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Sustainable land use optimization using Boundary-based Fast Genetic Algorithm

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ABSTRACT

Under the notion of sustainable development, a heuristic method named as the Boundary-based Fast Genetic Algorithm (BFGA) is developed to search for optimal solutions to a land use allocation problem with multiple objectives and constraints. Plans are obtained based on the trade-off among economic benefit, environmental and ecological benefit, social equity including Gross Domestic Product (GDP), conversion cost, geological suitability, ecological suitability, accessibility, Not In My Back Yard (NIMBY) influence, compactness, and compatibility. These objectives and constraints are formulated into a Multi-objective Optimization of Land Use (MOLU) model based on a reference point method (i.e. goal programming). This paper demonstrates that the BFGA is effective by offering the possibility of searching over tens of thousands of plans for trade-off sets of non-dominated plans. This paper presents an application of the model to the Tongzhou Newtown in Beijing, China. The results clearly evince the potential of the model in a planning support process by generating suggested near-optimal planning scenarios considering multi-objectives with different preferences.

1. Introduction

The well-known World Commission on Environment and Development (WCED, 1987) defined sustainability as "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*". This notion of sustainability refers to a specific type of development for the society. As the WCED Commission states "*in essence, sustainable development is a process of change in which the exploitation of resources, the direction of investment, the orientation of technological development and institutional change all are in harmony*". Land use allocation, as a type of resource allocation, can be understood as the process of allocating different activities or uses (e.g., residential land, industries, recreational facility, and green land) to specific units of area within a geospatial context. Sustainability often represents a primary goal for land use planning.

Comprehensive sustainability in land use allocation can be defined as a long-term balance between economic development, environmental protection, efficient resource use, and social equity. To pursue this balance can be treated as a multi-objective optimization problem. Generally, there are two types of methods: Pareto-front-based (Balling, Brown, & Day, 1999) and weighted sum (Aerts, Herwijnen, & Stewart, 2003) for such multi-objective optimization. All multi-objective optimization models are based on one of these two types of methods. Both types have their advantages and disadvantages. The Pareto-front-based methods focus on exploiting the diversity of the solutions, but often have issues of inadequate efficiency and effectiveness; while the weighted sum methods are straightforward to implement with superior efficiency and effectiveness, but requires prior knowledge.

The problem of land use allocation optimization is a complicated process as it involves determining not only what to do (selection of activities) and how much to do, but also where to do the selection. It also adds a whole extra class of variables to the problem when combined with the consideration of indispensable spatial optimization. The utility of optimization as a normative tool for spatial problems is widely recognized (Church, 1999, 2002; Cromley & Hanink, 2003; Malczewski, 1999). The complexity of the problem is attributed to the inclusion of multiple objectives that may not be linear or simple. The objectives within a spatial context must incorporate location information to all attributes which further increases the complexity of the problem. Moreover, geographic units and associated neighboring features are not independent. Such complicated non-linear multi-objective optimization problems as a type of Non-deterministic Polynomial (*NP*) hard problem require heuristic methods for executing optimization processes.

Various heuristic algorithms have been developed, such as simulated annealing (SA) algorithm, ants algorithm, and genetic

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algorithm (GA). While these heuristics may not be able to reveal the optimal solutions for every case, near-optimal solutions are often meaningful in many cases given the complexity of the problem. Generally, from the mechanistic perspective, GA is an appropriate choice for the process of land use optimization. GA, introduced by Holland (1975) and also described in detail by Goldberg (1989), is a type of heuristic algorithm based on the mechanics of natural selection to search for the global optimum for both linear and nonlinear formulations. GA is robust for identifying optimal solutions particularly in large and complex search space and the solutions found tend to be "good enough" (Goldberg, 1989). It has been applied to land use allocation optimization problems and has proved to be effective in earlier studies. However, efficiency is a challenge for solving large problems (Janssen, Herwijnen, Stewart, & Aerts, 2008; Stewart, Janssen, & VanHerwijnen, 2004).

In this article, the goal programming method – a specific type of weighted sum method – is utilized to construct a Multi-objective Optimization of Land Use (MOLU) model. First, this model comprising of eight different objectives is introduced. Subsequently, the Boundary-based Fast Genetic Algorithm (BFGA), including several revised crossovers and mutation operators, is described. Finally, the BFGA–MOLU model is applied to the Tongzhou Newtown, and the results and conclusions are discussed.

2. Related work

2.1. Selection of objectives

Land use allocation towards sustainable development involves a set of sustainability objectives related to economy, society, and environment. Leccese and McCormick (2000), in the "Charter of the New Urbanism", described a sustainable land use planning agenda. Their manifesto emphasized on infill development, environmental protection, compactness, and local geography as the main elements of a balanced urban development. Balling et al. (1999) considered the minimization of traffic congestion as a primary objective, followed by air pollution control, providing affordable housing, maximization of economic development, minimization of taxes and fees, conservation of historical and cultural sites, etc. Even though these objectives were comprehensive, some were hard to be quantified. Wang, Yu, and Huang (2004) considered the economic, forest cover, soil loss and water quality including nitrogen loss, phosphorous loss and Chemical Oxygen Demand (COD) discharge as objectives. Ligmann-Zielinska, Church, and Jankowski (2008) focused on the utilization of urban space through infill development, compatibility of adjacent land uses and defensible redevelopment to pursue the objectives of sustainability. By and large, economic benefit has been a key factor, while the social and environmental aspects are also important driving forces for sustainable development. Moreover, from a spatial perspective, objectives such as compactness, compatibility have also been examined by some scholars. In this paper, all of the aforementioned aspects are considered from the perspective of sustainable land use allocation.

2.2. Optimization models

In the past, various kinds of multi-objective problems, including land use allocation optimization, were usually solved using linear programming approaches. Chuvieco, Arthur and Aerts have integrated linear programming (LP) with geographic information systems (GIS) to carry out spatial land use allocation (Aerts, Eisinger, Heuvelink, & Stewart, 2003; Arthur & Nalle, 1997; Chuvieco, 1993; Stewart, 1991; Stewart, 1993; Zimmermann, 1978). However, spatial optimization objectives in land use allocation are often specified as non-linear functions.

Meanwhile, Pareto-front-based methods derived from Pareto's original work (Pareto & Page, 1971) are based on the characteristics of the Pareto set that presumes its independence of the relative importance of all these objectives. These methods have been widely applied for solving multi-objective spatial optimization problems (Balling et al., 1999; Chandramouli, Huang, & Xue, 2009; Xiao, Bennett, & Armstrong, 2002). However, the diversity of solutions brings low efficiency of convergence to the optimization process. In contrast, weighted sum methods can make the planning support process interactive and more efficient. Although these methods cannot yield non-convex optimal solutions, the improved weighted sum method – goal programming is suitable for land use optimization and, thus, will be adapted to establish the optimization model in this study.

The diversity of the methods described above poses needs for effective optimization tools to support land use allocation and various studies have addressed such needs. Aerts employed SA for land use allocation in a multi-objective linear programming context (Aerts, Herwijnen et al., 2003). Also, a density-based optimization model has been created by Ligmann-Zielinska et al. (2008) to obtain sustainable land use patterns based on the Hop–Skip–Jump (HSJ) method. From the perspective of mechanism, GA, as one effective heuristic method for this kind of optimization problems, has been successfully used to search for complex solution spaces in a variety of application domains (Goldberg, 1989; Michalewicz, 1996). Balling has also used GA to solve vector-based urban planning problems (Balling et al., 1999). In addition, Stewart et al. (2004) have taken advantage of general GA to perform multi-objective land use allocation in a small research area represented as grids. Janssen et al. (2008) utilized GA for land use planning support using the interactive operation on a small area (20 by 20 cells). However, all of these applications face the same limitations: one is that the objectives considered in these studies could not address sustainability objectives comprehensively due to limited numbers of objectives considered; the other is that the effectiveness and efficiency of grid-based optimization are inadequate for certain cases. In this article, more comprehensive objectives towards sustainable development on land use allocation and a more effective and efficient model, the BFGA–MOLU model, is developed for the study area – Tongzhou Newtown, Beijing, China to facilitate the planning support process.

