and internationally have conducted extensive research on land use allocation issues and the practical application of the NSGA2. However, few studies have applied the NSGA2 to solve MOO problems in land spatial optimization allocation. Therefore, research has filled this gap to provide a new solution and method for the optimization of urban land spatial allocation.

3. Optimal allocation of urban land space based on NSGA2

The OA of urban land space is a complex multi-objective problem. To optimize the spatial allocation of land in urban agglomerations, the study adopts maximizing GDP, reducing aerosol optical thickness and NPSP load, and reducing land use change costs and incongruity as optimization objectives. Three constraints are set simultaneously, including minimum construction land, water body, and cultivated land area. In addition, the NSGA2 is introduced to address the MOO problem, and the algorithm process is detailed.

3.1. Design of multi-objective system and constraint conditions for land spatial optimization

In the process of urban agglomeration development, the optimization of land space is a crucial consideration factor. To optimize land use space, a series of optimization objectives and limiting factors have been proposed in the study, among which the optimization objective system is shown in Fig. 1.

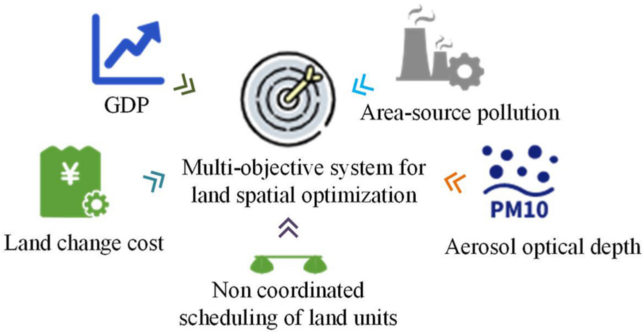

Fig. 1. Land spatial optimization objective system

Fig. 1 contains 5 objectives. Among them, GDP is the final result of production activities of all resident units in a country (or region) during a certain period of time. It is the core indicator of national economic accounting and an important indicator for measuring the economic status and development level of a country or region; Area-source pollution refers to various environmental pollutants without fixed discharge outlets, mainly composed of pesticides, various atmospheric particulate matter, etc., which enter the water, soil, or atmospheric environment through surface runoff, soil erosion, and other means; Aerosol optical depth (AOD) is a physical quantity that describes the degree of attenuation of light by aerosols. It represents the optical thickness of aerosol components due to extinction, which can reflect atmospheric turbidity and accurately reflect the air quality within a certain area; The Land change cost represents the cost of converting from the current land use type to another land use type; The Non coordinated scheduling of land units is a quantitative evaluation of the incompatibility between a certain land unit and its neighboring units. The sum of the disharmony indices of all land units is the disharmony of land units in the entire region. Promoting economic development is the primary task for the sustainable growth of urban agglomerations. In the optimizing of land use, urban agglomerations need to comprehensively consider population and economic factors [10]. GDP can be an important indicator when evaluating the economic benefits of land use change. In order to promote sustained economic growth, it is necessary to maximize GDP, which is the first goal in optimizing the land space of urban agglomerations. In the context of climate change characterized by extreme weather and global warming, to promote sustained economic growth, GDP remains a crucial indicator and one of the important goals to be pursued in optimizing land space in urban agglomerations. The specific calculation is shown in (3.1).

$$\mathrm{MAX}(Y_1) = \sum_{i=1}^{n} U_{\mathrm{GDPI}} \cdot A_i \tag{3.1}$$

In (3.1), Y_1 represents the total GDP of the region. U_{GDP} represents the unit GDP value of the i th land use type, which mainly represents the GDP generated by the i th land use type. $\mathrm{MAX}(X_1) = \sum_{i=1}^{n} U_{\mathrm{GDPI}} \cdot A_i$ represents the area of the i th land use type, while n represents the amount of land use types. According to the current situation of land use in general cities, land use types mainly include six types: meadow land, forest land, water area, cultivated land, construction land (including areas already prepared for construction and already partially built-up areas), and unused land [11]. However, the U_{GDP} of these six types of land use is difficult to decide, so the study introduces the regional weighting method to solve it, and the specific calculation is shown in (3.2).

$$U_{\mathrm{GDPI}} = \sum_{j=1}^{13} \mathrm{unitGDP}_{\mathrm{IJ}} \cdot \frac{S_J}{S} \tag{3.2}$$

