A spatial land use planning support system based on game theory

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Abstract

Spatial urban land-use planning is a complex process through which we aim to allocate suitable land-uses taking into consideration multiple and conflicting objectives and constraints under certain spatial contexts. Landowners should be modeled as players that are able to interact with each other so as to seek their best land-uses while considering multiple objectives and constraints simultaneously. Game theory provides us a tool with which land-use planners can model and analyze such interactions.

In this paper, spatial urban land-use planning is considered as a game to model local competitions between landowners, whose players(i.e., the landowners) play, in order to pick the most suitable land-use for themselves. The game is defined based on the objectives of consistency, dependency, suitability, compactness of land-uses, and the land-use per capita demand. In this paper, we designed three different scenarios for the players. In the first scenario, the players are greedy and just accept the most compatible land-use. In the second scenario, conversely, the players are fully collaborative and they care about other players' payoff. In the third scenario, players are first greedy but when they cannot achieve an agreement with other players, they change their attitude to become gradually collaborative for reaching the Nash equilibrium (NE). Furthermore, the dissatisfaction index (DI), which represents the number of unsatisfied landowners with their current land-use, is defined to compare the different scenarios. The proposed model is tested in a district of region 7 in Tehran (the capital of Iran) with 2710 parcels.

The results of the first scenario showed that, at the beginning of the game, 50% of the landowners were not satisfied with their current land-uses but after 50 iterations, about 100 landowners were dissatisfied with their land-use and this scenario was not able to reach the NE. The results of the second scenario indicated that, in order to reach an optimized layout, 325 parcels need to be changed. Also, after reaching the NE in this scenario, the values of the objective functions do not significantly improve. So, lowering the expectations of the players would not lead to appropriate results. The outcomes of the third scenario provided appropriate results, which could be achieved when the level of expectations of the players can be changed during the game; furthermore, the NE among the players was obtained and the objective functions improved 20% on average in comparison with the other scenarios.

Moreover, the results of the scenarios were compared with the optimized layout obtained with a genetic algorithm (GA) using different parameter values. The results of the comparison also revealed that the urban layouts produced by game theory improved the objective function values obtained by the GA in about 10% and improved the GA's running time in more than 85%, on average. .

Keywords: game theory, land-use planning, planning support systems, optimized arrangement

1- Introduction

Urban land-use planning (ULUP) is a complex process in which urban utilities are placed side by side so as to frame a layout that satisfies the conflicting objectives and constraints of landowners (Batty 2018; Cao et al. 2011; Guoxin et al. 2004; Kaiser et al. 1995; Ligmann-Zielinska et al. 2008; Song and Chen 2018). The generated layout can be referred to as a near-optimal arrangement of land-uses. To achieve an optimal layout, some criteria should be normally controlled in the study area (Maleki et al. 2017; Yanfang and Liang 2002). According to urban planning researches and resources (Couch 2016; Hall and Tewdwr-Jones 2010; Ma et al. 2011), and also the criteria which are employed in urban detailed plans in Iran (Afsharnia 2014), for urban planning, four types of criteria are generally considered. First, per-capita demand which comes from a comparison between present per-capita demand and related standards. Qualitative criteria are related to other three criteria: dependency, consistency and suitability in land-use sustainable arrangement (Maleki et al. 2017; Taleai et al. 2007). In urban areas, dependency is defined as the need of some land-uses to others for more functionality (Taleai et al. 2007). Consistency illustrates that the allocation of land to each land-use type should be designed to minimize undesirable impacts among adjacent land-uses (2010). Lastly, Suitability refers to the appropriateness of a land characteristic with its land-use type which is defined using many different factors in urban planning (Ghavami et al. 2016b). Most of the criteria used to optimize the layout of urban land-uses are often local, which illustrates the importance of local modeling of land-use planning (Ghavami et al. 2016b; Liu et al. 2015; Masoomi et al. 2013). However, some of the criteria have a general aspect. So, in land-use planning, both local and general aspects of these criteria should be considered.

The main goal of this research is to optimize the layout of urban land-uses considering the local interactions of landowners based on the four above mentioned criteria. These interactions can be modeled as a local competition between landowners in order to obtain the most appropriate land-use to parcels. Game theory, seen as a smart tool for modeling a cross-landowner competition can be used to model landowner interactions in land-use allocation. Hence, spatial land-use planning can be considered a game whose players, i.e., landowners, play in order to pick the most suitable land-use for themselves. The Nash equilibrium (NE) in game theory is a solution concept in which no player has an incentive to deviate from its strategy after considering other players' choices.

Various approaches have been applied in spatial land-use planning to model the interactions between land-uses and to reach a near-optimal layout. In recent research, optimization algorithms, cellular automata (CA) and agent-based models have been further addressed. In this field, the most commonly used approach is that of employing optimization algorithms (Haque and Asami 2014; Li and Parrott 2016; Masoumi et al. 2016; Masoumi and Mesgari 2015; Porta et al. 2013; Schwaab et al. 2017; Stewart and Janssen 2014; Z. Masoomi and M. S. Mesgari 2015). For example, in (Cao et al. 2012) a boundary-based fast genetic algorithm is applied so as to optimize the urban land-use layout; in (Cao et al. 2011), on the other hand, NSGA-II (as a multi-objective optimization algorithm) is applied to find a set of Pareto-optimal solutions. In these two research workss, the raster model was used in the optimization process in order to address some of the computational complexity involved but such tools are not appropriate to deal with real urban scenes. Masoomi et al. (2013) have used a Multi-Objective Particle Swarm Optimizer (MOPSO) to optimize urban land-uses in a vector environment. The main characteristic of the multi-objective algorithms is the generation of various optimal layouts. These algorithms are usually adopted to optimize land-use layouts in a general way, without incorporating local competitiveness.

The most common method for modeling local changes in urban land-uses is CA (Batty and Xie 1994; Liao et al. 2016; Stevens et al. 2007; Tan et al. 2015; Yang et al. 2016). In this method, with the definition of a neighborhood and the transition rules, the changeability of the land-use in cells is investigated. CA is mostly used for modeling land-use changes and urban growth modeling (Feng and Liu 2013; Li and Yeh 2000; Yang et al. 2008). In some studies, this tool is also used for land-use planning (Abolhasani et al. 2016; Liu et al. 2010). For example, in (Liu et al. 2010) a CA on an artificial immune system has been used to incorporate external interventions and generate different scenarios for urban land-use planning. Some disadvantages of CA include limited rules and a raster environment, which is not suitable for modeling an urban environment and a limited neighborhood.

Some of the work done on agent-based modeling in land-use planning includes (Arentze et al. 2010), (Ligtenberg et al. 2001) and (Ghavami et al. 2016a). For example, in (Ghavami et al. 2016a) social preferences are incorporated through the use of software agents which are trained by human actors. After completing their training process, agents in a negotiation process contribute in a land-use planning session.

Game theory has also been applied in the area of land-use planning combined with the above mentioned approaches (Liu et al. 2015; Tan et al. 2015). In (Liu et al. 2015), the spatial layout of each land-use was separately optimized by a GA in order to consider general aspects. Land-use suitability and compactness are the objectives considered in the spatial layout optimization of each land-use type. Using a dynamic game between farmers and government, a final decision is made to either change or keep the land-use of the land units. Other land-uses are considered unchangeable during the game. For urban growth modeling, the land-use maps were further converted to binary maps with only two categories: urban and non-urban land. One of the main characteristics of this study is the use of concepts of land-use competition zones as basic units with which to model the game in a raster format. Moreover, the raster data model is employed in this study. In (Tan et al. 2015) an extensive-form game is combined with CA to model human activities in urban growth. In these games, the number of players is limited to three players; the landowner, the land developer, and the government. The number of land-uses is also restricted to built-up, forest, cropland, water, and bare land.

In this paper, game theory has been employed to model the competition between landowners in urban land-use planning. This model consists of large-scale and simultaneous local-scale urban land-use planning which is considered as a game between landowners. Since, within the game, the number of players is equal to the number of land units; the number of land units, especially in urban environments, is usually too large. Therefore, one of the challenges facing this research was that of finding the NE for a large number of players. In order to do so, we proposed a new method to find the NE of the spatial land-use allocation in the form of a game with many players. In this regard, we introduced a new measure with which to evaluate the strategy profiles of the game.