3. Objectives and constraints

As the main aspects of sustainable development: economy, society and environment serve as three primary dimensions for land use planning, especially for land use allocation. Translations should be made from these dimensions to constitute a specific understanding of sustainable development for land use.

3.1. Maximization of economic benefit

As different land use configurations yield different economic benefit, optimizing the structure and layout of different land uses to maximize economic benefit is crucial. From another perspective, besides earning more, it is also very important to spend less to maximize economic benefit. Some planners may prefer to conserve certain land uses, which often minimizes the cost of land use conversion. Hence the Minimization of Conversion can contribute to economic benefit.

3.2. Maximization of environmental (including ecology and resource) benefit

Environmental sustainability is to ensure that interactions with the environment are pursued to keep the environment, including natural conditions, environmental, ecological capacity and resource consumption, as pristine and as natural as possible.

Land use planning has implications across multiple spatial scales, ranging from local, regional, to global. As Daniels (2003) argued, the understanding of the environment helps planners in "*shaping a community by protecting and improving air and water quality; conserving farming, forestry, and wildlife resources; reducing exposure to natural hazards; and maintaining the natural features and built environment that make a place livable and desirable*". From the environmental point of view, the suitability of geological conditions is an important factor to assure environmental benefit, thus making the planning safer and reducing the consumption due to construction. Besides, the ecological value for different land use types and spatial ecological suitability are also considered in this research to ensure the environmental and ecological benefit.

Sustainable land use planning requires that present-day encroachments on the natural environment should be restricted and the consumption of non-renewable natural resources should be minimized (Haavelmo & Hansen, 1991). Apart from the direct protection of the environment and ecosystem, the reduction of energy consumption and non-renewable resource consumption are also meaningful for sustainable development. As mentioned above, land use allocation should be responsible for the global environment. For instance, problems pertaining to CO_2 emission have already become a hot topic in the field of global warming and assumed significance in the context of the global environment. In urban areas, over 80% of CO_2 emission can be attributed to human and automobile activities (Koerner & Klopatek, 2002). Hence, in order to control non-renewable resource consumption, factors such as accessibility and compactness need to be considered.

3.3. Maximization of social benefit

Social benefit factors represent another essential aspect to be considered for sustainable land use planning. A social sustainable system should be constructed by consciously taking into account the well-being of people and their communities. Such systems strive for distributional equity, adequate provision of social services including living, health and education, gender equity, political participation, etc. These factors focus on the enrichment of human relationships and the achievement of individual and group aspirations. Although it is often difficult to quantify the social benefit factors, the notion can be simplified to formulate an accessible, compact, and compatible city to represent the social sustainability factors within the land use allocation problem.

3.4. Constraints

Within land use allocation optimization problems, some constraints must be satisfied. For example, the conservation land and the area of residential land should be treated as such under the consideration of the higher scale planning as well as enough space for accommodation of the population in the future.

4. Model formulation

Based on the understanding of sustainable development and the characteristics of land use allocation optimization problem, our objectives can be categorized as follows:

Maximization of GDP.
Minimization of Land Use Conversion.
Maximization of Geological Suitability.
Maximization of Ecological Suitability.
Maximization of Accessibility.
Minimization of NIMBY Influence.
Maximization of Compactness.
Maximization of Compatibility.

Subject to

Conservation area.
Minimal need of residential area.

A planning area can be represented as consisting of a grid with N rows and M columns. There are K different land use types' binary variables, which equals 1 when land use k is assigned to Cell (i, j) and equals 0 otherwise. Furthermore, B_{ijk} is set as the parameter of different objectives and it varies with location as it depends on specific attributes of the area according to each objective.

Accordingly, for each objective function described in the previous section, all these objectives are based on the grid with N rows and M columns. For each objective, the MOLU model is formulated as follows:

Minimize:

$$-\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M}B_{ijk}x_{ijk} \tag{1}$$

Subject to:

$$\begin{aligned}&\sum_{k=1}^{K}x_{ijk}=1 \quad \forall k=1,\ldots,K;\ i=1,\ldots,N;\ j=1,\ldots,M\\ &x_{ijk}\in\{0,1\}\\ &L_k\leqslant S_k\leqslant U_k\end{aligned} \tag{2}$$

Where:

$$\begin{aligned}&\sum_{i=1}^{N}\sum_{j=1}^{M}x_{ijk}=S_k \quad \forall k=1,\ldots,K;\ i=1,\ldots,N;\ j=1,\ldots,M\\ &\sum_{k=1}^{K}S_k=N\cdot M\end{aligned} \tag{3}$$

B is the parameter based on each cell for each land use type.

Formula (1) and (2) specify that one and only one land use type must be assigned to each cell, because decision variable x_{ijk} must be 0 or 1. Formula (3) restricts the number of cells S_k allocated to a certain land use type k between the up and low bound, depicted as L_k and U_k respectively.

For the multi-objective optimization, it is a combination of the above formulae.

For the general weighted sum method, this can be understood as:
Minimize

$$f_{obj}=-\sum_{o=1}^{O}\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M}\alpha_o B_{oijk}x_{ijk} \tag{4}$$

Subject to (2), (3)

where
$\forall o=1,\ldots,O$
B_{oijk} is the parameter based on each cell for each land use type of objective o
α_o are the weights of objectives o

(5)

The formulae above show that it is clearly a multi-objective problem, which entails a tradeoff involving all the objectives. While decision makers or planners know their goals, they have difficulties in valuing or weighting the relevant attributes directly.

This is particularly true when each objective value has a different scale. Goal programming is a commonly used method to aid decision makers with such kinds of task.

A revised goal programming approach (reference point) is used in this research. This approach can be defined as follows:

$$f_{obj} = \sum_{o=1}^{O} \alpha_0 \left[\frac{f_{objo} - I_o}{T_o - I_o} \right] \tag{6}$$

In this equation, f_{objo} is the value of each objective, I_o is the best possible (ideal) value for each objective o and T_o is the worst value for each objective. This approach addresses the scale differences of each objective value while helping planners capture preferences for different objectives.

5. Specification of the BFGA–MOLU model

5.1. Chromosome representation

Solving land use allocation problems using GA involves encoding land use types in the form of a chromosome. A straightforward chromosome representation can be a list of grid of genes, where the position of each gene (cell) represents a unit, and the land use type of the unit is determined by a value. This representation has been used in spatial analysis by many previous studies (Butcher, Matthews, & Sibbald, 1996; Ligmann-Zielinska et al., 2008; Seixas, Nunes, Lourengo, Lobo, & Condado, 2005; Stewart et al., 2004). Alternatively, Matthews, Sibbald, and Craw (1999) proposed two kinds of chromosome representations based on vectors. One is fixed-length representation which directly arranges the land uses to genes and is sensitive to the number of land blocks. The other is a variable-length representation focusing on the percentage and priority (PP) of the allocation of a land use, which is sensitive to the number of land use types. Considering various factors including computational cost and the complexity of optimization algorithms, in this paper, the commonly used method of fixed-length representation is chosen. This simply involves putting every line one by one together to represent one chromosome.

