http://dx.doi.org/10.1080/13658816.2011.570269
International Journal of Geographical Information Science
i*First*, 2011, 1–21

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Spatial multi-objective land use optimization: extensions to the non-dominated sorting genetic algorithm-II

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(Received 12 January 2010; final version received 6 March 2011)

A spatial multi-objective land use optimization model defined by the acronym 'NSGA-II-MOLU' or the 'non-dominated sorting genetic algorithm-II for multi-objective optimization of land use' is proposed for searching for optimal land use scenarios which embrace multiple objectives and constraints extracted from the requirements of users, as well as providing support to the land use planning process. In this application, we took the MOLU model which was initially developed to integrate multiple objectives and coupled this with a revised version of the genetic algorithm NSGA-II which is based on specific crossover and mutation operators. The resulting NSGA-II-MOLU model is able to offer the possibility of efficiently searching over tens of thousands of solutions for trade-off sets which define non-dominated plans on the classical Pareto frontier. In this application, we chose the example of Tongzhou New Town, China, to demonstrate how the model could be employed to meet three conflicting objectives based on minimizing conversion costs, maximizing accessibility, and maximizing compatibilities between land uses. Our case study clearly shows the ability of the model to generate diversified land use planning scenarios which form the core of a land use planning support system. It also demonstrates the potential of the model to consider more complicated spatial objectives and variables with open-ended characteristics. The breakthroughs in spatial optimization that this model provides lead directly to other properties of the process in which further efficiencies in the process of optimization, more vivid visualizations, and more interactive planning support are possible. These form directions for future research.

Keywords: spatial land use optimization; NSGA-II-MOLU; planning support systems; land use planning; multi-objective optimization; Tongzhou New Town, China

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ISSN 1365-8816 print/ISSN 1362-3087 online

http://dx.doi.org/10.1080/13658816.2011.570269
http://www.tandfonline.com

1. Introduction

Land use optimization is a method of resource allocation, defined as the process by which different activities or land uses are allocated to specific units of land area usually at city scale but sometimes at the levels of the neighborhood or the urban region. These activities usually comprise residential land, commercial activities, industry, recreational facilities, green space such as parks or green belts, and cognate uses and activities. In formal terms, these kinds of problems demand that multiple and often conflicting objectives need to be considered during the land use optimization process. Such problems were first articulated in the wave of urban modeling applications developed in the 1960s with models such as Schlager's (1965) linear programming (LP) model of land use plan design being the archetypal case. Many developments then built on these early applications, particularly in the field of location-allocation models (Ghosh and Rushton 1987), their generalization to multi-criteria optimization methods, and in the domain of landscape overlay analysis that has also been informed by such methods (Malczewski 1999).

Generally speaking, the implicit and longstanding goal of urban and regional planning is to pursue and achieve the sustainable development of a particular area. Comprehensive sustainability in land use optimization can thus be seen as a complicated balance between economic development, environmental protection, efficient resource use, and social equity. Leccese and McCormick (2000) described a sustainable land use planning agenda which emphasized infill development, environmental protection, compactness, and local geographic cohesion as the main elements of a balanced approach to urban development. Aerts *et al*. (2002) attempted to achieve the same goal through compromises between development costs and the spatial compactness of land uses. Balling *et al*. (2004) dwelt more specifically on minimizing urban change in terms of traffic congestion. Ligmann-Zielinska *et al*. (2008) focused on the efficient utilization of urban space through infill development, compatibility of adjacent land uses, and defensible redevelopment. Chandramouli *et al*. (2009) defined sustainable optimization more in terms of the provision and balance between green space and public amenities in terms of their compatibility in various planning scenarios. There have been many different blends of such objectives which serve to define the general focus of land use optimization as part of planning support systems (Brail 2008).

Land use optimization is complicated by the fact that decisions about the location of land uses must be made with respect to not only what activities to select but also how much land to allocate to each and where to allocate these land uses. There is a strong tendency in all applications to keep on adding extra classes of variables to the problem as the optimization process is all encompassing. As the area of the system and the spatial resolution required increase, this leads to a massive increase in the number of variables required. Hitherto many such kinds of problems have been solved using LP, and the increasing sophistication of LP and faster computers has allowed such problems to be handled ever more efficiently with respect to formalized single-objective optimization. With the recognition of the necessity for multi-objective problems, trade-offs can also be obtained using LP approaches by combining objectives together through the setting of suitable weights. Chuvieco (1993), Arthur and Nalle (1997), and Aerts *et al*. (2003a, 2003b) have integrated these kinds of LP approaches with geographical information systems (GIS) to undertake spatial land use optimization problems.

However, it is a major issue for planners to numerically quantify the relative weights of each of the defined objective. Moreover, non-convex optimal solutions cannot be obtained by minimizing linear combinations of objectives. An increased complexity of the problem usually follows from the inclusion of multiple objectives which makes the problem nonlinear and often complicated to the point of intractability. Spatial objectives add the spatial dimension to all attributes of the problem, increasing its complexity often because neighboring and distant areas or features cannot be treated independently. In short, spatial autocorrelation can dominate the problem if objectives and constraints are not formulated carefully. For general nonlinear multi-objective optimization problems, an efficient way is to combine all objectives directly, but the scale and weights of each objective are often confusing with respect to their definition. Besides, single-objective methods for multi-objective optimization are only able to generate one preference solution at a time and this is often another major obstacle affecting the efficiency of planning support.

In order to avoid setting the weights for different objectives as well as the characteristic of 'one preference solution at a time,' and not to miss non-convex solutions to the optimization problem, a method originating from the concept of Pareto optimality (Pareto 1965, originally published in 1896) called the 'Pareto Front based method' can be invoked. The Pareto set is usually independent of the relative importance of all the objectives, and it has become popular for solving multi-objective problems which focus on applications to spatial systems including land use planning (Balling *et al*. 1999, Xiao *et al*. 2002, Chandramouli *et al*. 2009).

No matter what method is used, the complexity of the optimization process increases not only because of the exponentially large number of variables but because of the increasing number of objectives. It is impossible for planners to think about and assess all such possibilities or handle this sort of problem by any kind of enumeration method. All these problem features described above create the need for effective optimization methods in land use optimization. A switch has of course occurred over the last two or three decades from strict optimization to the use of heuristics to help in the design of optimal solutions. Aerts *et al*. (2003b) have made use of 'simulated annealing' to perform land use planning in a multiple objective LP context. Duh and Brown (2007) used a knowledge-informed Pareto-simulated annealing to perform multi-objective spatial allocation.