Moreover, to model the real scene and dynamic of the urban areas, a vector model has been used which is not considered in most of the previous works such as (Arentze et al. 2010; Ghavami et al. 2016b; Ligtenberg et al. 2001; Liu et al. 2010). Also, various land-use types according to metropolitan requirements have been considered in this research.

The rest of the paper is organized as follows. A detailed literature review is presented in Section 2. The land-use allocation process based on game theory is explained in Section 3. In Section 4, we present first, the results of the implementation of the proposed model and then, their corresponding. In Section 5, we present the conclusions of this study.

2- Methodology

In this section, the methodology adopted for this research will be described. Additionally, we also provide some basic concepts of game theory and land-use planning along with some of their implementation issues.

2.1. Defining a Game for Urban Land-use Allocation to model local competitions

In the game theory, the definition of a game consists of three main steps. The first step is the definition of the players. The second step comprises defining the strategies that each player can choose in the game process, and the third step consists in defining the utility function of each player (Osborne 2004). In other words, a non-cooperative game is defined as a set $G = (N, S, U)$ wherein N indicates the players of the game whose number is equal to n, S specifies the strategy space of the game, and U refers to the utility functions of the players. As mentioned before, in this paper, landowners are considered the players of the game.

For each player $i \in N$, strategies that can be chosen are represented by S_i and the space for all strategies is defined as Equation 1.

$$S = S_1 \times S_2 \times \ldots \times S_n \quad (1)$$

In the definition of the game, landowners as the players of the game, can choose a land-use from a variety of options, aiming to attain the highest possible utility. Consequently, the set of land-uses is considered the strategy set of each player. In this game, the set of strategies is the same for all players.

The utility functions of players, $U = (u_1 . u_2 . \ldots . u_n)$, for each player $i \in N$ return a value according to the strategy adopted by the player ($u_i : S \to R$). The prioritization of land-uses for each player determines the utility of each land-use. The first-priority land-use is the most desirable for the player. Correspondingly, a land-use with lower priority has less desirability for the player. According to this definition, landowners tend to have land-uses with high priority. Hence, the utility function of a player is defined using Equation 2.

$$u_i(s) = \frac{1}{Rank(s_i)} \quad (2)$$

where the $Rank(s_i)$ function calculates the selected land-use (s_i) rank among all of the land-uses for player i. The ranking process is conducted by employing the weighted sum model (WSM) which is described in Section 2.1.1. The closer the rank score is to one, the higher the player's utility. The utility of each player depends on its selected strategy as well as on the neighboring players' selected strategy. For example, if most of the neighbors have chosen a residential land-use strategy, the player also tends to choose a land-use that is the most appropriate for residential use, which will improve its own utility and that of other neighboring players.

2.1.1. Computing land-use rank using WSM

In this section, the ranking process of land-uses for each parcel is described based on WSM.

2.1.1.1. Modeling the criteria

In the following section, the modeling process of urban land-use planning criteria is described.

- **Compatibility:** Compatibility of a land-use with the neighboring land-uses is calculated using the compatibility matrix proposeed by (Masoomi et al. 2013; Masoumi et al. 2019a). Then, the compatibility criterion is computed using 3.
$$F1 = \left\{\frac{1}{n}\left(\sum_{i=1}^{n}\frac{1}{n_i}\sum_{j=1}^{n_i}\alpha_{ij}\times C_{ij}\right) + Minimum\left(\sum_{j=1}^{n_i}\alpha_{ij}\times C_{ij}\right)\right\} \quad (3)$$
in which, i indicates the subject parcel and j indicates its neighbors, n is the number of the parcels, and n_i is the number of neighboring parcels of the subject parcel; C_{ij} is the quantified value of the compatibility between two land-uses of parcels i and j and α_{ij} is the distance function between i and j which is defined in Masoomi et al (2013).
- **Dependency:** The dependency matrix is similar to the consistency matrix proposed by (Masoomi et al. 2013; Masoumi et al. 2019a) and is used to calculate the dependency of a land-use with the neighboring land-uses. The related criterion is calculated using equation 4.
$$F2 = \left\{\frac{1}{n}\left(\sum_{i=1}^{n}\frac{1}{n_i}\sum_{j=1}^{n_i}\alpha_{ij}\times D_{ij}\right) + Minimum\left(\sum_{j=1}^{n_i}\alpha_{ij}\times D_{ij}\right)\right\} \quad (4)$$
D_{ij} is a quantified value of the dependency between two land-uses of parcels i and j.
- **Compactness:** Promoting compactness/controlling fragmentation has been a common and important goal of land-use planning toward sustainability (Cao et al. 2011; Li and Parrott 2016). Equation 5 shows the mathematical model of calculating the related criterion.
$$F3 = \frac{1}{n}\left(\sum_{i=1}^{n}\frac{sim_i}{n_i}\right) \quad (5)$$
sim_i is the number of neighboring parcels with a similar land-use of the subject parcel.

- **Physical Suitability:** The land-use suitability objective aims to identify the most appropriate land-uses for a specific urban parcel (spatial pattern) according to its physical characteristics. These characteristics include: area, access type, number of vertices, slope, ownership type, sound and air pollution, resistance to change, and the difference between the sizes of the subject parcel edges. Finally, physical suitability of each parcel is calculated employing all the previously mentioned characteristics (Masoumi et al. 2019).
$$F4 = \left\{\frac{1}{n}\left(\sum_{i=1}^{n}S_i\right) + Minimum(S_i)\right\} \quad (6)$$
S_i is suitability of the considered parcel.

It is worth indicating that the second part in the equations 3, 4, and 6 is used to maximize the minimum value of the criteria in the arrangements. This part of the equations could improve the criteria value in the parcels having a minimum value in comparison with their neighbors (Masoumi et al., 2019).

- **Per capita demand:** In order to apply this criterion, based on the population of the study area, first, the amount of current per capita demand for each land-use is calculated. Then, the current per capita demand is compared with the optimum per capita of land-uses in the study area obtained from (Maab-Consulting-Engineers 2010). For this purpose, per capita violation (PCV) is determined and incorporated into the model. The *PCV* is calculated using equation 6.

$$\mathrm{PCV_i} = \begin{cases} \frac{minA_i - A_i}{minA_i} & if\ A_i < minA_i. \\ \frac{A_i - maxA_i}{maxA_i} & if\ A_i > maxA_i. \end{cases} \quad (7)$$

where $minA_i$ and $maxA_i$ are the minimum and the maximum acceptable area which are obtained by multiplying the minimum and the maximum per capita of the land-use i, by the total population of the study area; A_i is the total area of the land-use i.

Finally, in order to calculate the values of all criteria in a layout (a land-use arrangement) for the rest of the methodology, equations 3 to 7 have been adopted.*2.1.1.2. Ranking urban land-uses for each parcel*

After calculating of the decision making criteria, the rank of each land-use is determined for subject parcel. The score of each land-use for the selected parcel is conducted using WSM according to Equation 8.

$$Score = \sum_{i=1}^{5} F_i \times w_i \quad (8)$$

where, F_i represents the value of the criteria for each land-use type which is defined in equations 3 to 7 and w_i is the weight of criterion i, which is given as input data in Equation 8. The weights of the criteria are computed using analytical hierarchy process (AHP) method. Using the AHP process, the following steps were followed to obtain the relevant weights. For more details about AHP, the readers can refer to (Saaty and Vargas 2012).

- Pairwise comparison: In the first step, paired comparison of the criteria using the designed questionnaires (considering the AHP's common questionnaires) is conducted. In this study, we used 10 questionnaires which were filled by 10 urban land-use modelers and planners. Our aim was to rely on urban planning experts' to fill out questionnaires. Anyhow, in this approach and other methods of criteria weighting, the weights depend on the expert's opinion.
- Generating a comparison matrix: A pairwise comparison matrix (*A*) is created using the results from the previous step. The components of this matrix are the preferences of criteria *i* over criteria *j* (Equation 9),

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad i, j = 1, 2, \ldots, 5 \quad (9)$$

In Equation 9, A is the pairwise comparison matrix and the a_{ij}'s show the elements of the comparison matrix which specify the importance of criterion i over j (we had 5 criteria here) ranging from 1 to 9 (Masoumi et al. 2019b),

- Calculating the weights: The vector of weights was calculated, $w=[w_1,w_2,...,w_5]$, based on Saaty's eigenvector method,
- Evaluation of weights: the consistency of weights wa examined and finalized in the last step.