5.2. Iteration process

5.2.1. Initialization of parent solutions

Initialization of parent solutions is the first and foremost step in the GA iteration process. It has been proved that this initialization is important to the efficiency of GA convergence. Certain settings of such initialization may lead to local optimum. In order to assure adequate efficiency and outcome of our optimization process, 100 randomly generated solutions are used as the initialization of parent solutions.

5.2.2. Selection

The fitness function is evaluated by formula (6). The nearer to the reference point a solution is, the better the solution. The process optimization evaluates all solutions created either by random generation of the parent solutions or operations such as crossover and mutation. The solutions are sorted based on the fitness function. The solutions with a higher fitness value have higher probability to be chosen for the next iteration.

5.2.3. Crossover

A crossover step creates a new gene combination by swapping genes from different chromosomes in accordance with certain or adaptive probability. GA tends to perform a general crossover by taking half of the solution from one 'parent' and the other half from the other. This means that if each cell is independently selected from one of the parents by random selection, the resulting child map will tend to be fragmented. A major problem related to crossover in optimizing land use allocation is to assure the compactness of the final result through appropriately swapping the genes. Herein, owing to the characteristic of this problem, the method shown in Fig. 1 is developed. If the randomly created cells in two parents are different and the neighbors of the chosen cell from the first parent have the same gene as the chosen cell from the second parent, then the offspring-1 will inherent all the cells except the chosen cell from the parent-1 and the chosen cell from parent-2, it iterates until all the solutions of the generation go through the crossover process. This crossover model was named as Boundary-based Crossover Operator (CBO), and can result into spatial compactness to some extent.

R1 and R2 are the randomly chosen cells from the parents. If the land use types of the two cells are different and the neighbors of R1 have the same kind of land use type as R2's land use type, the new offspring will be yielded by the crossover on this location or another location of cells for parents will be created until the operation is finished.

5.2.4. Mutation

Mutation is another important operator in generating good offspring as too many or too few mutations will negatively influence

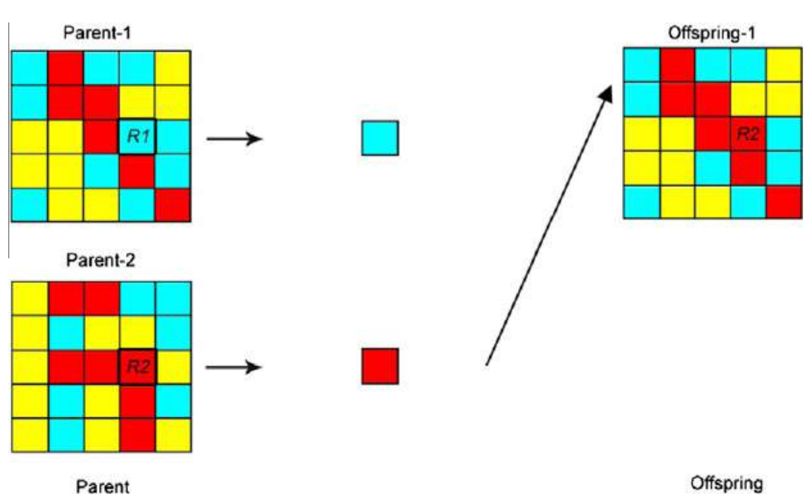


Fig. 1. Procedure of CBO.

the convergence and quality of optimization. Three mutation operators are developed in our GA. The first one is Patch-based Mutation Operator (MPO) for maintaining diversity among the solutions of a population; the second one is Boundary-based Mutation Operator (MBO); and the third one is Constraints Mutation Operator (MCO) for eliminating infeasible solutions from the population to satisfy the constraints (see Section 3).

5.2.4.1. MPO and MBO. With regard to MPO, the first step is to randomly choose the land use type of the mutation window and the shape of the window patch (choose seven cells from nine cells window, assuring that the chosen cells are linked). Then the randomly chosen location of the mutation will be matched with the mutation patch. Finally, the original solution will be replaced by the mutation patch. The difference between MPO and MBO is that MBO will be applied only if the neighbors of mutation windows have the same land use type as the mutation window (see Fig. 2).

5.2.4.2. MCO. For the constraints considered in our optimization problem solving, in addition to the conservation of special use of land patches, MCO could be used to satisfy the structure and spatial location of specific land use. The difference between MCO and MPO is that MCO will evaluate whether a solution is satisfied with the constraints. For example, if the area of one specific land use is more or less than its corresponding constraint, MCO will choose the random location and the required land use type to steer the solution to become feasible.

5.2.5. Generation gap (GG)

The diversity of each generation is an important factor for achieving global optimum searching. However, the large amount of solutions in one generation may have negative impact on the remaining optimization process when the searching direction is clearly sure. In this research, the weights of different objectives are chosen before the optimization process. Consequently, the generation gap can positively improve the efficiency of the optimization process with the GG parameter is set as 0.9, which is based on sensitivity analysis focusing on this parameter.

6. Case study

6.1. Study area

Tongzhou, located in the southeast region of Beijing, and is considered as Beijing's east gate. Tongzhou spans 37 km from east to west and 48 km from north to south, covering an area of 906.27 square kilometers. Tongzhou has 11 towns and four communities, with of 870,000 population. Tongzhou Newtown is the central urban area of Tongzhou, which promises to become a main city zone in the east of Beijing in the future.

As a rapid developing area, Tongzhou Newtown is subject to a debate on how to plan and manage the area in the future. There are countless possibilities of land use allocation scenarios. The BFGA–MOLU model is developed as a tool of planning support for the scientific evaluation of these scenarios. Considering both the characteristics of the research area and the model, the land use map of the area can be simplified into five land use types as follows: (1) residential land; (2) industrial land; (3) commercial land; (4) green land; and (5) undeveloped land. The resolution of the grid cells is set as 100 m by 100 m. The case study will demonstrate not only the effectiveness of the model on the study area to support land use planning in 2020, but also the generality of the model as a land use optimization tool (see Fig. 3).

6.2. Maximization of GDP

The GDP can be used to evaluate land use scenarios from an economic standpoint. As for the aforementioned five land use types (residential, industrial, commercial, green and undeveloped land), it is often difficult to obtain the real value of how much GDP the five land uses made per hectare, especially for the targeted planning time of 2020. However, using historical data and statistical methods, the correlation between these land use types can be obtained, which can be used to represent anticipated GDP in 2020. This sufficiently serves the purpose of this study. Based on the "Statistical Yearbook of Society and Economy in Tongzhou", the land use and statistical data in 2002 can be used to compute the land use status quo and the GDP value for three different domains *(Assumption: only industrial and commercial land make direct GDP*