Genetic algorithms (GA), first introduced by Holland (1975), provide another extremely effective heuristic used to search complex solution spaces in a variety of application domains and these have proved to be efficient as optimizers across a range of applications (Goldberg 1989, Michalewicz 1996, Feng and Lin 1999). Balling *et al*. (1999) utilized GA to solve vector-based urban planning problems, while Feng and Lin (1999) reported ways to generate alternative maps for urban planning using a GA. Stewart *et al*. (2004) have also used general GA to perform multi-objective land use planning in small neighborhood areas represented by spatial grids.

GAs are well suited to solving multi-objective optimization problems by searching the Pareto front step by step. Searching for the global optimum and the convergence ability of GA makes it possible to find a diverse set of solutions for difficult problems in non-convex, discontinuous, multi-modal solution spaces (Zhang and Leung 2000). There have already been some successful multi-objective optimization models such as the vector-evaluated GA proposed by Schaffer (1985). After these developments, a flurry of GA applications have been made, specifically the multi-objective (MOGA), the niched Pareto (NPGA), the random weighted (RWGA), the non-dominated sorting (NSGA), the strength Pareto evolutionary algorithm (SPEA), and the fast non-dominated sorting GA (NSGA-II) which is the basis of the extensions and applications proposed here (Fonseca and Fleming 1993, Horn *et al*. 1994, Srinivas and Deb 1994, Murata and Ishibuchi 1995, Zitzler and Thiele 1999, Deb *et al*. 2000). Matthews (2001) has successfully used MOGA to help land use planning based on vector representation, despite the fact that this restricts the diversity of solutions. With respect to these applications, the time taken to reach feasible and clearly good solutions has been a common problem and this has tended to make their use in planning support difficult (Geertman 2002).

In the rest of this article, we will sketch how we will build on this tradition, with respect to building new spatial optimization models with new requirements for efficient land use optimization, overcoming the limitations imposed by the non-convex search strategies in general optimization models. Spatial objectives and constraints have thus been suitably integrated to form what we call the multi-objective optimization of land use (MOLU), and this will then be synthesized with the NSGA-II model which will now include several new and efficient operators to be used in the applications proposed here. Furthermore, this NSGA-II-MOLU model will be demonstrated for problems of land use allocation in Tongzhou New Town, where the optimization will be based on three distinct objectives involving minimizing land conversion costs, maximizing spatial accessibility, and increasing land use compatibilities. The results from the application of the model will be verified, and then we will reflect on what we have developed, outlining future research directions by way of conclusion.

2. The MOLU model

2.1. Defining objectives

Land use optimization needs to meet many different types of objectives which are based on a deep understanding of the requirements pertaining to land development. The mission of land use planning which we ascribe to here is to achieve sustainable land development, focusing on the three dimensions of economic benefit, social equity, and environmental protection, although this is only one perception of land use optimization, albeit one that is increasingly dominant (Berke and Godschalk 2006). Although the objectives considered may vary from place to place, it remains a challenge to compromise such multiple objectives which optimize the process of land development. As the number of such generic objectives increases in their particularity, the complexity of these issues and thus the size of the problem's solution space increase exponentially.

As land use optimization is a spatial process, the need to represent spatial attributes and areas increases the computation time exponentially in terms of the size of the study area and the interrelationships between objectives and constraints. All the complexities noted above force us to consider a new and more focused model that not only is able to represent such problems, but can be adapted to this kind of optimization. Many objectives could be built into such optimization models. These include minimizing traffic congestion; maximizing the compactness and mix of land uses; maximizing economic, ecological, and environmental benefits; maximizing the capacity for more affordable housing; preserving historical and cultural sites; providing for social equity; and so on. One of the targets in this study is to formulate a model which provides an effective and relevant integration of such variety in objectives and their constraints.

2.2. Model formulation

Assume that the land area in question is divided into a regular grid with N rows and M columns. There are K different types of land uses within this area. A binary variable x_{ijk} is defined where x_{ijk} equals 1 when land use k is assigned to cell (i,j). Otherwise, x_{ijk} equals 0. B_{ijk} is defined as a parameter of the different objectives which depends on the attributes of the area and the objectives themselves.

The task of achieving optimization of the various objectives can be expressed as the following program:

MINIMIZE

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

where

$$x_{ijk} \in \{0, 1\}, \forall k = 1, \ldots, K; i = 1, \ldots, N; j = 1, \ldots, M \tag{2}$$

subject to

$$\sum_{k=1}^{K} x_{ijk} = 1;\; x_{ijk} \in \{0,\ 1\}, \quad \forall k = 1, \ldots, K;\ i = 1, \ldots, N;\ j = 1, \ldots, M \tag{3}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ijk} = S_k; x_{ijk} \in \{0,\ 1\}, \quad \forall k = 1, \ldots, K;\ L_k \le S_k \le U_k \tag{4}$$

$$\sum_{k=1}^{K} S_k = N\ M \tag{5}$$

Equation (3) specifies that one and only one type of land use can be assigned to each cell to ensure that the decision variable x_{ijk} is either 0 or 1. Equations (4) and (5) restrict the number of cells S_k allocated to a certain land use type k between upper and lower bounds, depicted as L_k and U_k, respectively.

3. The NSGA-II-MOLU model

3.1. The chromosome representation

GAs require us to choose a ‘chromosome’ by which to encode the land uses. A simple and direct chromosome representation is a list or grid of genes, where the position of each gene (cell) represents a unit and the land use of the unit is determined by its value. This method has been applied a number of times in spatial analysis (Butcher *et al*. 1996, Stewart *et al*. 2004, Seixas *et al*. 2005, Ligmann-Zielinska *et al*. 2008). Matthews *et al*. (1999) also proposed two different kinds of chromosome representations based on vectors. The first one is a fixed-length representation which directly arranges the land uses as genes, sensitive to the number of land blocks or parcels. The other is a variable-length representation focusing on the ‘percentage and priority’ in the allocation of the land use, and this is sensitive to the number of land use types. As the vector-based optimization method requires *a priori* knowledge of the districts, and this influences the maneuverability of the optimization process, the grid-based optimization model will be used here and chosen to represent the chromosome.

3.2. *Principles of NSGA-II*

NSGA-II, developed by Deb *et al*. (2000), which is an improved version of NSGA, is an efficient multi-objective evolutionary algorithm using the elitist approach which consists of sorting the population at different 'fronts' using the non-dominated ranking method with a particular bookkeeping strategy. The crowding distance sorting is another essential part in ranking the population, and the best individuals in terms of non-dominance and diversity are then chosen. A sketch of the algorithm which indicates how a solution P_t is progressed to P_{t+1} through the front using the crowding distance sorting is shown in Figure 1.