In (3.2), $\mathrm{unitGDP}_{\mathrm{IJ}}$ represents the U_{GDP} of the j th type of land in the SSth city. $\mathrm{unitGDP}_{\mathrm{IJ}}$ denotes the area of the j th city, and S represents the total area of the urban agglomeration. NPSP is caused by surface runoff bringing various pollutants into water bodies. Although the formation of NPSP is caused by natural processes, the pollution situation is further exacerbated with human land use. Reasonable development and utilization of land can help reduce NPSP, so the study considers minimizing the total load of NPSP as the second major optimization goal. The specific optimization objective calculation is denoted in (3.3).

$$\mathrm{MIN}(Y_2) = \sum_{(i,j)}^{U} U_{\mathrm{nps}(i,j)} \cdot A(i,j) \tag{3.3}$$

In (3.3), Y_2 represents the total annual NPSP load of the study area. $U_{\mathrm{nps}(i,j)}$ represents the unit NPSP load in land unit (i, j). X_2 represents the area in land unit (i, j), and U represents all land units in the study area. The calculation of $U_{\mathrm{nps}(i,j)}$ is shown in (3.4).

$$U_{\mathrm{nps}(i,j)} = \mathrm{EMCs} \cdot P \cdot a \cdot 10^{-7} \tag{3.4}$$

In (3.4), EMCs represents the annual average concentration of pollutants in rainfall runoff. P represents the annual average rainfall. a represents the annual surface runoff coefficient, and 10^{-7} represents the unit conversion coefficient. AOD is an important indicator reflecting atmospheric turbidity and air quality, and the specific calculation is shown in (3.5).

$$\mathrm{MIN}(Y_3) = \sum_{i=1}^{n} U_{\mathrm{AOD}i} \cdot A_i \tag{3.5}$$

In (3.5), Y_3 represents the total AOD value of the region, and U_{AOD} represents the unit aerosol load of the ith land use type. At the same time, the study uses the regional weighting method to process the unit AOD of six land use types, and its calculation is denoted in (3.6).

$$U_{\mathrm{AOD}i} = \sum_{j=1}^{13} \mathrm{unitAOD}_{\mathrm{IJ}} \cdot \frac{S_J}{S} \tag{3.6}$$

In (3.6), unitAOD_{IJ} represents the unit AOD load of the ith land type in the jth city. In the process of optimizing land use, it is also needs to consider the conversion costs between different types of land use, and its calculation is shown in (3.7).

$$\text{MIN}(Y_4) = \sum_{(i \in U)} \text{change}_i \tag{3.7}$$

In (3.7), Y_4 represents the cost of land change within the study area, and change_i expresses the cost index of the ith land unit changing from the current land use type to another type. The research mainly aims to minimize the non coordinated scheduling of land units as another land spatial optimization objective, and its calculation is shown in (3.8).

$$\text{MIN}(Y_5) = \sum_{Z_i}^{Z_i \in U} \sum_{Z_j}^{Z_j \in U} C(\text{landuse}(Z_i), \text{landuse}(Z_j)) \tag{3.8}$$

In (3.8), Y_5 represents the non coordinated scheduling of land units in the study area, and $C(\text{landuse}(Z_i), \text{landuse}(Z_j))$ represents the non coordinated index between the ith land unit and the jth land unit in the neighborhood. $C(\text{landuse}(Z_i), \text{landuse}(Z_j))$ represents the jth land unit in the neighborhood of the ith land unit.

The current demand for construction land is increasing, but excessive construction land may lead to excessive development of land resources and environmental damage. Therefore, the study aims to establish construction land area as a constraint in land use planning. Meanwhile, farmland is the foundation of agricultural production, and setting constraints on farmland is of great significance in land use planning. In addition, water bodies are an important component of ecosystems and have important ecological functions. Setting constraints on water bodies can protect their ecological functions, prevent excessive development and pollution, and maintain the health of ecosystems [12, 13].