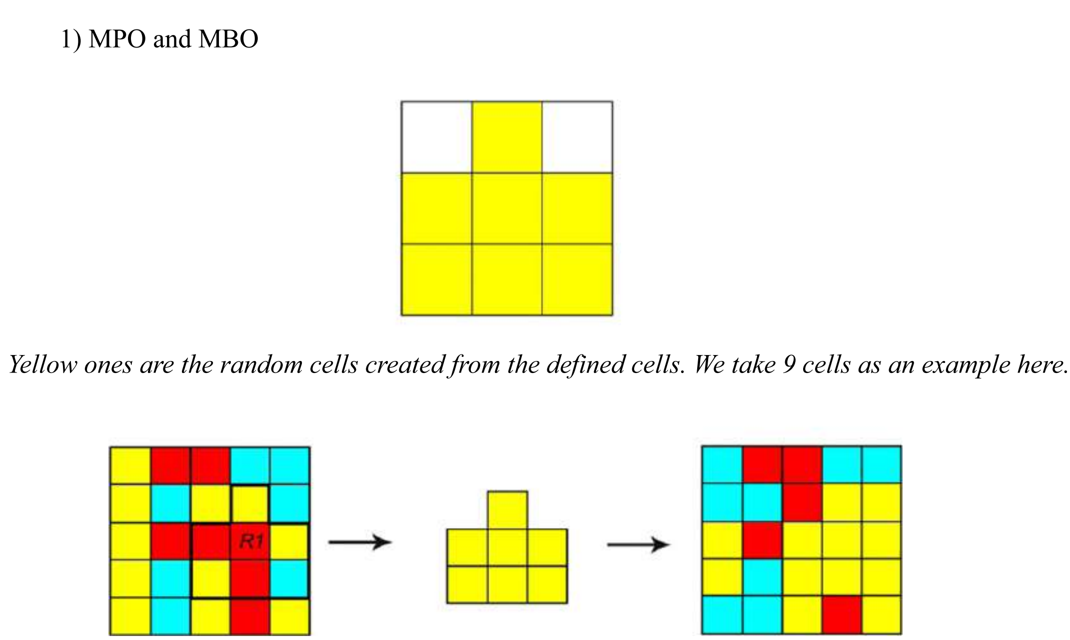


Fig. 2. Procedure of MPO and MBO. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

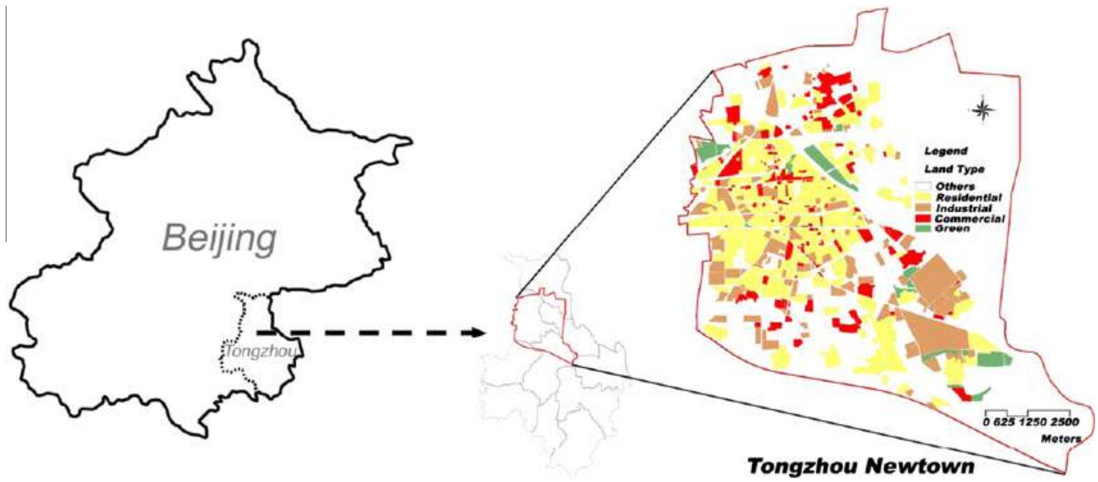


Fig. 3. Study area – Tongzhou Newtown (Cao et al., 2011).

Table 1
GDP statistical data for different types of land use (SDTZ, 2002).

2002 statistic data	Industrial	Commercial
GDP (Ten thousand)	45,927	161,254
AREA (Ha)	766.43	319.19
GDP value (Ten thousand/Ha)	59.92	505.20

Table 2
Economic benefit.

Land use types	GDP ratio (different land use)
Residential	0
Industrial	59.92
Commercial	505.20
Green	0
Undeveloped	0

benefit and the ratio of GDP value made by industrial and commercial land is assumed to be similar from 2002 to 2020.) (see Table 1).

In this model, we make use of derived data above to represent the economic objective as follows (see Table 2).

6.3. Minimization of Conversion

From another point of view, the minimization of conversion cost for different land uses decreases the expenditure of the social capital while enhancing the economic benefit of the society. Evidently, the cost of different land use types is different. However, under the consideration of data limitation and the inaccuracy by Delphi method, the minimization of conversion can be simplified to the minimization of land use change.

6.4. Maximization of Geological Suitability

Geological suitability is of great significance to influence land use suitability and sustainability. Fig. 4 shows the geological suitability map of Tongzhou Newtown extracted from the geological suitability map of Beijing.

As shown in Fig. 4, the district for geological construction has a trend of degradation from I to IV. Hence, the maximization of the sum of all the cells' suitability values can bring about a better solution.

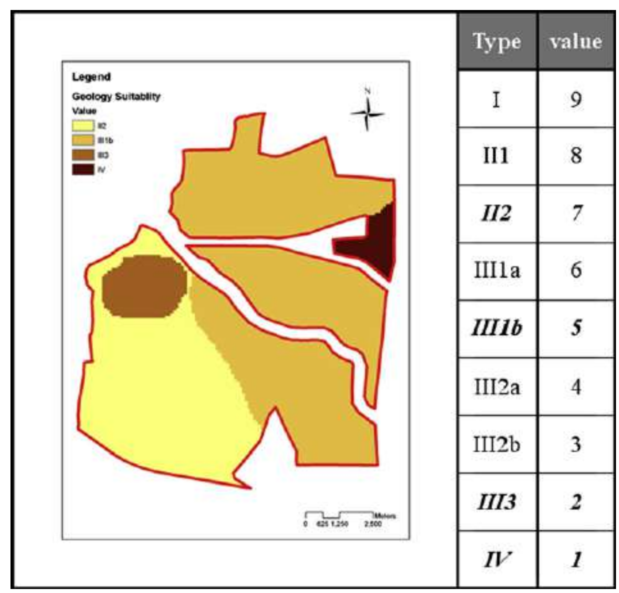


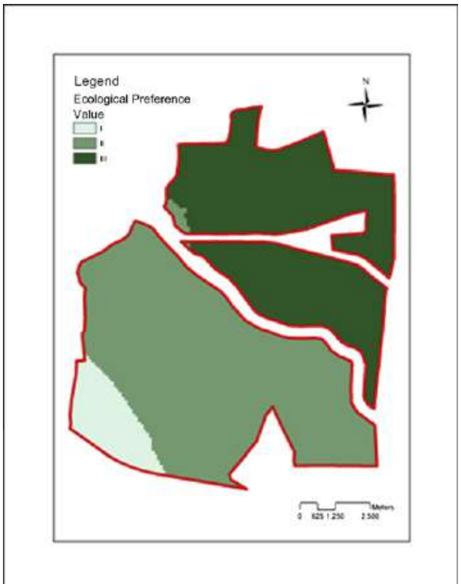
Fig. 4. Geology suitability (BJIG, 2005).

Table 3
Ecological value per unit (Costanza et al., 1997).

Land use types	*E*-value
Green	2242.25
Residential	165
Industrial	165
Commercial	165
Undeveloped	0

6.5. Maximization of Ecological Suitability

Ecological factors need to be incorporated as part of sustainable land use allocation. Despite the availability of numerous criteria for evaluating the ecological benefit of the world apart from the environment, many of these continue to lack representation and quantification. In addition, effective data acquisition continues to pose challenges. This study considers the value of the world's ecosystem services and natural capital (Costanza et al., 1997) for the evaluation of the ecological benefit. Table 3 below shows that green land



Ecological Value	Green	Others
I	1	2
II	2	1
III	3	0

Fig. 5. Ecological suitability (BMEPB, 2005).

yields the maximum ecological benefit among the given land use types. Then again, the ecological planning of a higher scale also needs to be accounted for.