3.2.1. Non-dominated sorting

In order to sort a population of size N according to the level of non-domination, each solution must be compared to every other solution in the population to check if it is dominated. This requires $o(ON)$ computation where ON in the brackets stands for the number of objectives. For enumeration to reflect the entire first Pareto front, this requires $o(ON^2)$ comparisons, while, for the worst situations, the computation to obtain all the fronts, level by level, requires $o(ON^3)$ comparisons. Within NSGA-II, the bookkeeping strategy can be utilized to decrease the computations to $o(ON^2)$ at most.

3.2.2. Crowding distance

The crowding distance is another essential concept proposed by Deb et al. (2000) for the NSGA-II algorithm, the target of which is to generate an estimation of the density of solutions surrounding a particular solution in the population. The crowding distance for a point i is the estimate of the size of the largest cuboid enclosing the point i without any other point in the population being part of this. It calculates the average distance between two points on either side of this point along the objective axes (as shown in Figure 2).

The following algorithm outlines the computation process for the crowding distance in a population of M solutions. To choose the crowding distance assignment, we set

$$m = M,\ \text{and then for each } i,\ \text{set } M_{i(\text{distance})} = 0,$$

$$\text{And for each objective } o,\ M = \text{sort}(M, 0),\ M[1]_{\text{distance}} = M[m]_{\text{distance}} = \infty.$$

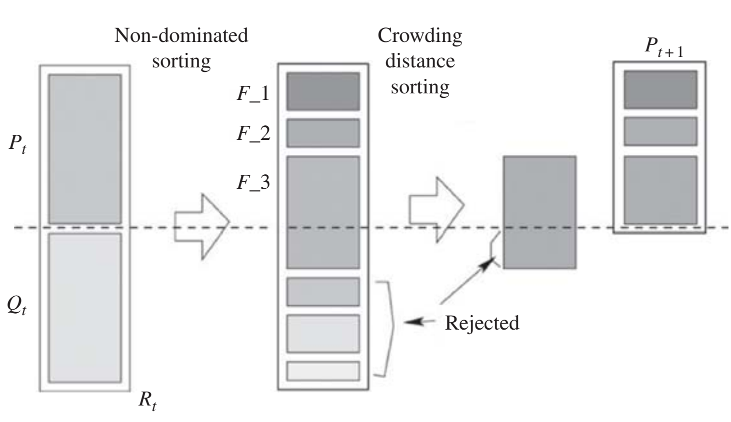


Figure 1. A sketch of NSGA-II (after Deb *et al*. 2002).

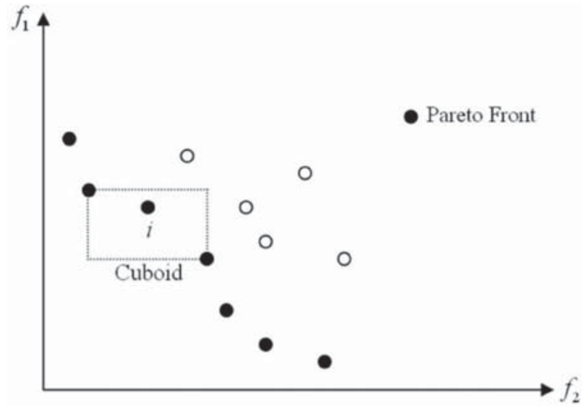


Figure 2. The crowding distance calculation (Deb *et al*. 2002).

$$\text{Then for } i = 2 \text{ to } (m-1),\ M[i]_{\text{distance}} += \frac{M[i+1]\cdot o - M[i+1]\cdot o}{\text{Max}[fo] - \text{Min}[fo]}$$

In the first line, M is the size of the population, $M[i].o$ refers to the oth objective function value of the ith individual in the set M, $Max[fo]$ and $Min[fo]$ are the maximum and minimum values of the oth objective function. Following this operation, we activate a loop responsible for the computation of all crowding distances for each solution. In the complementary part of the non-dominated ranking, each solution in the population will provide enough information to enable a ranking.

3.3. Operators for NSGA-II-MOLU

NSGA-II is clearly an excellent algorithm with a particularly good Pareto front searching ability which gives a sufficient diversity in the solutions generated (Deb *et al*. 2002), In the land use planning problem however, which has dimensions of spatial location (cells or 'patches'), the initialization, crossover, and mutation operators can be improved from the original method to a more feasible form. In our applications, the initialization operator, a crossover operator, and two mutation operators have been developed to improve the process and the results of the optimization in the manner indicated as follows.

3.3.1. The initialization operators

Initialization of the population is a very important stage during the process of optimization based on GA. Good initialized populations can generate the Pareto Front more quickly and yield more feasible solutions while the algorithm is less efficient if the initial solutions are chosen badly. In land use optimization problems, data pertaining to the existing land use *status quo* should be used as part of the iteration process, and then the initialization operators will create 90% random solutions and 10% land use *status quo* solutions as part of the initialized population. This initialization operator is called the problem-based initialization operator (PBIO).

3.3.2. The crossover operator

The function of a crossover operator in GA is to exchange randomly selected sets of genes between two chromosomes in order to exploit beneficial parts of a search space. The final target in the land use optimization problem is the trade-off of the patches or cells for different land use types. Instead of a single point or multi-point crossover, the patch or cell exchange is more suitable for achieving an evolutionary process in such kinds of problems. The crossover usually operates between the parents that are the two chromosomes from the population. However, in terms of the characteristics of the solution, self-reproduction might be made more efficient for each chromosome. The single parent crossover operator (XSP), which represents the two-dimensional structure of the spatial landscape, is thus applied to the land use optimization based on NSGA-II as shown in Figure 3.

In this study, the XSP operator is based on a 3 × 3 cell window. This is realized by randomly choosing the locations and the shape of the crossover patches in one chromosome and then swapping the two patches as the offspring for the next step in mutation and selection.

3.3.3. Mutation operators

For land use optimization problem, two mutation operators are developed to operate the GA. The first is the mutation of patch cells (MPC) operator which maintains diversity among solutions in a population, and the second is the mutation by constraint steering (MCS) which erases infeasible solutions from the population and enables the constraints to be met. The MPC is depicted in Figure 4.

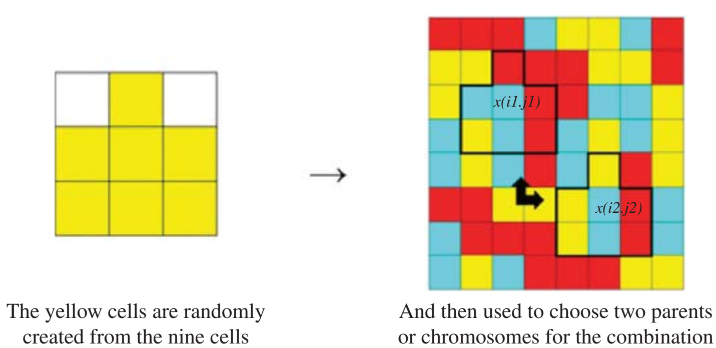


Figure 3. Procedure of the XSP operator.