Table 1 represents the computed weights employing the AHP method. It is worth indicating that w_5 (the weight of PCV_i) is negative.

Table 1. The weights of the criteria

Criteria	Weights
Compatibility	0.30
Dependency	0.27
Compactness	0.08
Suitability	0.20
PCV	0.15

In this study, the weights in Table 1 are the input data for computing the parcel scores based on the expert's opinion. Finally, the rank of each land-use type for the selected parcel was prioritized based on their scores obtained by Equation 8.

2.1.2. The concept of the Nash Equilibrium in ULUP

Strategy profile $s^* \in S$ is NE if for each player *i* there is no strategy that can improve the utility of the player while the other players' strategies remain unchanged (Equation 9).

$$u_i(s^*) \geq u_i(s_i.s_{-1}^*) \qquad (9)$$

The concept of the NE in ULUP occurs when none of the parcels can achieve a higher utility if its land-use changes.

2.1.3. Defining a dissatisfaction index

In this research, an indicator called dissatisfaction index (DI) is used to evaluate the land-use layouts as a strategy profile. This index shows the number of parcels that are dissatisfied with their current land-use. If a land-use layout has a smaller amount of dissatisfaction, it means that it is closer to the NE. In the NE, all parcels are satisfied with their land-uses. Consequently, in the NE, the DI should be zero. In order to calculate the DI in each strategy profile, the chosen strategy of each player is investigated and if the player is dissatisfied with its land-use, one unit is added to the amount of the DI. The satisfaction status of the player can be determined according to the rank of its current land-use.

According to the characteristics of the study area, four types of constraints are considered in allocating the land-uses to urban parcels, which are defined as follows:

- Area constraint: this constraint determines the minimum and the maximum parcel area for each land-use type. This constraint prevents the allocation of the land-uses to the parcels with an inappropriate area. The parcel area ranges for each land-use were extracted from (Habibi and Masaeli 1999).

- Accessibility constraint: The accessibility of land-uses is an important constraint in the development pattern of district 7 of Tehran. This constraint is defined according to the detailed municipality plan (Farnahad 2005) in the study area.
- Restriction to change constraint: Some regional level land-uses are restricted to change. These types of land-uses are considered as unchangeable land-uses in the land-use allocation procedure.

The land-use with lower *PCV* is selected if all of the land-uses are invalid for a given parcel. The process of calculating the dissatisfaction index of each layout is integrated into the land-use allocation procedure to be used as an indicator for evaluating layouts produced in the procedure.

2.1.4. The procedure of land-use allocation to reach an NE

Figure 1 illustrates the whole process of allocating land-uses to parcels in order to achieve a NE. As shown in Figure 1, in order to obtain an NE layout, the procedure generates a random layout while considering the criteria and constraints. This generated layout is a strategy profile in which each player has a land-use as a strategy. The players who have appropriate land-use are satisfied with their strategy; conversely, players who do not have appropriate land-use tend to change their land-use for an appropriate land-use. To determine the appropriateness of each land-use, firstly, the valid land-uses are selected for the given parcel considering the constraints. Then, these land-uses are ranked by WSM. The utility of the land-uses are determined by its rank. Based on this utility, players who are not satisfied with their land-use will choose another land-use. Three scenarios are defined to determine the satisfaction of the players::

- In the first scenario, players choose only the first priority, and lower-priority land-uses will dissatisfy the players regarding their land-uses. In other words, the players are greedy in selecting the most compatible land-use and just accept the best one. This scenario may never converge to an NE. Therefore, the second and third scenarios are defined to reach a NE.
- In the second scenario, if the land-use of the player is between the first three priorities, the player is satisfied. In this case, the players are fully collaborative and care about other players' payoff. If the land-use is not among the top three priorities, the player will choose the first-priority.
- In the third scenario, players are first greedy but after some iteration when they cannot achieve an agreement with other players, they change their characteristic to be gradually collaborative to reach a NE. In this scenario, according to the definition of satisfaction factor, a player is satisfied if its land-use rank is less than or equal to the sat factor. This factor is defined as Equation 10. In the definition of the *sat* factor, by increasing the iterations, players will be gradually collaborative.

$$sat = [\frac{itr}{Q}] + 1 \quad (10)$$

where itr is the number of iterations in the allocation procedure and Q is a variable that controls the rate of convergence.

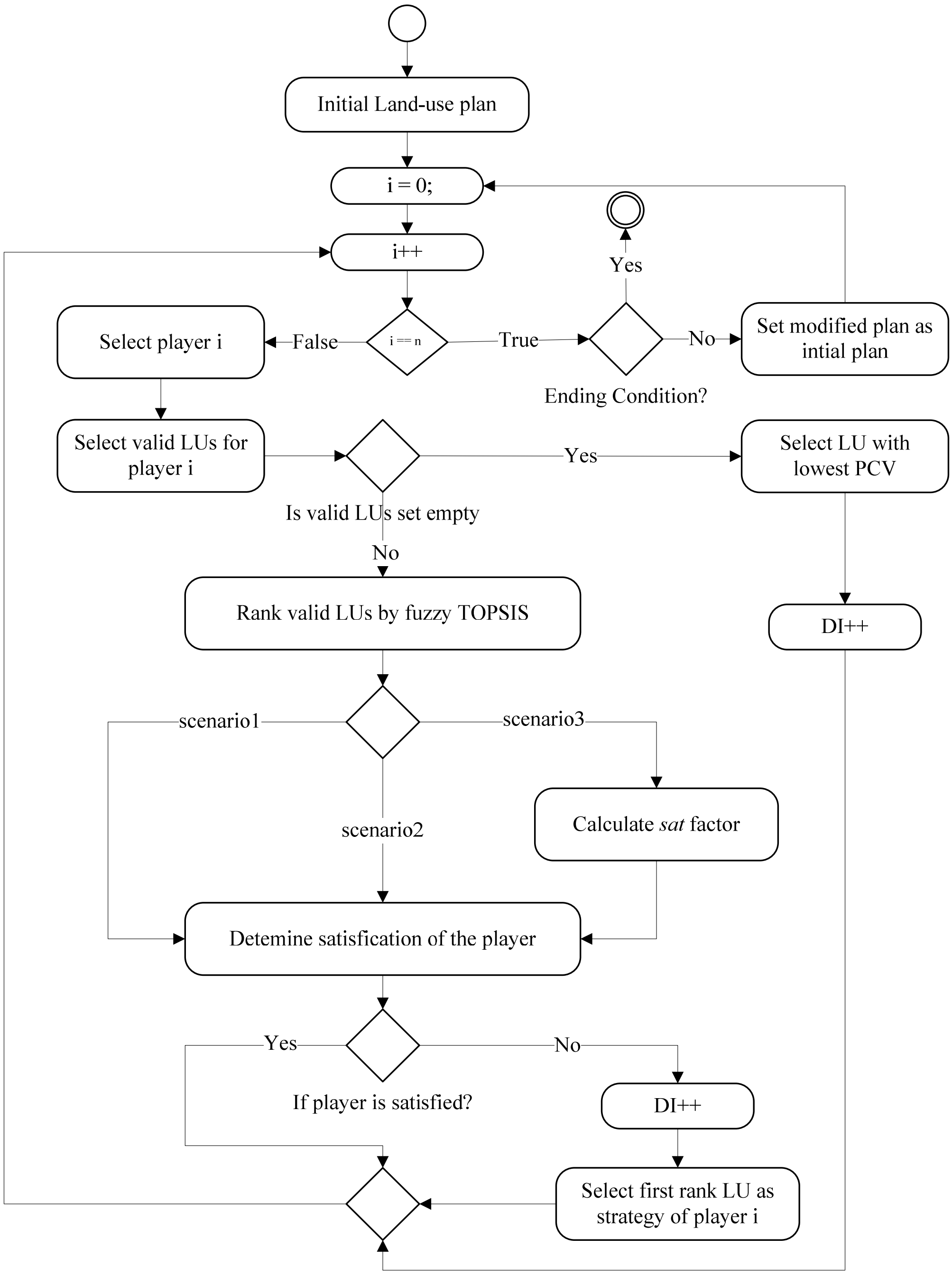


Figure 1. The whole process of allocating land-uses to urban parcels to achieve a NE using game theory