3.2. Solution of urban land spatial optimization allocation problem based on NSGA2

Traditional genetic algorithms typically use fitness functions to transform MOO problems into single objective problems for solution. Improper selection may lead to falling into a local optimal solution [14, 15]. The NSGA2 algorithm improves the shortcomings of traditional genetic algorithms, proposes fast non dominated sorting and crowding comparison operators, introduces elite strategies, reduces the computational time of the algorithm, and can obtain a multi-objective Pareto optimal solution set, ensuring individual diversity. It has become one of the better algorithms for multi-objective solving problems. Meanwhile, when optimizing urban land use, it is necessary to consider various factors such as economy, society, and ecology, so land use optimization is a classic MOO problem. Therefore, the study introduces the NSGA2 to solve the multi-objective problem of land spatial optimization allocation in urban agglomerations. The specific steps are to first preprocess the relevant parameters, including the unit area GDP, unit area AOD, and annual average rainfall of the urban agglomeration. The research mainly uses the GDP prediction method per unit land area to calculate the unit area output value of agriculture, forestry, animal husbandry, fishery, secondary industry, and tertiary industry in different cities in different years. At the same time, it calculates the unit area GDP of different types of land in the simulated year based on the annual growth rate. In the preprocessing of unit area AOD, the study first used dark pixel method and deep blue algorithm to invert MOD04_3K aerosol data products, in order to obtain daily and annual average AOD data for urban agglomerations. Subsequently, AOD annual data from different years are spatially overlaid with land use grid data to calculate the unit area AOD of different land types in each city. The average value of nearly three years represents the unit area AOD of the urban agglomeration simulation year. In addition, in order to simulate the rainfall of a specific year, the study uses spatial interpolation data of rainfall over a period of 15 years. The Cell Statistics tool is used to calculate the average annual rainfall during this period in ArcGIS and used as rainfall data for the simulated year [16, 17]. After parameter preprocessing, genetic operations such as selection, crossover, and mutation need to be performed through chromosome encoding. The research mainly adopts real number encoding, which mainly represents a land use plan for each chromosome, and each gene value represents a land class. The number of genes means the area of the land type. The chromosome structure is shown in Fig. 2.

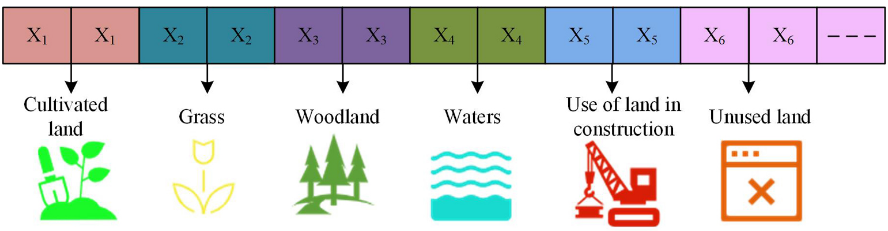

Fig. 2. Chomosome structure

In the optimization of land spatial allocation, it is not possible to completely overturn and reuse the already used land, but to improve it on the ground of the existing land use status. Therefore, the study adopts the current land use status as the basis for the initial population to better reflect the actual situation. Subsequently, fitness calculation is performed. In the NSGA2, the fitness value of an individual cannot be directly calculated based on the objective function, but rather the priority level of the individual is determined by their non dominant level and crowding distance [18–20]. Among them, the non dominant level represents the relative advantages and disadvantages of an individual in MOO compared to other individuals. For minimizing the two individuals x_A and x_B in MOO problems, if A accounts for more than B, it can be expressed as (3.9).

$$\forall i = \{1, 2, \ldots k\} : f_i(x_A) < f_i(x_B) \tag{3.9}$$

In (3.9), f_i means the target value of the i th target, and k represents the amount of targets. If A weakly dominates B, it can be expressed as (3.10).

$$\begin{cases} \forall i = \{1, 2, \ldots k\} : f_i(x_A) \le f_i(x_B) \\ \exists i = \{1, 2, \ldots k\} : f_i(x_A) < f_i(x_B) \end{cases} \tag{3.10}$$

When A is not superior to B and B is not superior to A, it indicates that A and B are in a non dominant level. Crowding distance is used to measure the distribution of individuals in the solution space, and its calculation is expressed in (3.11).

$$d = \sum_{i=1}^{k}\left(\left|f_i^{n+1} - f_i^{n-1}\right|\right) \tag{3.11}$$

In (3.11), d means the crowding distance of the n th individual, and f_i^{n+1} is the objective function value of the i th objective of the i th individual. The schematic diagram of individual crowding distance is indicated in Fig. 3.

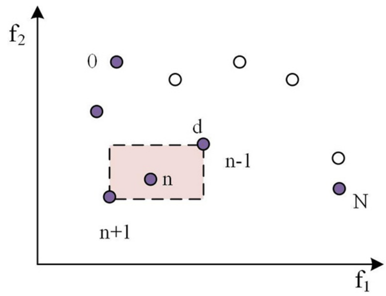

Fig. 3. Schematic diagram of individual crowding distance

When calculating congestion, the NSGA2 algorithm first determines the size sorting of individuals in the current dominating layer through function values. Then define the crowding distance corresponding to boundary individuals as infinite, and finally obtain the crowding distance of the remaining individuals in that layer. The equation for calculating congestion using the NSGA2 algorithm is shown in (3.12).

$$P\left[i\right]_{\text{distance}} = \sum_{k=1}^{r}\left(f_k \cdot P\left[i+1\right] - f_k \cdot P\left[i-1\right]\right) \tag{3.12}$$