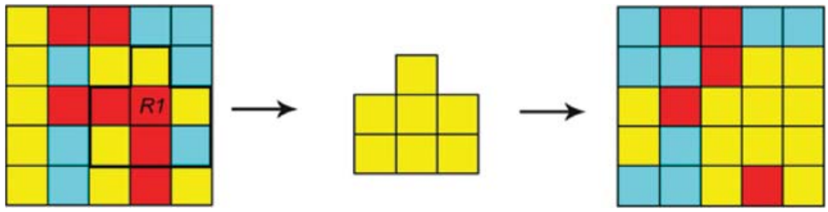


Figure 4. Procedure of the MPC operator.

This is very similar to the XSP crossover operator. The first step is to randomly choose the location of the mutation window and the shape of the patch with some probability, and randomly choose one land use type as the mutation direction; then the algorithm computes if the same land use types surround the mutation patch; if this is so, the original solution will be replaced by the mutation patch; if not, it needs to move to the first step.

In terms of the constraints steering mutation, for the constraints considered in this kind of problem, besides the conservation of special land use patches, the MCS can improve the structure and spatial location of specific land uses. Generally, the MCS mutates a very small number of single cells to some special land use types. MCS can also evaluate whether or not the solution meets the constraints, if the area of one specific land use is more or less than the requirements. The mutation cell thus chooses some specific land use which steers the overall solution toward an improved change.

4. Applications to new town planning

4.1. The Tongzhou case study area

Tongzhou which is located to the southeast of Beijing is considered the capital's eastern gateway. It is about 37 km east–west and 48 km north–south, covering an area of some 906 km^2. Eleven towns and four communities comprise the area with a population of 870,000. Tongzhou New Town is the core urban area of Tongzhou as shown in Figure 5.

As a rapidly developing area, Tongzhou New Town is the subject of a vibrant and important debate with respect to how to plan and manage this area in the future. Since there are countless possibilities for different land use planning scenarios, to produce an efficient and scientific evaluation of possible future layouts, the NSGA-II-MOLU model is likely to be an efficient tool for planning support. In terms of the land use plan, we have defined a simplified land use map which includes five land use types: residential land (R), industrial land (I), commercial land (C), green (open space) land (G), and undeveloped land (U) which are represented using a grid at a resolution of 400 m × 400 m. We define three optimization objectives based on minimizing land use conversion costs, maximizing accessibility, and maximizing the compatibility between the neighbors of the land use cells. We consider this case study to be a good basis for demonstrating and verifying that the

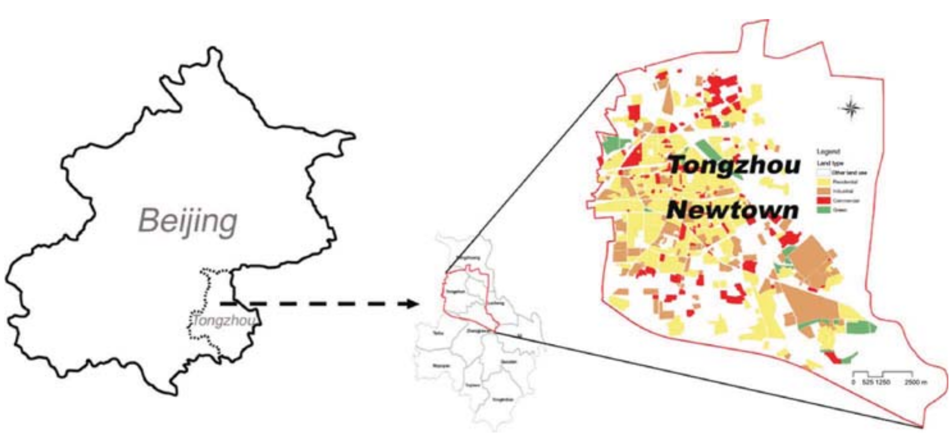


Figure 5. The location of Tongzhou New Town.

model is a novel and effective tool for land use optimization and thus constitutes a good basis for planning support systems.

4.2. Minimizing conversion

From another angle, minimizing conversion costs for different land uses will lead to a decrease in the spending on social capital, thus improving economic benefits to the wider society. As for such conversion costs, it is difficult to assess the extent to which such costs relating to one land use impact on another because these costs are influenced by building type, plot ratio, and so on. Here we will simply convert the minimization of conversion costs to the minimization of land use changes which clearly leads to greater economic benefits.

4.3. Maximizing accessibility

As another criterion for sustainable development, accessibility is important for land use planning not only because it reflects the operational efficiency of a city, but also because good accessibility planning can also improve social equity and lead to decreases in CO_2 and related emissions which are largely generated inside the city from various human and automobile activities. Accessibility is thus central to the performance of land use optimization particularly in terms of planned transportation lines that will be constructed by 2020 in Tongzhou New Town. In China, according to the 'Regulations for gradation and classification on urban land' (GAQS 2001), the road system can be divided into three types: roads that primarily serve residential neighborhoods, major routes for all transportation, and routes that serve commercial and mixed uses.

The influence index in Table 1 is obtained as the mean of the range set by the regulation whose function value with respect to each type of road is calculated by

$$f_i^R = 100 \times I_i^R \tag{6}$$

where f_i^R is the function value and I_i^R is the influence index for the ith type of road R. The index is thus calculated for commercial use as

$$e_{ij}^R = (f_i^R)^{1-r} \tag{7}$$

and for residential and industrial as

$$e_{ij}^R = (f_i^R)(1-r) \tag{8}$$

Table 1. The influence index of different road types (GAQS 2001).

	Residential	Industrial	Commercial
Residential roads	1	0.7	0.875
Major transportation routes	0.7	1	0.7
Roads for mixed and commercial use	0.875	0.875	1

where e_{ij}^R is the influence value of ith road to jth point and r is the suitably normalized distance between the ith road and the jth point. These definitions are those used in the general regulations (see GAQS 2001).

The road network in the study area is shown in Figure 6 along with the patterns of accessibility intensity for the three types of roads.

For green land which is park and open space as well as for undeveloped land, there are no restrictions posed by accessibility measures with respect to their layout and location. However, in order to make use of the accessibility measure to its full potential, green and undeveloped land is best allocated in locations that have lower accessibilities. The equivalent function for these two land uses is shown in Figure 7 where it is clear that more remote places are favored, that is, those with lowest accessibility in terms of the street pattern. For each scenario, the evaluation of the accessibility is based on the functions shown in Figures 6 and 7 which are incorporated into the optimization so that the overall accessibility is optimized for each land use.