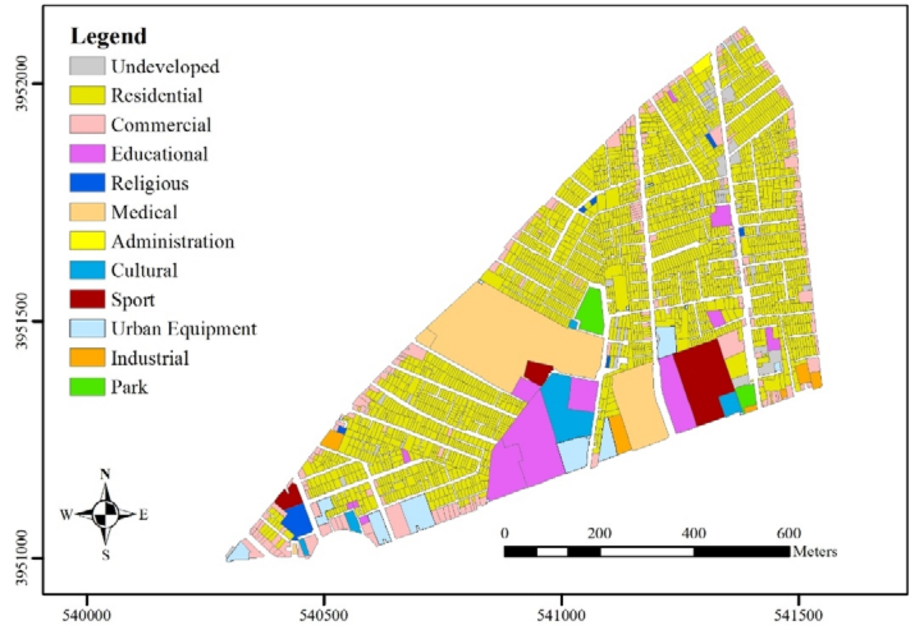
2.1.5. Defining the overlap percentage between two iterations

The overlap percentage of layouts is calculated in the results for evaluating and comparing the resultant layouts using the following steps: In the spatial database, one of the attributes of each parcel is its land-use type. First, at each iteration, the resultant land-use type for each parcel is compared with the land-use type of the same parcel in the previous iteration. Then, the similarity index (SI) is defined based on this information in which, if the above-mentioned land-use types are the same, one unit is added to the SI and finally, the SI percentage of two iterations in the whole number of parcels (2710 parcels in Figure 2) is calculated and reported as an overlap percentage.

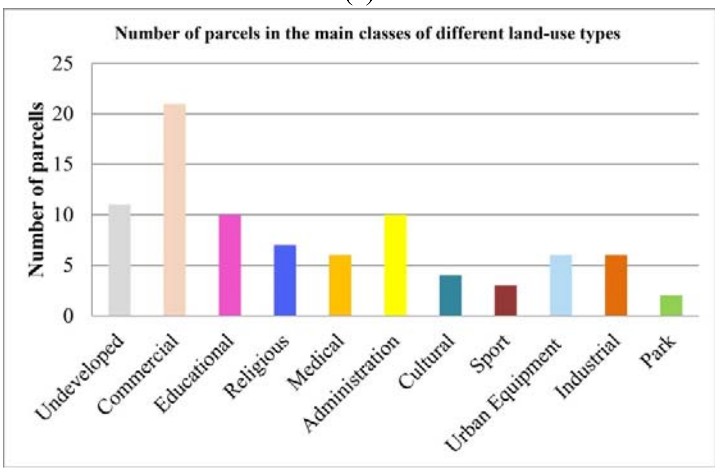
2.2. Study Area

The 1:2000 scale map of district 1 of region 7 of Tehran is used as an illustrative example (Figure 2 (a)). This region includes a variety of land-uses with high external impacts at local, district and regional levels. The number of parcels is 2710 in the study area and they are classified into 36 sub-classes and 12 main classes in this research according to the land-use types used in the municipality (this is shown in Appendix 1). Most of the area consists of residential land-use, but at the same time there are some special land-uses such as sports complex, hospital and university that show the variety of land-uses. Figure 2 represents the map of study area categorized based on the main use types and also shows the number of parcels for each of the main classes of land-use type except for residential land-uses.

The main data used to create the spatial database in this study is as follows: population information sorted by age and extracted from the national census of 2011 and an urban land-use map of scale 1:2000. Finally, the required data in the vector format was edited in the GIS environment and linked to attribute data.



(a)



(b)

Figure 2. The general land-use layout of the study area and the number of each main classes, (a). The map of study area categorized based on land-use types, (b). Number of parcells in each land-use type classes.

3. Results and Discussion

In this section, the results of the three scenarios are presented and compared with a genetic algorithm on district 7 of Tehran.

3.1. Results of ULUP as a Game

The results of the three scenarios are presented and explained below, respectively.

3.1.1. Results of the first scenario

As mentioned before, in the first scenario, all players are satisfied only if they take the first-ranked land-use for their parcel. Therefore, the DI shows the number of players who have not taken the first-ranked land-use. In this scenario, the game does not fully convergence after 50 iterations, and some of the players are always dissatisfied with their land-use. Figure 3 shows the evolution of DI values versus the number of iterations in the first scenario.

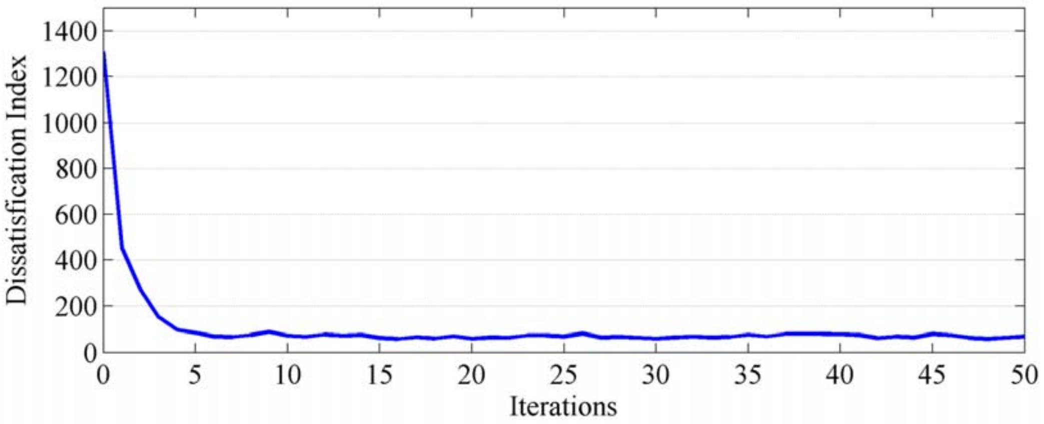


Figure 3. The results of the first scenario in the iterations and evolution of the dissatisfaction index versus the number of iterations in the first scenario

As shown in Figure 3, DI values do not reach zero in 50 iterations. After the fifth iteration, this index converges to almost 100, and then it has little fluctuations. In other words, in the first scenario, the game will never converge to an NE, and around 100 of 2710 players are always dissatisfied with their strategy. Because of the dissatisfaction of some players through the iterations, the land-use of some parcels varies in the process. For this reason, the overlap percentage of the layouts does not reach 100% in this scenario.