In (3.12), $P\left[i\right]_{\text{distance}}$ represents the crowding distance of individual i, and $f_k \cdot P\left[i\right]$ refers to the function value of individual i on sub objective f_k. When encountering situations where the crowding distance between two individuals is equal, the NSGA2 algorithm usually randomly deletes one of the individuals, resulting in a decrease in the accuracy of the calculation results. At the same time, the NSGA2 algorithm mainly uses a fixed crowding degree method for individual sorting. However, when many low crowding individuals gather in a region, this method may eliminate all individuals in that region, resulting in a decrease in the diversity of the final solution set. Therefore, the study first designed left and right congestion indicators to change their original congestion distance. The specific steps are to initialize the crowding degree and assign the maximum crowding degree value to the boundary nodes. Then, the left crowding degree and right crowding degree are added to the non boundary nodes, and both are initialized to 0. After completing the above operation, the sub objective function values will be rearranged in a certain order, and the left and right crowding degree of non boundary nodes will be calculated, and finally the crowding degree of nodes will be obtained. When conducting genetic operations, the study adopts the tournament selection method, and its selection probability calculation is shown in (3.13).

$$C = \frac{F_i}{F} \tag{3.13}$$

In (3.13), F_i represents the fitness of the ith individual, and F represents the sum of the fitness of all individuals. During the crossover process, the method used in the study is to simulate binary crossover, and its calculation is shown in (3.14).

$$\text{Offspring} = \frac{\text{Parent1} + \text{Parent2}}{2} + \beta \cdot \frac{\text{Parent1} - \text{Parent2}}{2} \tag{3.14}$$

In (3.14), Offspring represents the offspring and Parent represents the parent. β represents a parameter that controls the degree of intersection, with a general value range of [0,1]. In the process of mutation, the research mainly adopts polynomial mutation, and its calculation is shown in (3.15).

$$v_i = x_i + (x_i - x_{\{i1\}}) \cdot (1 - r)^q \tag{3.15}$$

In (3.15), v_i represents the individual value after mutation. x_i represents the original individual value. $x_{\{i1\}}$ represents the value of another randomly selected individual in the current population. r is a random number between [0, 1], and q denotes the index of polynomial variation. The Pareto optimal solution, also known as non inferior solution, for any solution x, if it is the Pareto optimal solution in the solution set X, then $F(x')$ is not superior to $F(x)$. Among them, $x' \in X$. The representation of $F(x)$ and $F(x')$ is shown in (3.16).

$$\begin{cases} F(x) = (f_1(x), f_2(x), \ldots, f_i(x)) \\ F(x') = (f_1(x'), f_2(x'), \ldots, f_i(x')) \end{cases} \tag{3.16}$$

The flowchart of the NSGA2 is shown in Fig. 4.

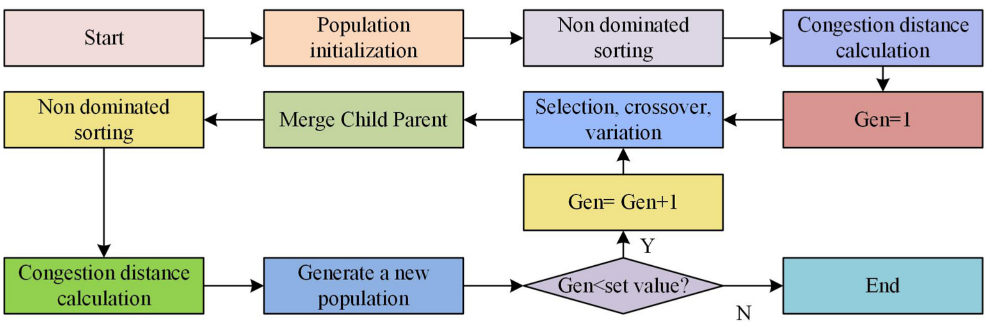

Fig. 4. Flow chart of NSGA2

4. Optimization results and validation of land spatial allocation in urban agglomerations

Land use optimization in urban agglomerations is an important research field aimed at maximizing land use efficiency, optimizing urban spatial structure, and achieving sustainable development. This chapter first verifies the performance of the NSGA2 in two typical multi-objective testing functions, and compares it with the other two optimization algorithms for analysis. Then, it is applied to the actual optimization of land spatial allocation in urban agglomerations to verify its optimization effect and feasibility.

4.1. Experimental analysis of NSGA2

To verify the function of the NSGA2, a test function set was applied to compare the performance of the NSGA2, NSGA, and Adaptive Weighted Genetic Algorithm (AW-GA). The evaluation of MOO algorithms mainly considered three aspects: solution set quality, solution efficiency, and robustness. The experimental environment is denoted in Table 1.