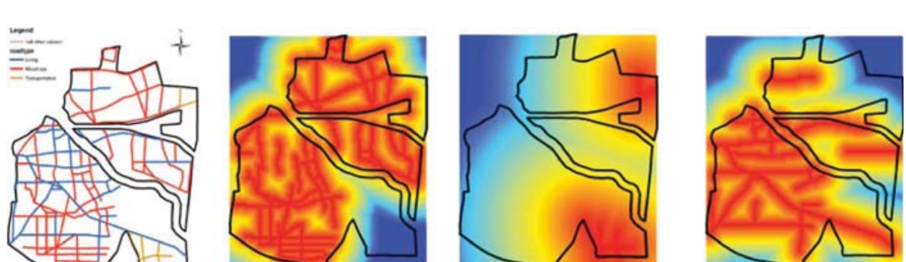
4.4. Maximizing compatibility

There are different preferences for the neighbors of the five different land uses which we illustrate in Figure 8. These reflect different degrees of compatibility over a range from 0 to 1.

Each land use type has its own preference with respect to its compatibility in a neighborhood of different land use types. As shown in Figure 8, for each land use k in its immediate neighborhood, we can judge the compatibility of the scenario by summing the compatibility indices shown in the right table of Figure 8. The compatibility indices are obtained from the stakeholders' response to a dialogue or debate between them with respect to their expertise. The higher the sum of the indices, the more compatible the scenario.

For setting the values of land use compatibility, it is feasible to generate the indices from the opinion of experts; however, compatibility scores are likely to change from one expert to another, and even for the same expert, it is hard for him/her to find out the relationship between every two land use types at the same level. The pair-wise comparison approach below can be used to generate these values. Table 2 refers to the opinion of a typical planner from Chinese Academy of Urban Planning and Design. Only the pair that has the same land use will be compared.

After computations for extracting the structure of this matrix in terms of weights using the Saaty AHP method (Saaty 1980), the final compatibility values shown in Table 3 can be generated.



Street network | Residential | Industrial | Commercial and mixed use

Figure 6. The street network and the accessibility intensities for the three classes of roads.

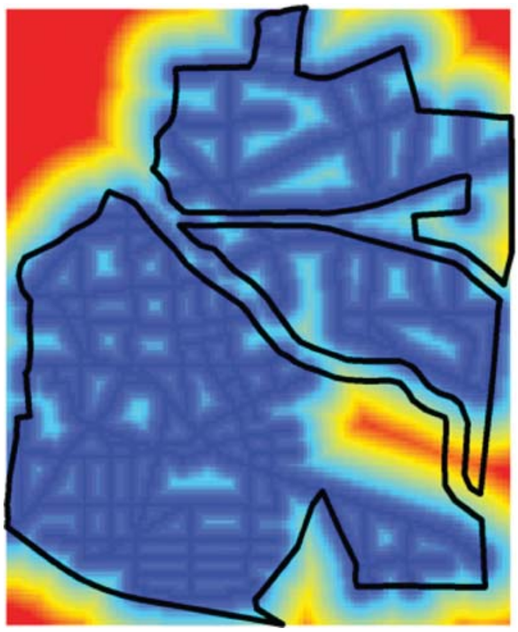


Figure 7. Accessibility surface for green and undeveloped land.

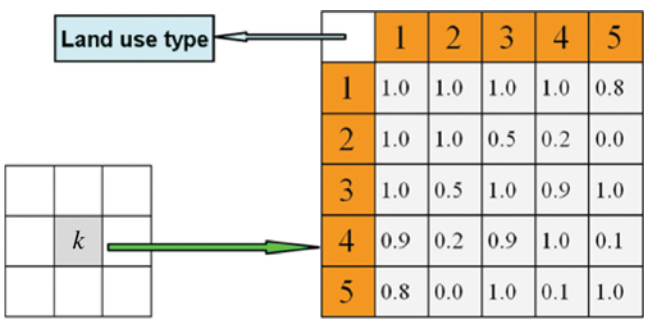


Figure 8. Compatibility scores.

Table 2. Relative compatibilities based on comparisons of pairs of land uses.

	RI	RC	RG	RU	IC	IG	IU	CG	CU	GU
RI	1.000	3.000	3.000	1.500	1.500	1.000	2.000			
RC	0.333	1.000	1.000	0.500	0.500			0.667	0.500	
RG	0.333	1.000	1.000	0.500		1.000		0.500		0.667
RU	0.667	2.000	2.000	1.000			2.000		1.000	1.500
IC	0.667	2.000			1.000	2.000	2.000	1.500	0.667	
IG	1.000		1.000		0.500	1.000	0.667	0.667		0.667
IU	0.500			0.500	0.500	1.500	1.000		0.500	1.500
CG		1.500	2.000		0.667	1.500		1.000	0.667	1.000
CU		2.000		1.000	1.500		2.000	1.500	1.000	2.000
GU			1.500	0.667		1.500	0.667	1.000	0.500	1.000

Table 3. The extracted compatibility values.

	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

The objective is thus to maximize the sum of the compatibilities of all the cells inside the study area. The overall objective function is composed of these three single objectives – conversion costs, accessibility and compatibilities – and these are assembled as a simple weighted and normalized linear function which defines the overall objective function $\{B_{ijk}\}$ in basic program defined in Equations (1)–(5).

4.5. Constraints

Within the model, there are also other constraints that need to be satisfied such as those posed by restricted areas, the need to minimize the extent of residential areas which serve the future population, and the fact that each cell can only have one land use type. In particular, the following constraints are considered as shown in Figure 9. Restricted areas in the

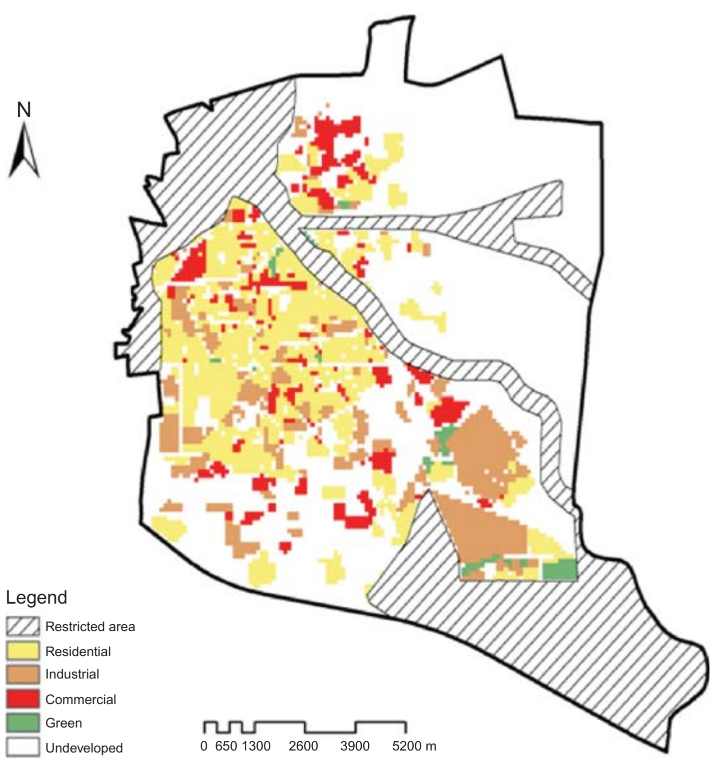


Figure 9. Restricted land in Tongzhou New Town.