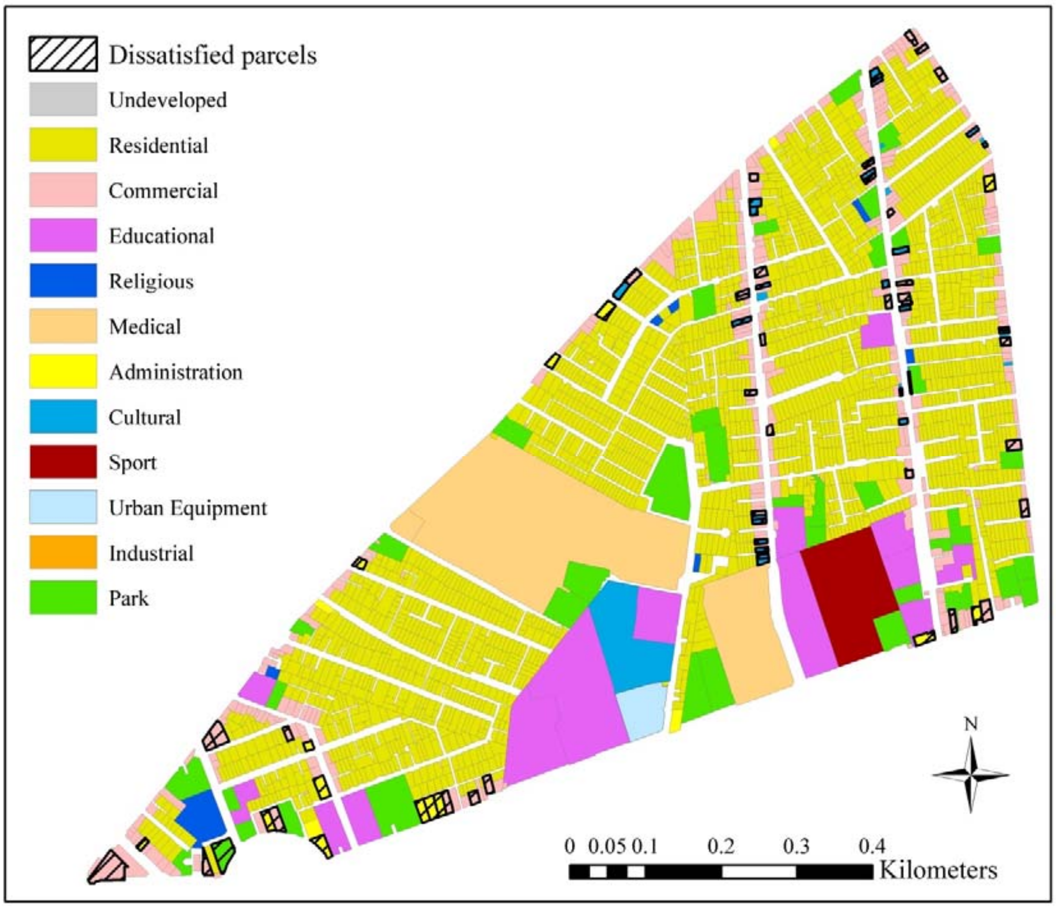


Figure 4. The final land-use layout obtained from the first scenario after 50 iteartions using a population which is initially randomly generated, dissatisfied parcels are presented as a dashed area

Figure 4 shows the land-use layout of the first scenario after 50 iterations. The number of dissatisfied parcels in this case is 75. As seen, the applied constraints have operated well and have prevented the allocation of invalid land-uses to parcels. For example, most parcels in minor streets are assigned to residential use. Commercial use also overlooks the main arteries of the study area. However, in this scenario, the generated layout is not an NE arrangement.

To investigate the land-use arrangement in the current status, we use the current status in the study area as an initial population for three scenarios. Figures 5 presents the results of scenario 1 for the current status as an initial population. In this figure, part (a) indicates the optimized layout proposed by scenario 1, part (b) shows the values of 4 objectives in the optimized layout and the current status, and part (c) represents the percentage of changes in the optimized layout in comparison with the current status with their related land-uses.

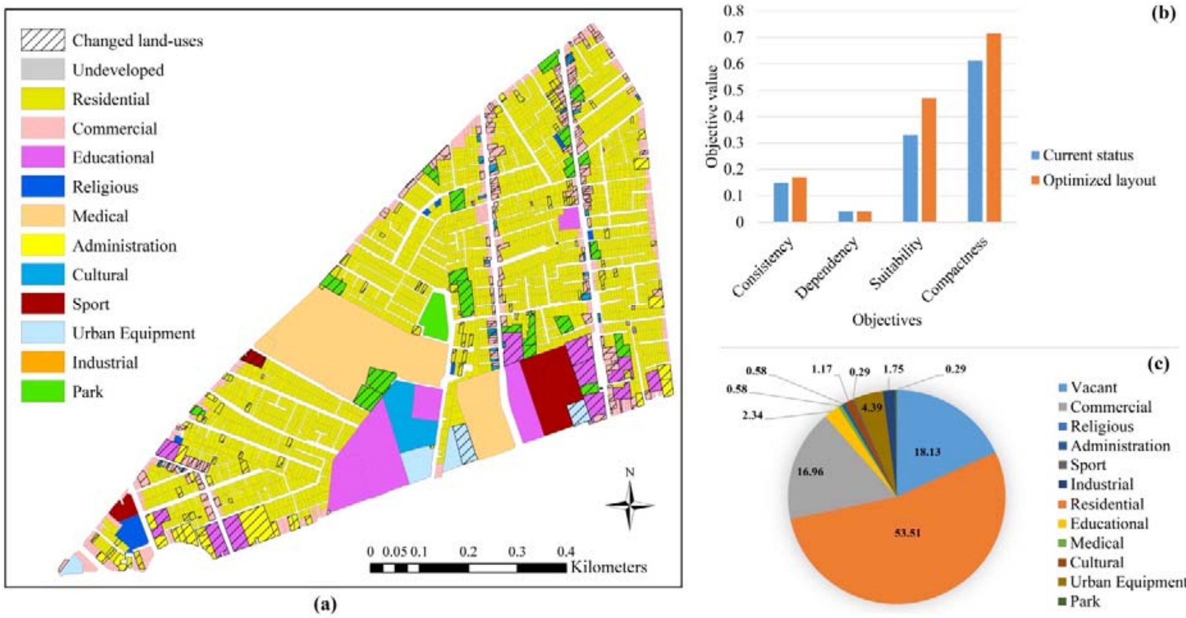


Figure 5. Results of scenario 1 for the land-use arrangement in the current status as an initial population and the changed parcels in the results, (a). Optimized layout employing the current status as an initial population, (b). The values of 4 objective functions in the current status, and (c). The percentages of changes in land-uses in the optimized layout in comparison with the current land-use arrangement

As seen in figure 5, to reach an optimized layout in the current status, some parcels (304 parcels) need to be changed. Also, the values of the objective functions are better than the current arrangement. Moreover, to compensate the deficiency in the current land-use arrangement, residential land-uses changes more than other land-use types. The comparison of optimized layouts in figures 4 and 5 illustrates that the results of game theory are not so sensitive to the initial population.

3.1.2. Results of the second scenario

In the second scenario, the expectations of players are considered lower. In this scenario, if the player's land-use is among the top three priorities in the land-use ranking, such a player will be satisfied with its land-use.

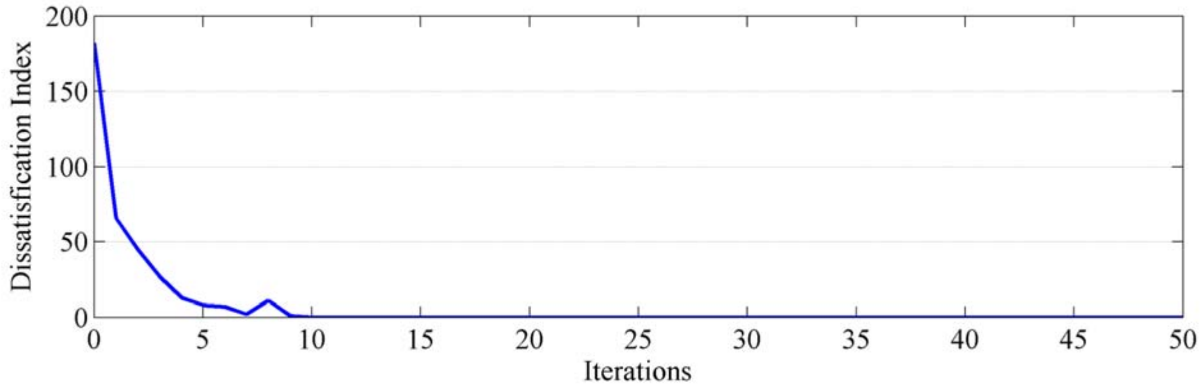


Figure 6. The results of the second scenario in the iterations and the evolution of the dissatisfaction index values versus the number of iterations in the second scenario

Figure 6 shows the evolution of the DI values versus the number of iterations in the second scenario. As shown in this figure, the number of dissatisfied players in the first iteration is 180. Meanwhile, in the first scenario, the number of dissatisfied players in the first iteration is around 1300. The convergence process of the DI in the second scenario happened quickly and reached zero in only 10 iterations. In this scenario, the game reached a NE in approximately the tenth iteration. Of course, it is worth noting that the definition of the NE in the first scenario differs from that of the second scenario. Furthermore, around 93% of the land-uses remain unchanged in the first iteration. It can be concluded that in the second scenario, a small variation was required to achieve the NE. To achieve the NE, only around 7% of the players needed to change their land-use. However, in the first scenario, around 50% of the players at the beginning of the game were dissatisfied with their strategy and changed it during the game. In the first scenario, however, they did not reach an NE.