It is evident from Fig. 5 that districts indexed by I, II, and III, are more suitable for allocating green land. The contribution value at the bottom (Fig. 5) can be counted if a district is allocated within green land. Thus the maximization of the sum of the contribution value can be considered as the objective to maximize the amount of green land as well as to maximize the feasibility of the green land layout.

6.6. Maximization of Accessibility

Accessibility is another essential factor that contributes to sustainable land use. Accessibility not only influences operational efficiency, but also enhances the overall social quality of urban life. Moreover, it can contribute to decreasing more than 80% of the CO_2 emission resulting from human and automobile activities within city limits. Furthermore, the planned transportation network, which will be finished by 2020, should be considered by the optimization process. In China, according to ''The Regulations for Gradation and Classification on Urban Land'', the roads can be divided and categorized to: (1) main road for living; (2) main road for transportation; and (3) main road for mixed use.

According to the regulations, the influence indices in the table have been obtained by the mean of a range set. Also derived from the regulations are the function values that are calculated as follows:

$$f_i^R = 100 \times I_i^R \tag{7}$$

where f_i^R is the function value of i type road; and I_i^R is the influence index of i type road (Table 4).

Table 4
Influence index for different roads (GAQS, 2001).

	Residential	Industrial	Commercial
Main road for living	1	0.7	0.875
Main road for transportation	0.7	1	0.7
Main road for mixed use	0.875	0.875	1

The influence decreasing index is calculated as follows:

$$\text{for commercial}: e_{ij}^R = (f_i^R)^{1-r}; \text{and} \tag{8}$$

$$\text{for residential and industrial}: e_{ij}^R = f_i^R(1-r) \tag{9}$$

where e_{ij}^R is the influence value of i type road to j location point; f_i^R is the function value of i type road; and r is the related distance between j point to i type road.

The roads network of the study area can be seen in Fig. 6.

The roads function decreasing maps of three kinds of roads are as follow (see Table 5):

There is no restriction of accessibility for the layout of green and undeveloped land use types. Nevertheless, the green land and undeveloped land should be allocated at such place where accessibility situation is not good so as to exploit accessibility sufficiently *(the road, trees are not included due to the 100 m by 100 m resolution)*. Hence, the similar function decreasing map of green land and undeveloped land can be obtained as below *(taking all the roads into account, the influence index equals 1 and influence decreasing index is obtained from Formula (9))* (see Fig. 7).

For each scenario, the evaluation of the accessibility is based on the function decreasing maps; and the maximization of the total value will lead to the best accessibility situation.

6.7. Minimization of NIMBY Influence

The term of NIMBY (Not in My Back Yard) was coined in the 1980s by a British politician Nicholas Ridley. This term is used to refer to the opposition by residents to new developments in their proximity. It may not be easy to change the location of projects such as railways, landfill fields, or power stations, etc. However,

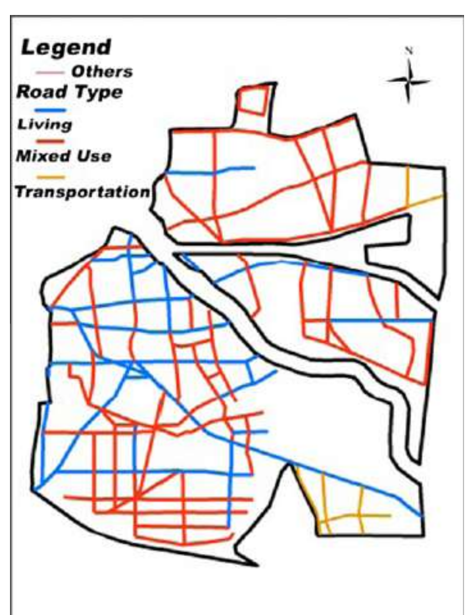
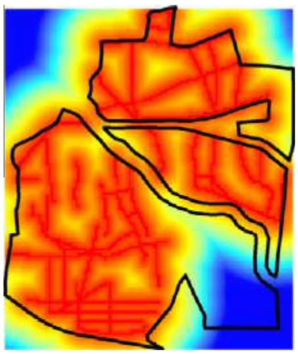
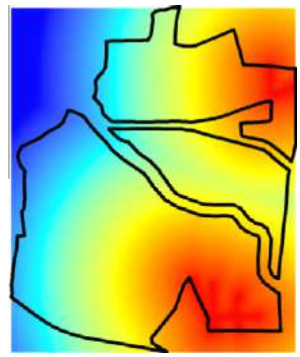
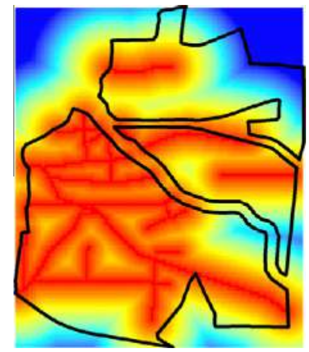


Fig. 6. Roads network (Cao et al., 2011).

Table 5
Function decreasing maps of different roads (Cao et al., 2011).

Residential (living)	Industrial (transportation)	Commercial (mixed use)
		

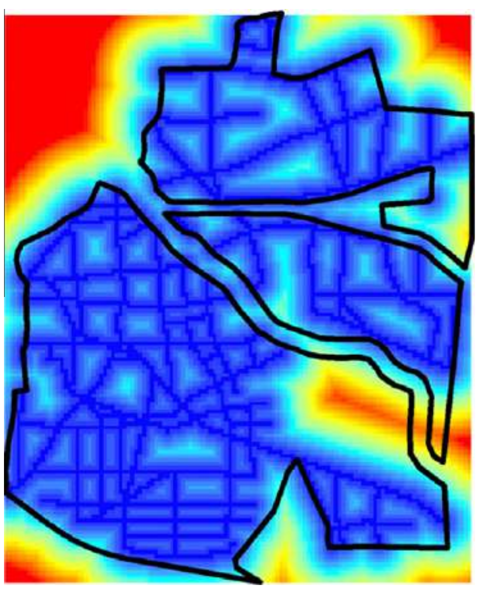


Fig. 7. Function decreasing map for green and undeveloped land (Cao et al., 2011).

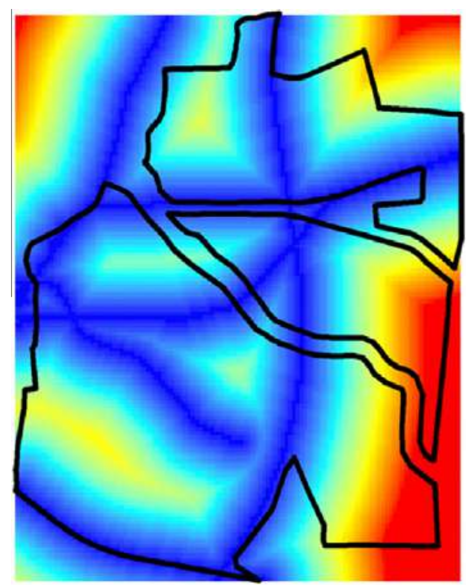


Fig. 8. Function decreasing map for NIMBY.

a better location can surely be chosen for residential land and commercial land where is crowded. This study takes a novel attempt to address the NIMBY factor. With the target of sustainable planning in 2020, several facilities can be reallocated to a suitable location. Owing to data limitation, only railways are considered in this research. The Euclidean distance based function decreasing map of railways is shown in Fig. 8. The purpose of this objective is to minimize the occurrence of residential and commercial land inside the high influence value of railways in the city. The influence value is calculated in a manner similar to the accessibility of green land and undeveloped land.