Tongzhou New Town include the Grand Canal and the reserved green open space in the northwest and southeast. The maximum and minimum number of cells for different land uses (the lower and upper bounds) also need to be defined; these are based on the prediction of the future population in Tongzhou New Town in 2020, and this suggests that the lower bound on the number of residential and commercial land use cells should be at least 200 developed cells.

4.6. Implementation and evaluation

The NSGA-II-MOLU model was executed over 1000 generations to optimize the three objectives subject to the constraints on restricted green space and the area available for residential land use. The execution of the model with the PBIO, the XSP crossover operator (which shows that the comparison is better than traditional two parents crossover operator), and the MPC and MCS mutation operators required less than 10 minutes of computation to yield 1000 generations of 100 populations on a standard (*ca.* 2010) general PC. In Figure 10, we show the progress of this iteration. The blue points represent the initialization of the population by random means. The green and blue points represent the 300th and 600th generation solutions, while the red points are the final solutions produced by the last generation.

Figure 10 shows that along with the step-by-step iterations, the solutions become better and better with respect to the overall optimization as well as achieving a greater and greater spread across the three objectives. Through the iterations, the improvement in the solutions becomes smaller and smaller ultimately reaching a convergence. When we examine any two of these objectives in two dimensions, the effects are as follows. Figures 11–13 show that the solution process is extremely well behaved across all three objectives when these are considered in pairs.

Figures 11–13 also demonstrate similar trends to those in Figure 10 with the solutions improving through the iterations indicating a convergence of the compromise process. However, the crossing phenomenon due to the action of the various operators which occurs

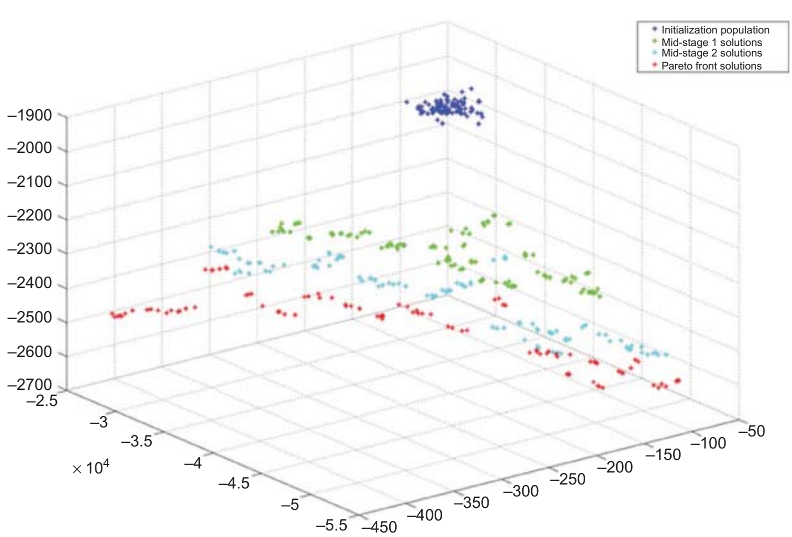


Figure 10. Convergence of different generations in optimizing the three objectives.

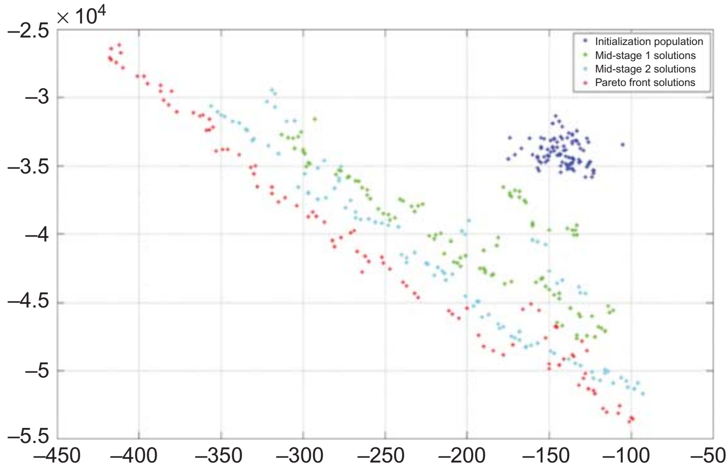


Figure 11. Convergence of different generations (first and second objectives).

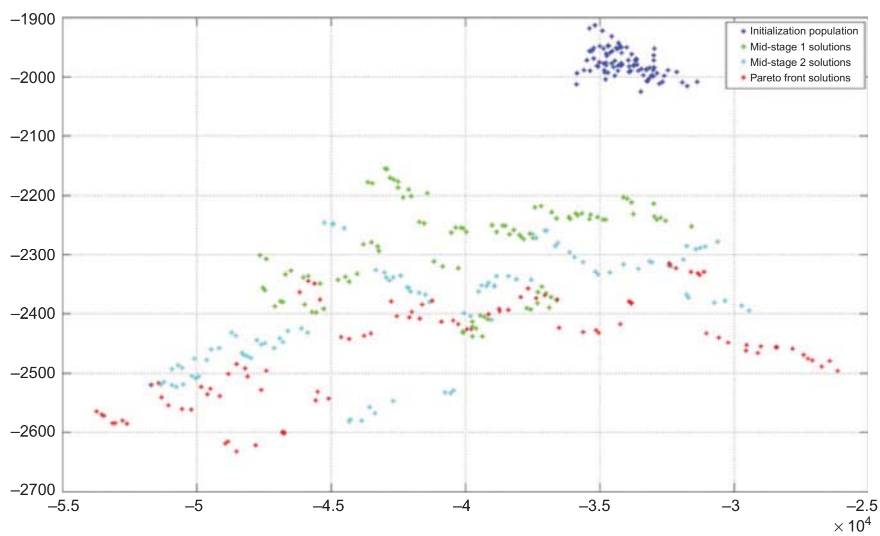


Figure 12. Convergence of different generations (second and third objectives).

among these different generations is obvious and this can be seen from the differences between the visualizations of the two- and three-objective optimization.