Table 1. Experimental environment

Project	Parameter
Program	Python
Operating system	Windows 8.1
Running memory	4G
CPU	2.4G

The experiment first selected Binh and Korn (BNH) functions to detect the effectiveness advantages of the algorithm. Among them, the BNH test function is a MOO problem. The Pareto solution set distribution of each algorithm on the BNH test function is shown in Fig. 5. As shown in Fig. 5, in the BNH problem, the Pareto frontier distributions obtained by the three algorithms were similar. But the number of Pareto frontiers found by the NSGA2 was much

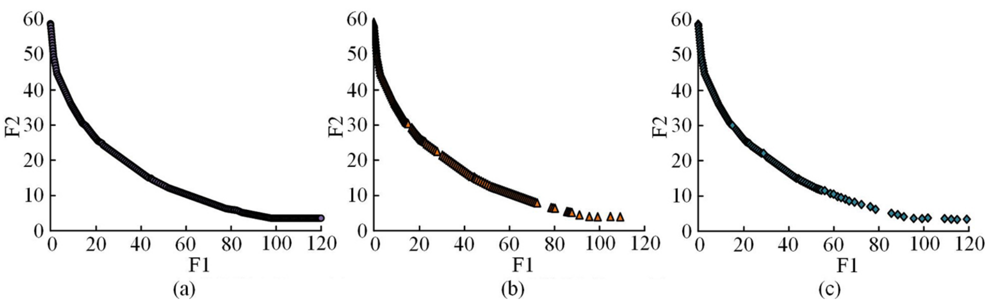

Fig. 5. The Pareto solution set distribution of each algorithm on the BNH test function: (a) NSGA2, (b) NSGA, (c) AW-GA

higher than other algorithms, followed by the AW-GA and the NSGA. The NSGA2 could find more Pareto frontier solutions when solving BNH test functions, which had better diversity and convergence performance.

The experiment then selected the Walking Fish Group (WFG) test function for performance verification, which is a three objective optimization problem. The distribution of Pareto solution sets found by each algorithm on the WFG test function is shown in Fig. 6. From Fig. 6, in the WFG three objective testing problem, the NSGA2 found the most Pareto frontiers, while the NSGA algorithm found the least, with a significant difference compared to the other two. This indicated that the NSGA2 also had better convergence performance when solving MOO problems.

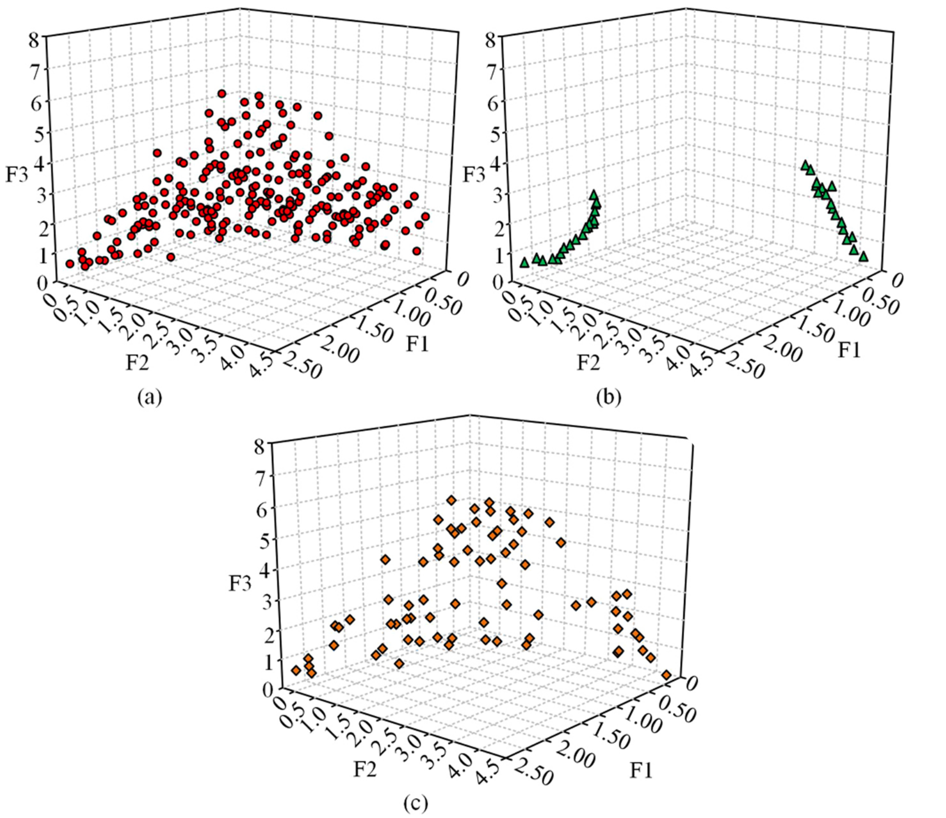

Fig. 6. The Pareto solution set distribution of each algorithm on the WFG test function: (a) NSGA2, (b) NSGA, (c) AW-GA