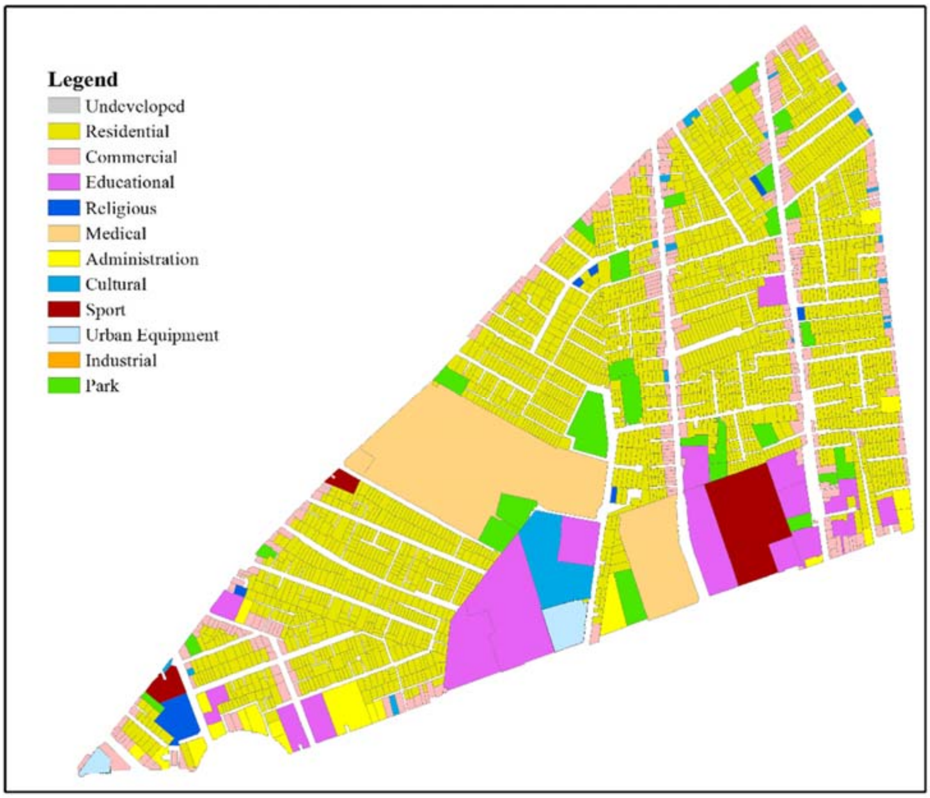


Figure 7. The final land-use layout obtained from the second scenario

Figure 7 shows the final land-use layout obtained by this scenario. As seen in Figure 7, in this scenario, allowed land-uses were allocated to parcels. Of course, this map only saw modest changes, and the players changed only around 7% of the urban parcels' land-uses.

Figure 8 also represents the results of the second scenario for the current status as an initial population. As seen in Figure 8, to reach an optimized layout in the current status, some parcels (325 parcels) need to be changed. Also, here, the values of the objective functions do not significantly improve.

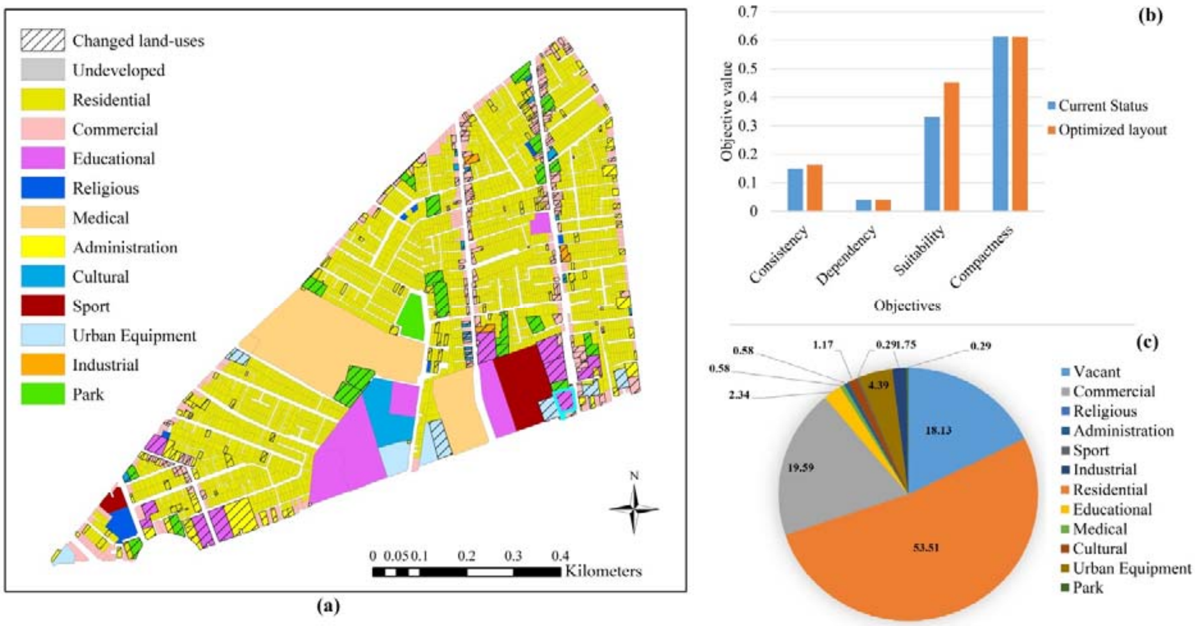


Figure 8. Results of scenario 2 for the land-use arrangement in the current status as an initial population, (a). Optimized layout employing the current status as an initial population, (b). The values of 4 objective functions in the current status and its related optimized layout, and (c). The percentages of changes in land-uses in the optimized layout in comparison with the current land-use arrangement

3.1.3. Results of the third scenario

In the third scenario, the players were initially treated rigorously and the only land-uses with the first priority were satisfactory. But with a lot of iterations in the game and not achieving a NE, the players gradually reduced their expectations and satisfied the second, the third as well as the next priorities until they reached an NE. According to Equation 10 in Section 2.1.4, when defining the satisfaction factor, a parameter called Q is defined to control the convergence of the algorithm. In order to test the sensitivity of the results of the third scenario to this value, the weighted sum of the objective functions (based on the weights obtained in Table 1) was calculated for values 1 to 25 for Q. Figure 9 shows the weighted sum of the objective functions for different Q values. As can be seen, the weighted sum of the objective functions improves to approximately 15 for Q , and then there is no improvement. Therefore, in this study, the value of 15 for Q is considered. For values higher than 35, convergence is not achieved and the results get close to the first scenario. In this case, the DI does not converge to zero.

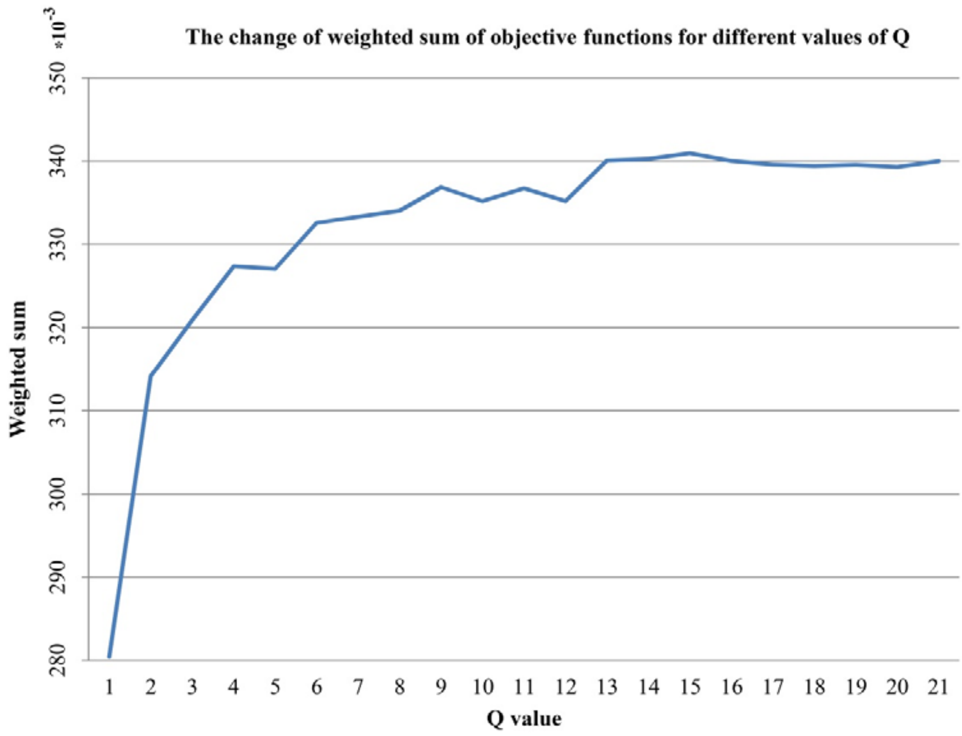


Figure 9- The sensitivity analysis of the algorithm's convergence to different values of Q based on the change in the weighted sum of the objective functions