In order to check how well the algorithm has improved the Pareto optimality from generation to generation, a sampled 'global generation' is created through all 1100 solutions including the first generation and every 100th. After calculation of the 1100 solutions, we can identify the 'global Pareto front solutions' for the sampled global generation. Of the 1100 solutions in the global generation, there are a total of 139 solutions on the Pareto front. From generation to generation, the number of the global Pareto front solutions increases sharply as shown in Figure 14. The global optimal searching ability of the NSGA-II-MOLU model is clearly demonstrated. We also show the average objective value

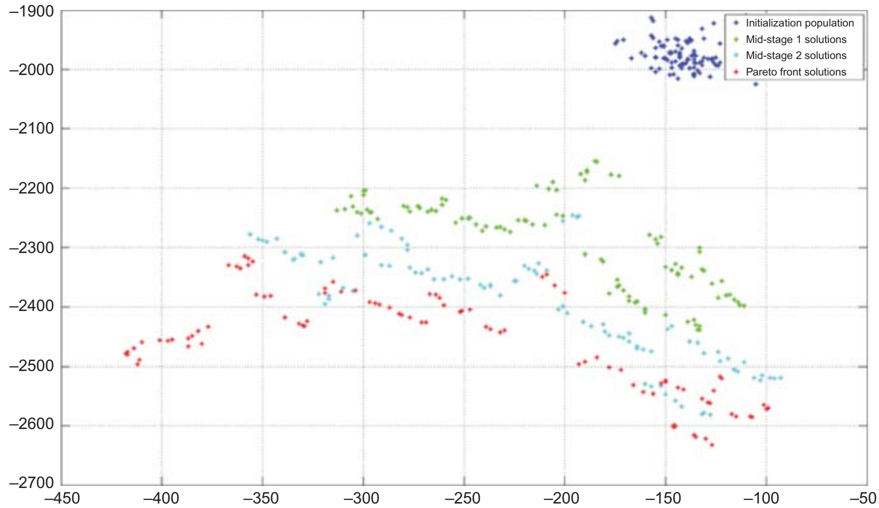


Figure 13. Convergence of different generations (first and third objectives).

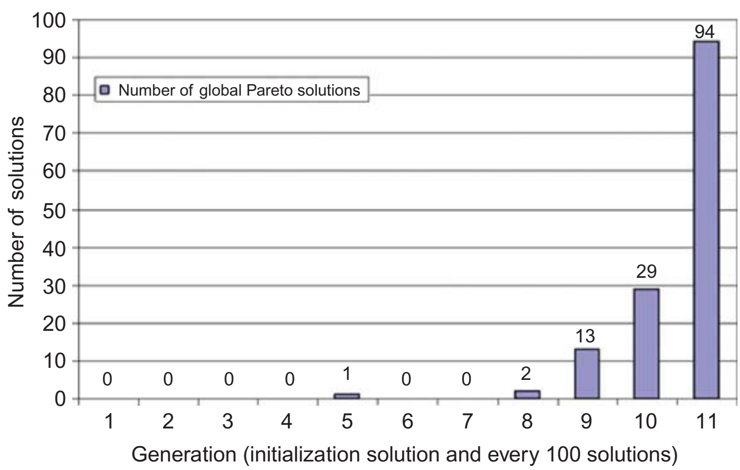


Figure 14. The number of global Pareto solutions (the number in each column represents the number of the final Pareto Front solutions in each generation).

after normalization in Figure 15 which indicates the changing trend in the objective value thus demonstrating once again the convergence of the optimization.

After the verification of the model, the 139 solutions on the Pareto font can then be used to derive a suitable solution when considered against the qualitative requirements of different users. Herein, taking each solution as equally weighted and each preferred solution as an example of the effectiveness of this model, we can generate the following solutions for each of the three objectives as shown in Figure 16.

From the scenarios above, we can find that the equal weight preferred solution has the most balanced land use distribution with respect to compact and required residential land, well-distributed commercial land and green space, as well as industrial land located in three main industrial zones. As for the other solutions, these tend to be extremes,

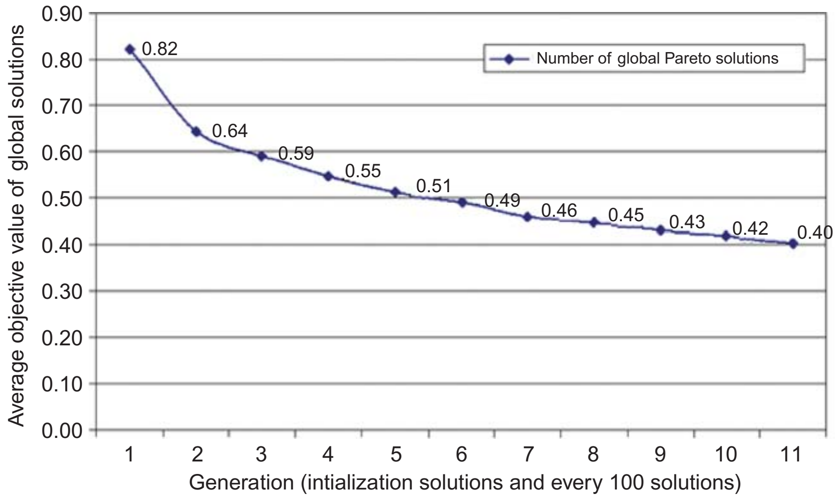


Figure 15. The average objective value of each global solution (after normalization).

but they definitely reach the best scores with respect to their preferred single objectives. The Objective 1 preferred solution is obviously similar to the land use *status quo*, the Objective 2 preferred solution has the best compatibility with transportation facilities, and the Objective 3 preferred solution presents the most compatible layout of these land uses. Besides the plans shown in Figure 16, according to the attribute information associated with these four scenarios, we also find that each objective-preferred scenario has the best objective value according to their own specific optimizations. The equal weight scenario has the most balanced values of these three objectives. As for the different land use cells in the different scenarios, all satisfy their constraints. Both the maps and the attributes demonstrate the effectiveness of the model as shown in Figure 16 and Table 4.

5. Reflections, conclusions, and future research

First, with respect to the novel formulation of the MOLU model, Euclidean distance and decreasing functions of accessibility with respect to land uses and transport are used to reflect the spatial structure of the system, while the pair-wise comparison method is used to generate appropriate sets of land use compatibility indices from the various specialists who contribute to the planning process as stakeholders and professionals.