6.8. Maximization of Compactness

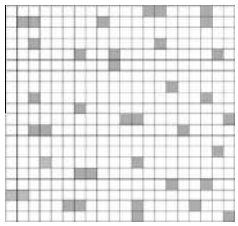
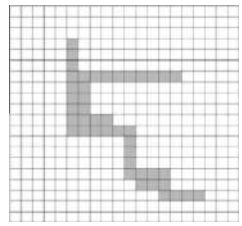
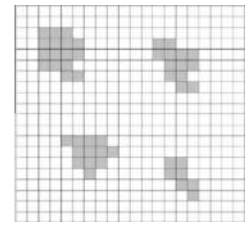
The compactness can be considered as the most promising form of urban intensification that is positive towards sustainable development of a city. Compactness not only assuages the pressures of expansion, but also results in the effective utilization of available land (Williams, 1999). Also, compact and mixed use neighborhoods have been proven to be useful in increasing accessibility to city facilities for residents, which in turn serves to promote social equality. Moreover, it is helpful in decreasing resource consumption.

Contiguity is another part of the spatial objective, and is akin to compactness in our study. However, from the study's perspective, the clarification is provided to eliminate any ambiguity between these terms. Contiguity requires all cells of the same land use to be connected. Compactness arranges cells to clusters. Generally, compactness includes contiguity. Therefore, the two aspects are encapsulated in the form of a single objective, compactness (see Table 6).

This is an important objective in grid-based land use optimization problems. During the process of optimization, it is difficult to extract reasonable solutions without such an objective.

Several measures of compactness have been mentioned and used by previous studies: (1) non-linear integer programming (IP)-neighbor method; (2) linear IP-neighbor method; (3) linear IP using buffer cells; (4) linear IP using "aggregated blocks"/minimization of the number of clusters per land use types; (5) minimization of shape index; (6) spatial autocorrelation (Aerts & Heuvelink, 2002; Cliff & Ord, 1973; Kurttila, Pukkala, & Loikkanen, 2002; Ligmann-Zielinska et al., 2008; Stewart et al., 2004; Wardoyo & Jordan, 1996). After a detailed investigation and comparison of these representative methods, the basic Eight-neighbor method is chosen for evaluating compactness in this study.

Table 6
Difference among random, contiguity and compactness.

Random	Contiguity	Compactness
		

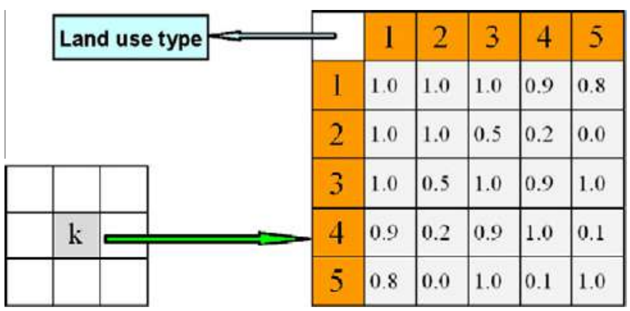


Fig. 9. Compatibility.

Table 7
Compatibility values (Cao et al., 2011).

	R	I	C	G	U
R	1				
I	0.41	1			
C	0.95	0.48	1		
G	1	0.88	0.62	1	
U	0.47	0.75	0.41	0.74	1

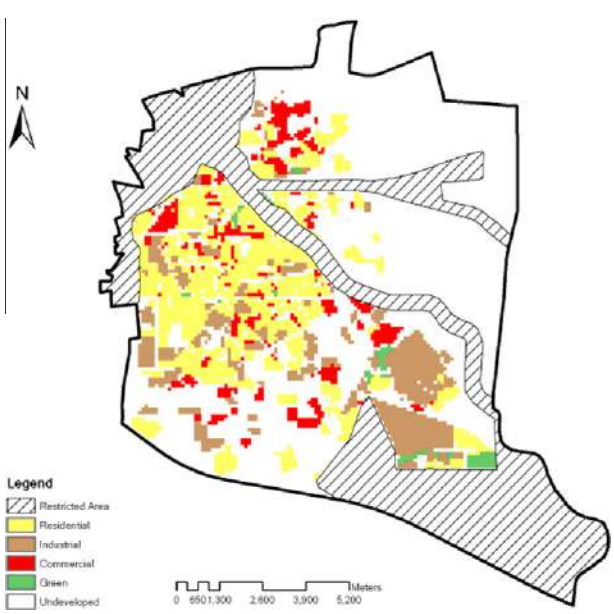


Fig. 10. Restricted land (Cao et al., 2011).

Table 8
Parameters used for optimization. *(The selection of these parameters is based on the results published by previous studies and extensive experiments performed in this study.)*

Size	Iteration	Population	Crossover	Mutation	Generation G
141 * 119	5000	100	100/ 16,779	(14,16)/ 16,779	0.9

6.9. Maximization of Compatibility

For the neighbor of different land uses, there are different preferences (Fig. 9).

Each land use type has its own preference to choose the land use type of neighborhood. As can be seen from Fig. 9, for each land use *k* on the left, the compatibility of the scenario can be evaluated by adding all the compatibility indices in the right table according

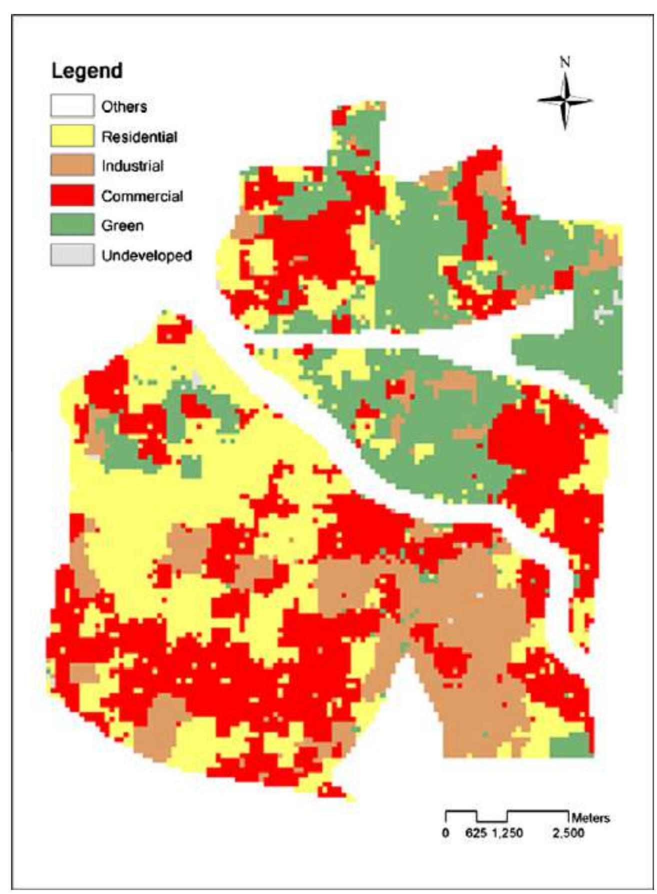


Fig. 11. The best solution found based on BFGA–MOLU model.