The study continued to analyze the algorithm using General Distance (GD), Inverted General Distance (IGD), Hypervolume (HV), and Spacing. The indicator values of each algorithm on the BNH test function and WFG test function are shown in Fig. 7. From Fig. 7, on the BNH test function, the GD value of the NSGA2 was only 0.048%. The IGD value of this algorithm was only 4.14%. Meanwhile, the Spacing value of this algorithm was only 4.28%. In addition, the HV value of this algorithm was as high as 78.66%. On the WFG test function, the GD value, IGD value, and Spacing value of the NSGA2 were 0.11%, 9.29%, and 5.49%. Meanwhile, the HV value of this algorithm was as high as 94.73%. This indicates that the NSGA algorithm has more significant convergence and diversity

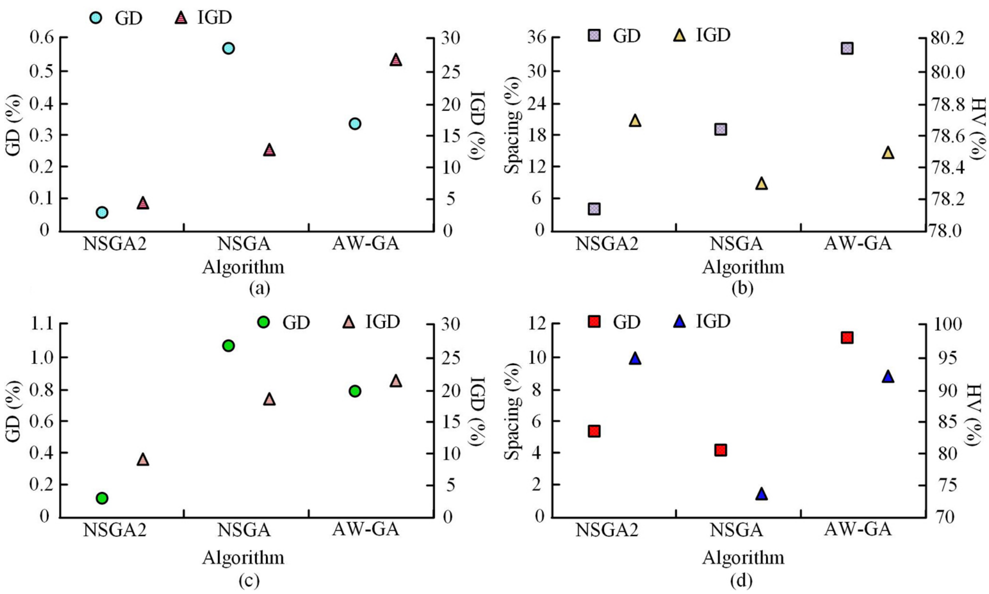

Fig. 7. Index values of various algorithms on BNH test function and WFG test function: (a) The values GD, IGD for the BNH test function, (b) The values of Spacing, HV for the BNH test function, (c) The values GD, IGD for the WFG test function, (b) The values of Spacing, HV for the WFG test function

4.2. Optimization analysis of land spatial allocation based on NSGA2

To prove the practical application effect of the NSGA2, the study selected land in the Beijing Tianjin Hebei urban agglomeration as the experimental object, and used the NSGA2 to optimize land spatial allocation. The changes of each objective with the iteration times are shown in Fig. 8. In Fig. 8, during the iteration process, the target values gradually decreased. Among them, GDP increased from 1.228×10^5 billion yuan reduced to 1.210×10^5 billion yuan, mainly due to the gradual reduction of construction land units, leading to a decrease in land use efficiency. However, the final GDP value was still higher than the actual and predicted GDP value, indicating that the optimization process of land use has promoted the improvement of GDP. Meanwhile, NPS decreased from 128.69 tons to 128.54 tons. AOD dropped from 2.471×10^7 to 2.469×10^7. The cost of land change has been reduced from 780 to 660. The degree of land unit disharmony increased from 2.148×10^5 reduced to 2.134×10^5. This indicated that the NSGA2 had good practical optimization results.