On the other hand, in multi-objective optimization for land use allocation planning problems, there has been hardly any development of the non-dominated optimization model in searching for comprehensive and diverse optimality which is central to the mission and process of new town planning (Stolk and Broemmelstroet 2009). Most analysis has focused on how to combine multi-objectives into one single objective and there has been hardly any work on examining the limitations of non-convex characteristics of the solution space. Here we have developed and revised the NSGA-II model by including an innovative initialization operator, a new crossover operator, and two mutation operators while also coupling this with the MOLU model, so that we might achieve Pareto front solutions and obtain the comprehensive optimal results.

Finally, this simple application to a relatively well-defined new town planning process has not only verified the effectiveness of the NSGA-II-MOLU model, but demonstrated

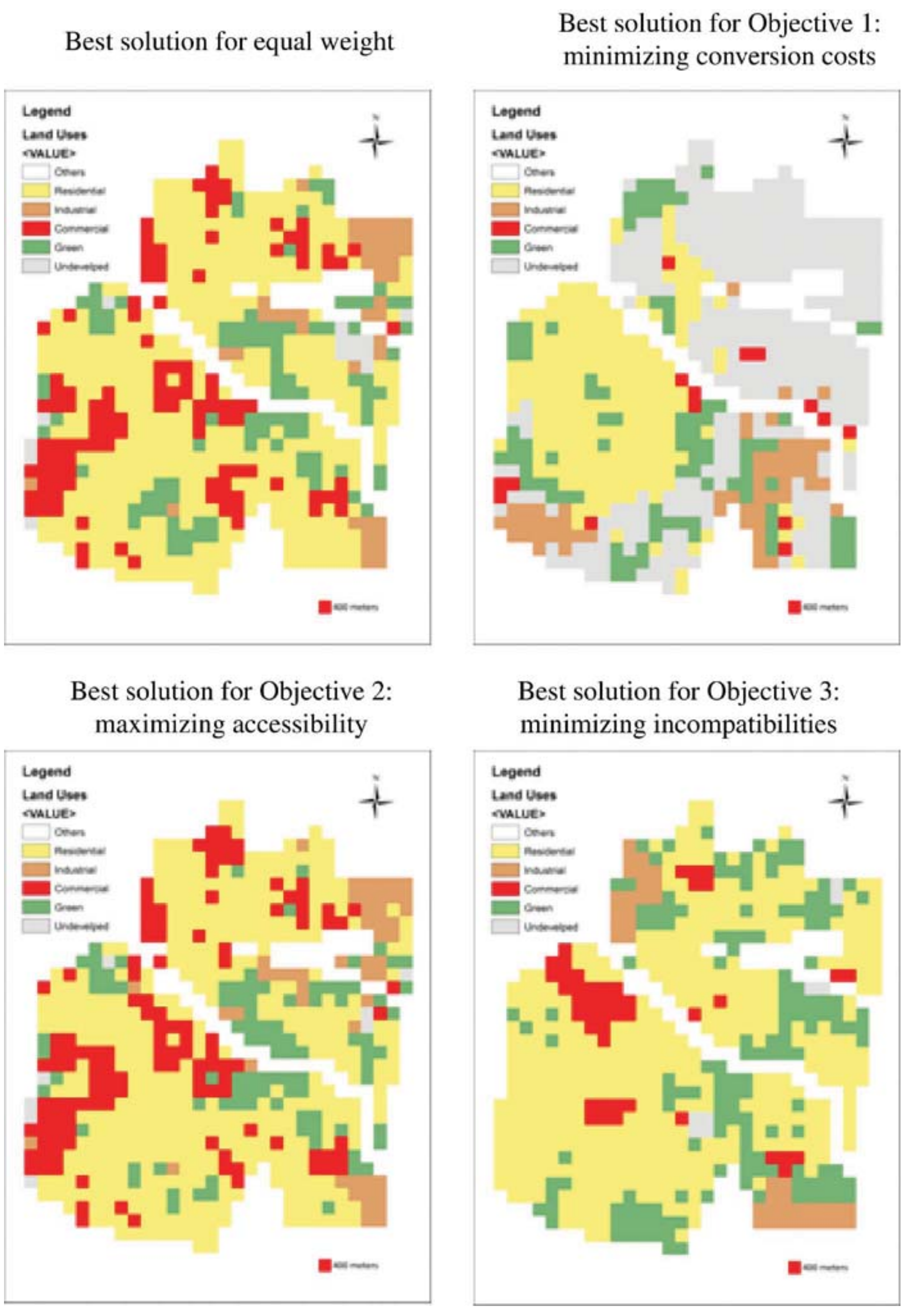


Figure 16. The best solutions for the equal weight and single-objective optimizations.

the generality of the model to deal with more objectives, more variables, and different representation methods. In this sense, our model framework is essential to broadening the domain of planning support systems that deal with land use allocation in contexts where development is immediate and rapid.

Table 4. Attribute information associated with the four solutions.

	Equal weights solution	Objective 1 solution	Objective 2 solution	Objective 3 solution
Value of Objective 1	−115	−418	−101	−127
Value of Objective 2	−53, 039	−27, 087	−53, 729	−48, 508
Value of Objective 3	−2, 585	−2, 479	−2, 565	−2, 632
Number of residential cells	416	200	412	444
Number of industrial cells	45	58	50	38
Number of commercial cells	116	15	124	45
Number of green space cells	97	97	94	153
Number of undeveloped cells	14	318	8	8

As we have been at pains to emphasize, land use allocation is only one kind of multi-objective optimization problem which has characteristics of spatiality in terms of its objectives and variables. In this article, the MOLU model was built to integrate a variety of optimization objectives defining the land use planning process, then coupling this to the revised NSGA-II model with all its features of optimization using GA which involves special initialization, crossover, and mutation operators. These then define the extended NSGA-II-MOLU model. We have demonstrated and verified the model by applying it to solve an optimization problem with three spatial objectives based on minimizing conversion costs, maximizing accessibility, and maximizing the compatibilities of five different land use types.

Our results show that the model is useful as a planning support tool to optimize land uses under the complicated conditions of interacting spatial objectives and variables. Although only three objectives were used in this application, the potential of the model for handling many more spatial objectives and variables is very clear from its open-ended form. Nevertheless, the current model can be further improved in its efficiency and effectiveness. We could integrate the model into an application plug-in for a GIS which might form the basis for some sort of extended planning support system. The core algorithm could form the basis of an interactive planning support in which planners as experts and stakeholder might interact with the model with respect to choosing weights and filtering out solutions as the iterative process of generating a solution occurs. These are all important directions for future research.

Acknowledgements

The authors would like to thank Jinyeu Tsou and Jie He for their data support, and Hui Lin and Yee Leung for their helpful comments. We would also like to thank the anonymous reviewers for their meaningful and perceptive comments and suggestions on previous versions of this article.

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