Figure 10 shows the convergence trend of the DI for the third scenario. The DI in the third scenario converged rapidly to zero in the initial iterations but did not reach zero. Near iteration 16, according to Equation 10, the definition of satisfaction of players includes the second priority in land-use rankings. For this reason, from iteration 15, the DI reached zero, and the game reached an NE.

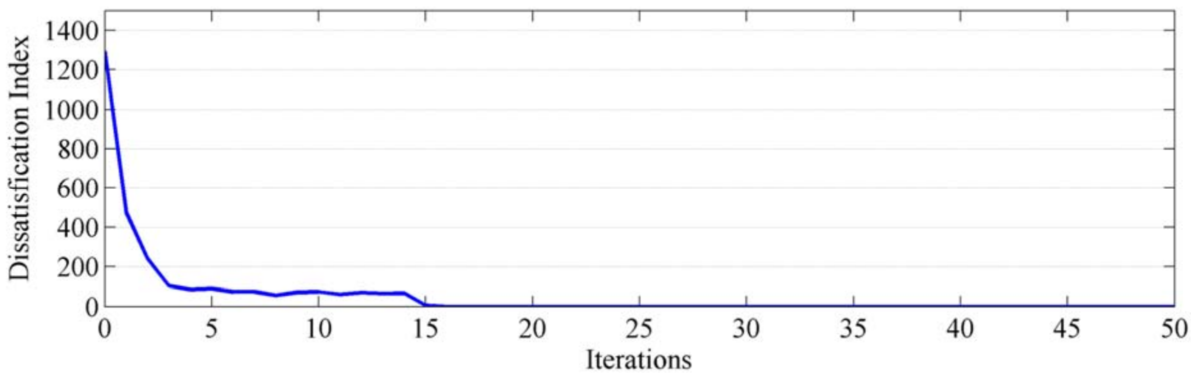


Figure 10. The results of third scenario and the evolution of the dissatisfaction index values versus the number of iterations

According to the DI, the overlap percentage of solutions also reached 100% in the 15 iteration (Figure 10). Following the fifteenth iteration, all players were satisfied with their land-use and were unwilling to change their strategy. For this reason, there is no change in the layout of the land-uses after the fifteenth iteration.

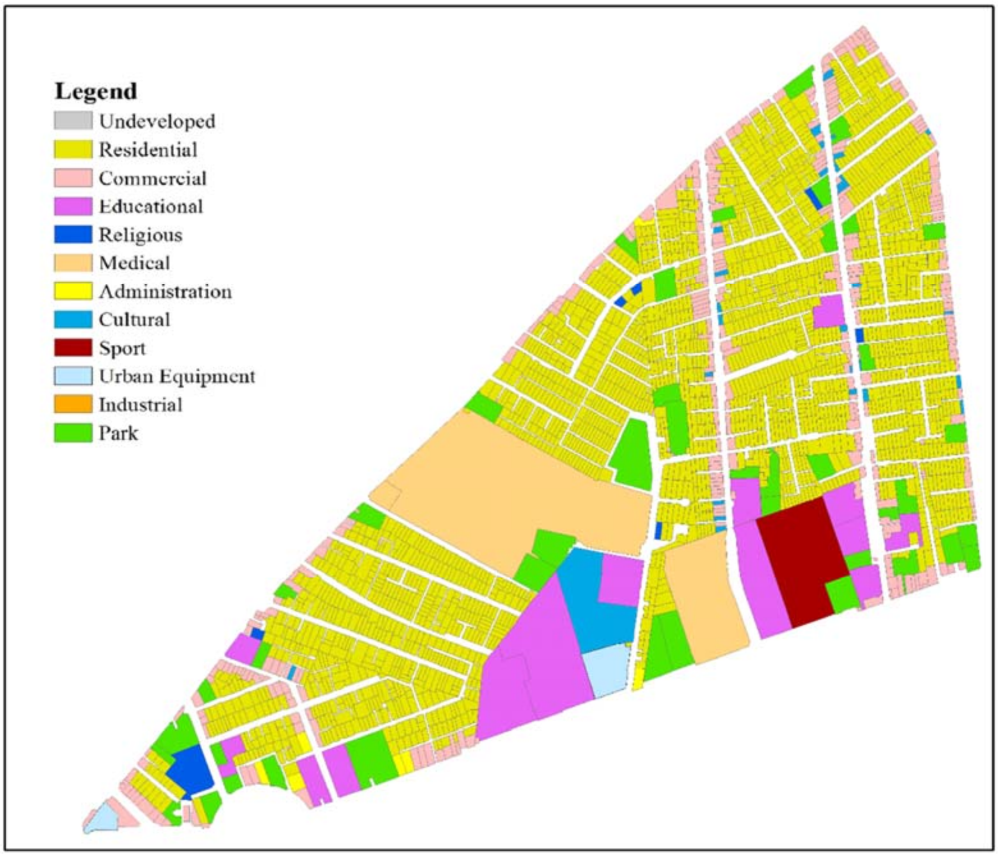


Figure 11. The final land-use layout obtained from the third scenario.

Figure 11 shows the final layout obtained from the third scenario. This layout has small changes compared to the first scenario. However, according to the NE definition in the third scenario, this layout is an NE. The results of the three scenarios are evaluated in the next section.

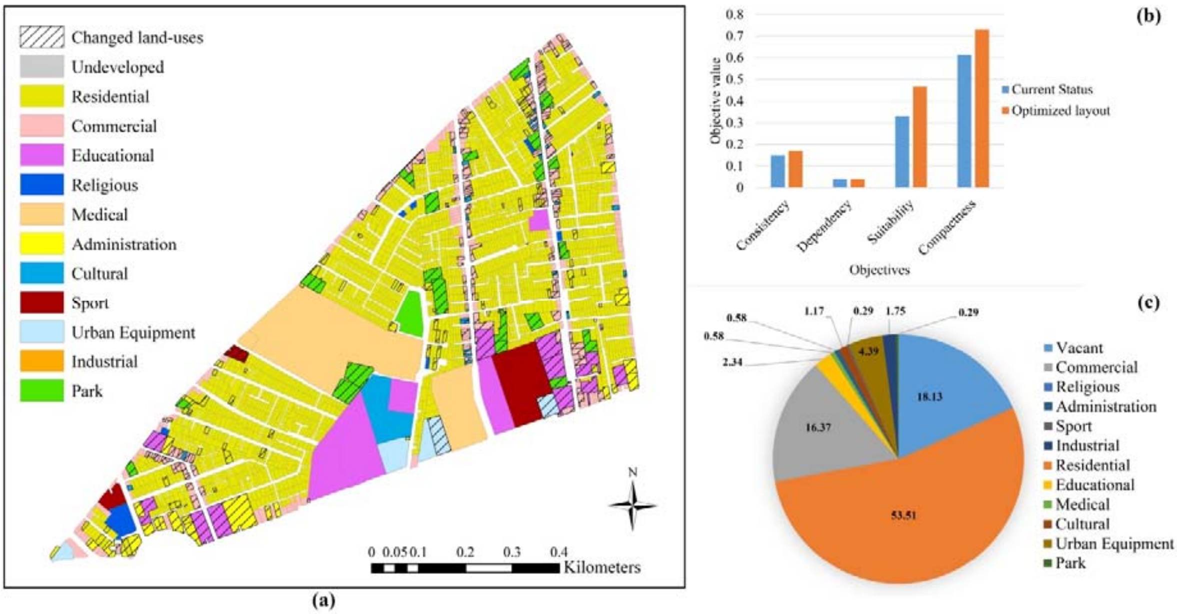


Figure 12. Results of the third scenario for the land-use arrangement in the current status as an initial population, (a). Optimized layout employing the current status as an initial population, (b). The values of 4 objective functions in the current status and its related optimized layout, and (c). The percentages of changes in land-uses in the optimized layout in comparison with the current land-use arrangement

Figure 12 also denotes the results of the third scenario for the current status as an initial population. As can be seen in this figure, in order to reach an optimized layout in the current status, 309 parcels need to be changed. Also, the values of the objective functions improve in comparison with the current land-use arrangement. Moreover, here, similar to the results of the other scenarios, residential land-uses need to be changed in a higher percentage.