Due to the fact that decision-makers mainly selected the land spatial optimization scheme from the Pareto optimal scheme in the last iteration, the study discussed the Pareto optimal scheme by comparing the four minimization objectives in pairs. The comparison outcomes are

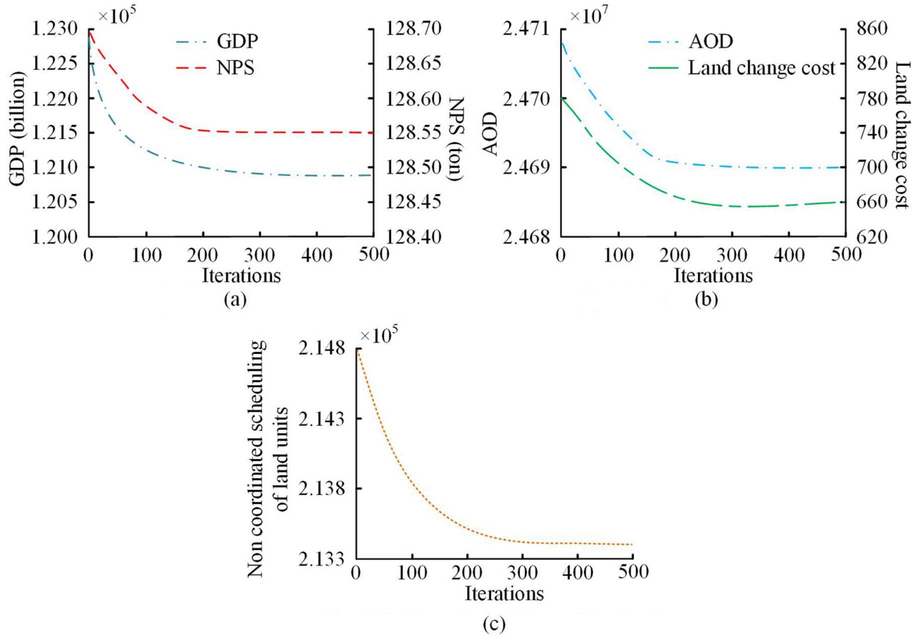

Fig. 8. The variation of each objective with the number of iterations: (a) GDP, NPS, (a) AOD, Load change cost, (c) Non coordinated scheduling of land units

indicated in Fig. 9. From Fig. 9, during the process of land spatial optimization, the red dot was closer to the origin, indicating that the final iteration scheme had smaller target values than the first iteration in all minimization goals. In addition, the distribution of green dots was relatively concentrated, while the distribution of red dots was more dispersed, indicating that the optimized solution had a larger space for selection. The Pareto optimal solution marked in the figure indicated that there were still multiple optimal solutions when comparing targets in pairs. This meant that in the process of balancing goals, decision-makers could choose land use plans that are suitable for the local situation from the Pareto optimal solution set.

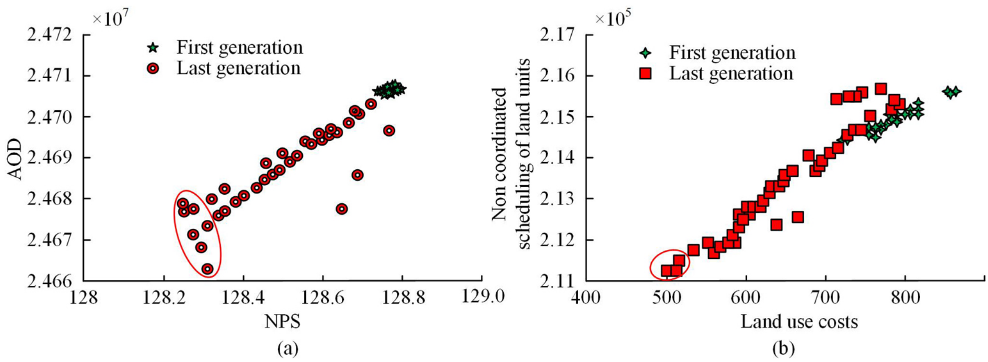

Fig. 9. Comparison results of Pareto's optimal solutions: (a) NPS and AOD, (b) Land use costs and non coordinated scheduling of land units

The study selected 10 Pareto optimal solutions from the individuals in the last iteration by comparing non dominated levels and crowding distances. The minimum, maximum, average, and standard deviation of the target values are expressed in Table 2. From Table 2, although the individual distribution in the last iteration was relatively dispersed, the difference between the max and mini values of the Pareto optimal solution was not significant. Among them, the standard deviation of GDP was only 1.641×10^3, the standard deviation of NPS was only 2×10^{-1}, the standard deviation of AOD was only 1.814×10^4, the standard deviation of land change cost was only 75, and the standard deviation of land unit non coordinated scheduling was only 1.308×10^3. This was because as the iteration progressed, the competition between objectives also intensified, making it more difficult to optimize each objective.