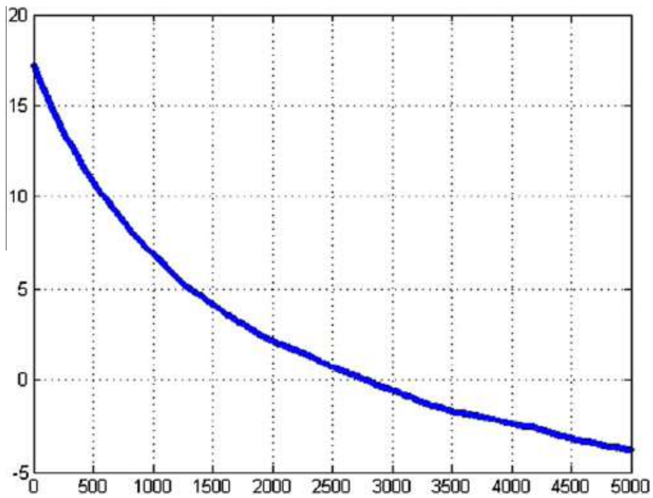


Fig. 12. Convergence curve of the optimization process (y axis is the fitness function, x axis is the iteration number).

to the five land use types. The compatibility indices can be obtained from specialists and professionals. The more the indices are, the more compatible the scenario will be.

For setting compatible values, it is feasible to cite the indices from the opinions of experts. Nevertheless, there is some subjectivity involved in the evaluation of compatibility. This not only applies to the difference in values reported by different experts, even for the same expert, it is also difficult to detect subtle relationships between every two land use types at the same level. This problem can be solved to a reasonable extent using a pair-wise comparison approach. After computation, the final compatibility values are summarized as Table 7.

The objective is to maximize the sum of compatibility of all the cells within the study area.

6.10. Constraints

The constraints implemented within the model include the restricted area, and the minimization of accommodation area (including residential and commercial area) to accommodate future population. Each cell only can have one land use type.

The following constraints are integrated for the case study:

Restricted areas in Tongzhou Newtown including the Grand Canal and the reserved green land in the northwest and southeast of Tongzhou Newtown (pre-defined cells with special land use types) (Fig. 10).

Based on the prediction of the population in Tongzhou Newtown in 2020, the lower bound of the residential cells should be 3150 cells.

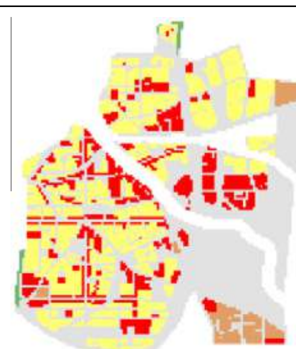
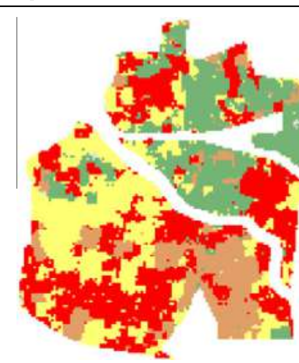
6.11. Implementation and Evaluation

The BFGA–MOLU model was executed for 5000 iterations using the following parameters: eight objectives including Maximization of GDP (obj-1); Minimization of Conversion (obj-2); Maximization of Geological Suitability (obj-3); Maximization of Ecological Suitability (obj-4); Maximization of Accessibility (obj-5); Minimization of NIMBY Influence (obj-6); Maximization of Compactness (obj-7); Maximization of Compatibility (obj-8), and the constraints with restricted green space and the area of residence.

In the table, 100/16,779 means 100 cells will join crossover over at one time, (14,16)/16,779 means taking 4 by 4 cells windows, randomly choosing 14 cells to join the mutation process at one time. Before the final optimization was carried out, each single objective above has been optimized on its own by this model. Subsequently, the minimization value and the maximization value of each objective were obtained to normalize the objectives to form the final fitness function. In addition, the robustness of experiments has also been pursued to assure the efficiency and effectiveness of the model by extensively considering different parameters with different objectives and research areas (as Table 8). The execution of the model on a 141 by 119 cells area with CBO MPO, MBO and MCO mutation operators require about 5.5 h for the 5000 generations of 100 population on a MacBook Pro laptop computer with an Intel(R) Core (TM)2 Duo CPU P7550@2.26 GHz and 2 GB RAM.

As for the comparison of performance between this algorithm and simple GA on the same environment without the suggested operators, it spends 45.5 h for more than 300,000 iterations to reach convergence.

Table 9
Comparison of planned scenario and optimized scenario.

		Planned scenario	Optimized scenario	
Figures				
Objectives	Obj-1	−815497	−1963535	140.78%
	Obj-2	−1425	−2937	106.11%
	Obj-3	−47762	−59880	25.37%
	Obj-4	−7352	−13784	87.49%
	Obj-5	−509218	−738895	45.10%
	Obj-6	−563381	−479555	−14.88%
	Obj-7	−61392	−67346	9.70%
	Obj-8	−37600	−40789	8.48%

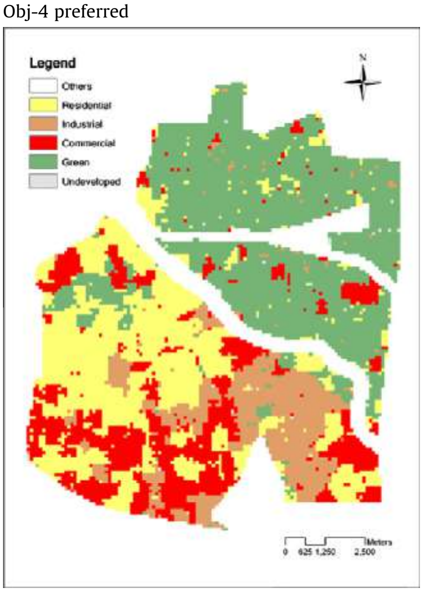
The equal weight optimized result is summarized in Fig. 11. From the best solution found, the main commercial area in the future focuses on the northern part near the old urban center, and another focus of commercial area is on the eastern city center where another dispersed new center of Tongzhou Newtown is located. This multi-center development is beneficial because it helps reduce urban energy consumption and transportation pressure caused by rapid urbanization. Also, from the old commercial center to the southern part, the commercial density is increasing. Sufficient residential land can also be developed around these commercial centers to accommodate future population. On the other hand, the green land is primarily situated in the southern and northern regions of the Tongzhou Newtown. These areas are not suitable for built-up area due to both the geological conditions and the high-level ecological planning background. Moreover, in the middle of the old commercial center, there is some green land. The green land enhances the ecological benefit while contributing to the health of residents. The industrial area is primarily located in the northeast and southeast, replete with green land that can isolate residents from the pollution of industry. Furthermore, there are some industrial areas dispersing around the old industrial area that is more suitable for light industries. Several commercial and residential areas are also located within some industrial areas, which can provide workers with sufficient living space (see Fig. 12).

In summary, the best solution found under the balanced consideration of these eight objectives seems to notably contribute to the actual planning process. In order to prove the rationality of the optimization process, the comparison of the solutions and the planned scenario is shown below (the legend is the same as Fig. 11. Meanwhile, the undeveloped land of the planned scenario locates among other space except the four land use types).

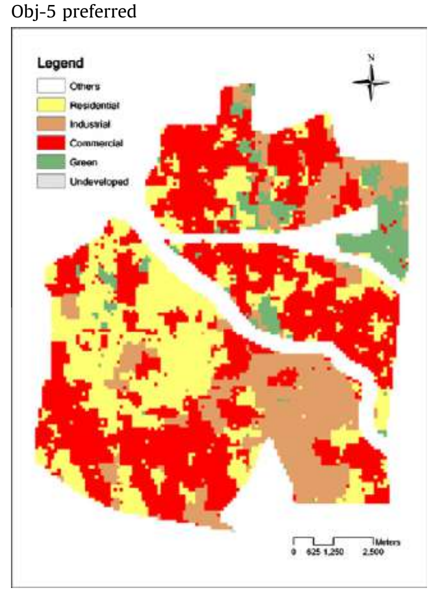
As shown in Table 9, significant improvements are observed in all the objectives except for the objective-6. Compared to the planned scenario, the GDP, conversion cost and ecological suitability have increased by 140.78% 106.11% and 25.37% respectively. Also, the geological suitability, accessibility, compactness, and compatibility have also increased by 87.49%, 45.10%, 9.70%, and 8.48% in the optimized scenario. Only objective-6: the NIMBY influence, decreases by 14.88%, which can be neglected and

Table 10
Four optimized scenarios of obj-4 preferred, obj-5 preferred, obj-7 preferred and obj-8 preferred.