Table 2. Mini, max, average, and standard deviation of target values

Index	**GDP**	**AOD**	**NPS**	**Land change cost**	**Non coordinated scheduling of land units**
Maximum value	1.241×10^5	2.476×10^7	1.296×10^2	7.964×10^2	2.147×10^5
Minimum value	1.207×10^5	2.458×10^7	1.278×10^2	5.737×10^2	2.119×10^5
Average value	1.211×10^5	2.463×10^7	1.280×10^2	6.959×10^2	2.135×10^5
Standard deviation	1.641×10^3	1.814×10^4	2.000×10^{-1}	75.000	1.308×10^3

Finally, the simulation analysis of land use change in the Beijing Tianjin Hebei urban agglomeration was conducted, and compared with the simulation scheme of the cellular automaton (CA) model. the CA model is a grid dynamics model that is discrete in time, space, and state, with local spatial interactions and temporal causal relationships. It has the ability to simulate the spatiotemporal evolution process of complex systems. The comparison results between the Pareto optimal plan simulated by the NSGA2 algorithm and the CA simulation plan for newly added construction land are shown in Fig. 10. From Fig. 10, it can be seen that

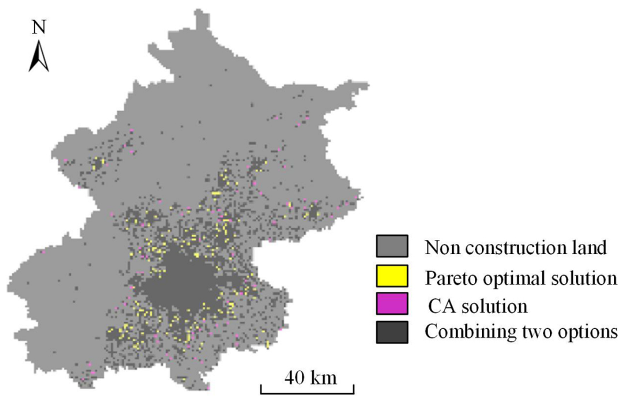

Fig. 10. Comparison of two model simulation plans for newly added construction land

according to the spatial distribution of newly generated construction land, the construction land units generated by the NSGA2 multi-objective model are closer to the current construction land and more densely distributed than those generated by the CA model. The land unit disharmony of clustered land use plans is lower, indicating that the NSGA2 multi-objective model is feasible and effective in land use optimization. The resulting plan set not only meets the set goals, but also has a higher degree of land use conservation and intensification, which can provide decision-makers with greater choice space.

5. Conclusions

Land use issues are an important consideration factor in the development of urban agglomerations. To optimize land use space, a series of objectives and limiting factors were proposed in the study, and the NSGA2 was used to solve multi-objective problems. The results showed that in the two test functions, the NSGA2 found a much higher number of Pareto frontiers than other algorithms. On the WFG test function, the GD value, IGD value, and Spacing value of the NSGA2 were 0.11%, 9.29%, and 5.49%, respectively, which were lower than the other two algorithms. Meanwhile, the HV value of this algorithm was as high as 94.73%, which was 20.72% and 2.15% higher than NSGA and AW-GA, respectively. In practical applications, the optimized GDP ranged from 1.228×10^5 billion yuan reduced to 1.210×10^5 billion yuan. NPS has decreased from 128.69 tons to 128.54 tons. AOD dropped from 2.471×10^7 to 2.469×10^7. The cost of land change has been reduced from 780 to 660. The degree of land unit disharmony increased from 42.148×10^5 reduced to 2.134×10^5. In addition, the difference between the maxi and mini values of the Pareto optimal solution was not significant. Among them, the standard deviation of GDP was only 1.641×10^3, the standard deviation of NPS was only 2×10^{-1}, the standard deviation of AOD was only 1.814×10^4, the standard deviation of land change cost was only 75, and the standard deviation of land unit non coordinated scheduling was only 1.308×10^3. This indicated that the NSGA2 had excellent solving performance and good practical optimization results. However, this study only analyzes the optimization of general urban land space, and has not yet considered complex and special spatial planning such as the spatial relationships between different land use areas. At the same time, the spatial planning process is very complex, and research only simplifies and analyzes it from a general perspective, so the reference for cities with special land use conditions is limited. In the future, more planning variables will be considered to further study the optimization of urban land space, in order to enhance its application scope.

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