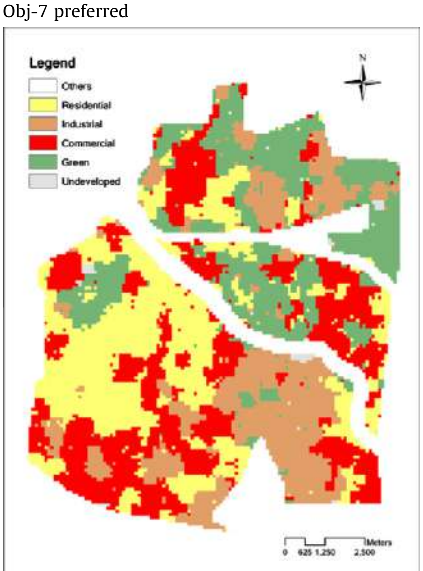
Obj-4 preferred



Obj-5 preferred



Obj-7 preferred



Obj-8 preferred

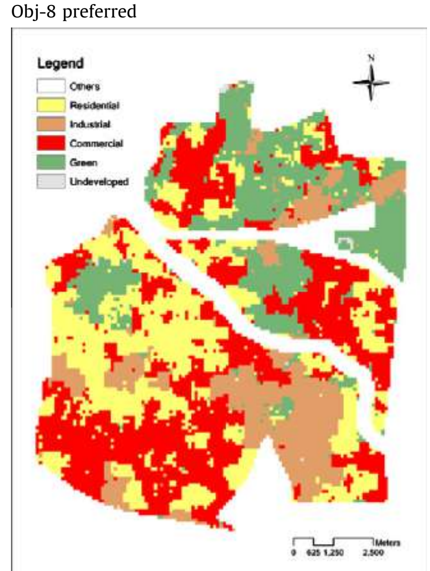


Table 11
Comparison of the objectives' values and the structural allocation of obj-4 preferred, obj-5 preferred, obj-7 preferred, obj-8 preferred, and equally preferred optimization scenarios.

	Obj-4 preferred	Obj-5 preferred	Obj-7 preferred	Obj-8 preferred	Equal preferred
Obj-1 value	−1109589	−2607065	−1678282	−2011305	−1963535
Obj-2 value	−2554	−2771	−2670	−2686	−2937
Obj-3 value	−58136	−60420	−60298	−60439	−59880
Obj-4 value	−19172	−9214	−13493	−12987	−13784
Obj-5 value	−605109	−878397	−743050	−754180	−738895
Obj-6 value	−566809	−397661	−524439	−486601	−479555
Obj-7 value	−69990	−68390	−69324	−67214	−67346
Obj-8 value	−40953	−40849	−40874	−41017	−40789
Residential	3150	3153	3161	3173	3153
Industrial	1451	2137	2285	1747	1658
Commercial	2024	4907	3051	3774	3690
Green	4235	685	2330	2168	2351
Undeveloped	32	10	65	30	40

understandable. These results reinforce that our optimization approach yields better planning scenarios than the ones that solely depend on subjective opinions according to the evaluation standard discussed above. This approach may serve as a valuable reference for planners or policy makers for devising plans and making decisions. Although the planned scenario may be more close to the real planned scheme, it is obvious that more green land could be found in the scenario found with the satisfied ecological need, higher suitability, more compact and mixed use of the commercial, residential, and green land, and more compatibility between different land use types. In fact, the study of Tongzhou Newtown is mainly a simple case of applying the optimization approach. This does not imply that the actual planning could be replaced, or the optimization solution must be better than the planned scenario, it is just one planning support scenario based on different preferences of different users. We argue that our approach is useful to aid the evaluation of trade-offs quantitatively and hence facilitate the comprehensive analysis on the area under planning.

For different preferences, the final results are understandably different. Besides optimal result based on the equal weight setting, there are also some other attainable optimized solutions. Within the four optimization operations, each objective preferred is maintained by the weight setting as 2. The results are summarized in the following table (see Table 10).

The comparison table shows that the constraint of residential areas satisfies the residential and consumption needs of 2020 residents. For obj-4 preferred solution, the value of obj-4 is larger than those from the other solutions; and for the optimized result, there is much more green land, which is more suitable to allocate green land under the consideration of the upper level ecological planning. On the other hand, the value of obj-1 is only 1,109,589, which is the worst among these solutions because of the limited land occupation by green land. As for the obj-5 preferred optimized solution, the value of objective-5 is much higher than the other solutions by nearly 15% to 50%, which signifies the better accessibility of this solution. It is worth noting that along with the development of accessibility, the economic benefit (obj-1 value) is also the best among these solutions, which evinces the importance of transportation on economic development. As for the obj-7 and obj-8 preferred optimized solutions, the objective value of obj-7 and obj-8 are not much better than the other solutions, due to the characteristics of the two objectives. From the optimized results, it can be clearly found that the compactness of obj-4 preferred optimized solution is a little more than the obj-7 preferred optimized solution, which is attributed to the correlation between the two objectives. For the obj-8 preferred optimal solution, the improvement is insignificant. However, it is arguably the best among these solutions according to the quantified evaluation model, which demonstrates that our optimization method is particularly meaningful to help planners or policy makers in finding the scenario that is better suited for their preferences. For the equally preferred solution, all these objectives are under the same consideration and the value of each objective is also among these values of other solutions with different preference on different objectives. For the optimized result that has been compared to the planed scenario above balanced by each objective, which is appropriate to guide the sustainable land use allocation according to the equal weight preference. On the other hand, all of these five optimization results show not only the effect, but also the robustness of the model (see Table 11).

7. Conclusion and discussion

The reasonable layout of resources is of paramount importance to attaining sustainability in land use planning. The primary objective of this paper is to develop a MOLU model and to exploit the BFGA method to obtain optimized solutions for land use allocation based on five simplified land use types: residential land, industrial land, commercial land, green land, and undeveloped land. A generalized goal programming (GP) approach is used to specify the fitness function. The eight objectives that were devised based on the notion of sustainable land use and the realization operation of the optimization are as follows: Maximization of GDP, Minimization of Conversion, Maximization of Geological Suitability, Maximization of Ecological Suitability, Maximization of Accessibility, Minimization of NIMBY Influence, Maximization of Compactness, and Maximization of Compatibility. Moreover, some constraints including on conservation area, minimal or maximal need of special land use are also taken into account.

The GP was used as the fitness function to search for the optimized solution based on efficient GA: BFGA, which makes use of some efficient crossover and mutation operators, and is also integrated with real-code and generation gap for efficient iteration. The case study on Tongzhou Newtown, where the model is applied, demonstrates the potential of the BFGA–MOLU model in supporting the land use planning and decision making.

The case study is a straightforward application of the model. On the other hand, there are some other extensions that are of interest to future research. For instance, the application can be integrated into an expert system for giving intuition-based suggestions to planners or decision makers assisted by visualization of suggested alternative solutions. The interactive operation during the planning support process may also be added into the model. Furthermore, the integration of grid and vector representation of this type of problems is under investigation pertaining to this area.

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