3.2. Evaluation and Discussion

To evaluate the results of the land-use allocation through game theory in the three scenarios, we require the assistance of an independent approach to generate a near-optimal land-use layout.

Since the goal of this study is to use game theory for a land use planning support system, and the proposed algorithm was designed based on seeking the best values for the objective functions to achieve optimum layouts in the urban areas, we compared the proposed algorithm with respect to a simple genetic algorithm (GA) which finds the best layout based on the optimization of the corresponding objectives. The GA is the most commonly used optimization algorithm in land-use allocation (Haque and Asami 2014; Li and Parrott 2016; Stewart et al. 2004) which is the reason why we selected it for comparing our results. Since, the running time and the results of the GA depend on its parameter values such as: population size, maximum number of generations, crossover rate, and mutation rate, here, three different settings of the population size and the maximum number of generations were adopted to analyze their effect on the peformance of the GA. . The results generated with these three different settings of the GA are shown in Figure 13.

We have used the WSM method to achieve the overall objective function for the GA using Equation 20.

$$Mixim ize\ F = w_1 \times F_1 + w_2 \times F_2 + w_3 \times F_3 + w_4 \times F_4 \qquad (20)$$

in which F_1 to F_5 are defined in equations 3 to 7, and the overall objective function weights $(w_1 . w_2 . w_3 . w_4)$ are specified in Table 1. To obtain tvalid solutions in the GA, per capita demand is considered as a constraint in the model.

Figure 13 shows the values of the fitness function obtained by the three scenarios in game theory and for three different settings for the GA (different population sizes and maximum number of iterations). As shown in this figure, the first scenario is able to improve the value of the fitness function and achieves the same results as the different settings of the GA. The second scenario, given that the players were satisfied with their land-uses in a few iterations, has not changed much in the layout and, therefore, the value of the fitness function is improved. The third scenario also works better than the other scenarios in terms of the value of the fitness function and can provide better results. The third scenario reached its maximum value in the fitness function in only around five iterations. The convergence of the GA occurs approximately at iteration 100 when using population sizes of 100 and 500. Moreover, we examined the performance of the GA with a population size of 1000, but there was no significant change in the final values of the objective functions. In the last iterations of the GA, the running time increases, but the value of the fitness function does not signficantly change. The results obtained by the GA are clearly related to the values of its parameters.

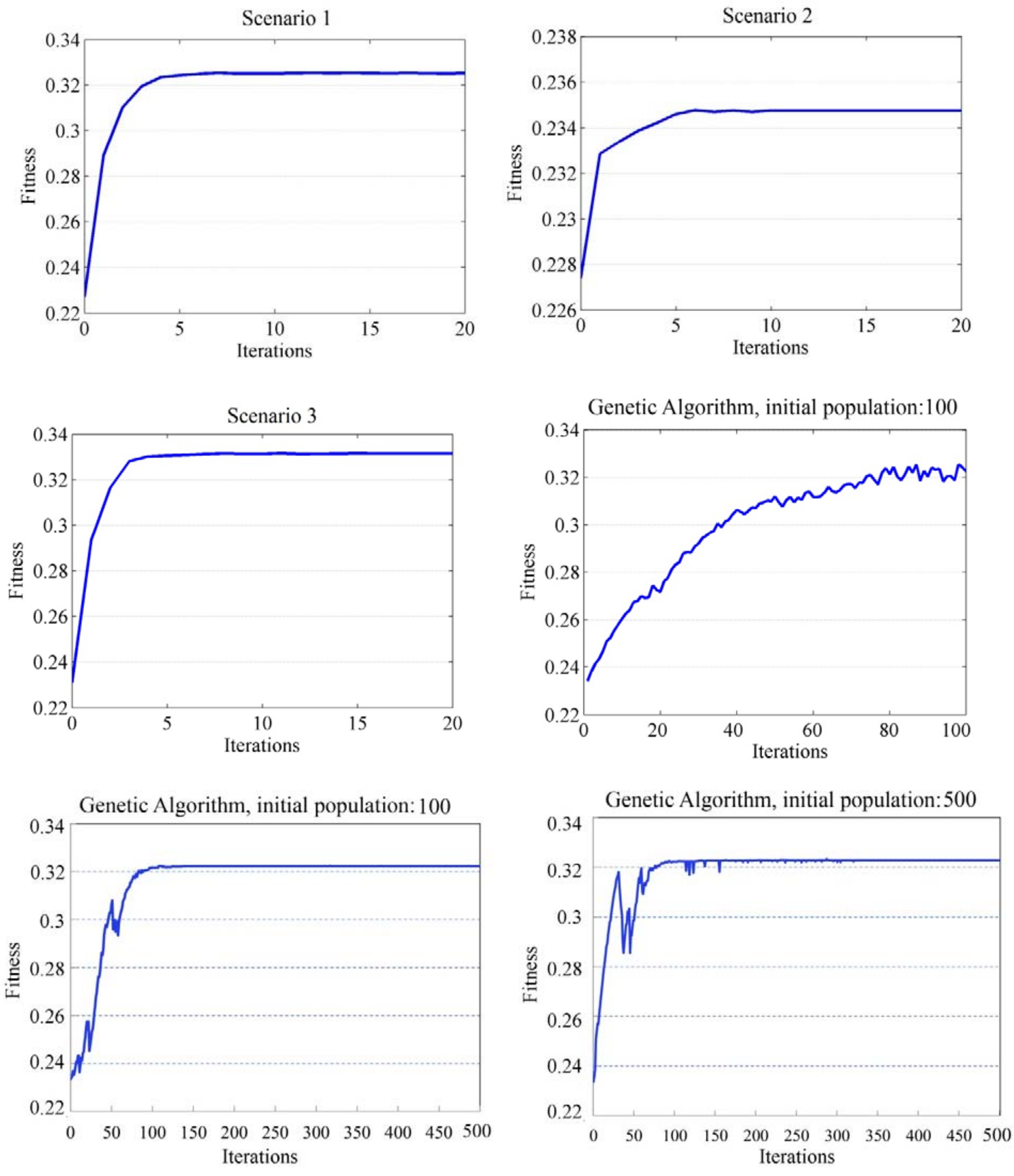


Figure 13. The value of the fitness function for different scenarios and the GA with different settings for its population size and maximum number of iterations in urban land-use allocation

Table 2 shows the final values of the objective functions for different scenarios and different settings of the GA. The third scenario operates better than other scenarios and even better than the GA. In this table, the values of the objectives for the current status of the land-use layout are also shown. The second scenario is the weakest scenario, and has not even been able to improve the objective functions from a random solution to the current status.

Table 2. The final value of the objective functions for the current status, different scenarios and the GA results.

	Consistency	Dependency	Suitability	Compactness
Current Status	0.1493	0.0403	0.3318	0.6127
Scenario 1	0.1783	0.0409	0.3951	0.6871
Scenario 2	0.1514	0.0408	0.3713	0.3755
Scenario 3	0.1783	0.0408	0.4762	0.7008
GA (pop:100, it:100)	0.1642	0.0404	0.4704	0.6139
GA (pop:100, it:500)	0.1692	0.0404	0.4705	0.6351
GA (pop:500, it:500)	0.1703	0.0405	0.4705	0.6403

Figure 14 shows the overlap percentage of the solutions in different scenarios and the results of the different GA runs. As shown in this figure, all four methods of land-use allocation have reached a relative convergence. The second and third scenarios achieved a 100% overlap percentage between two consecutive solutions. However, the first scenario and all the settings of the of GA, after several iterations, failed to achieve 100% overlap convergence.

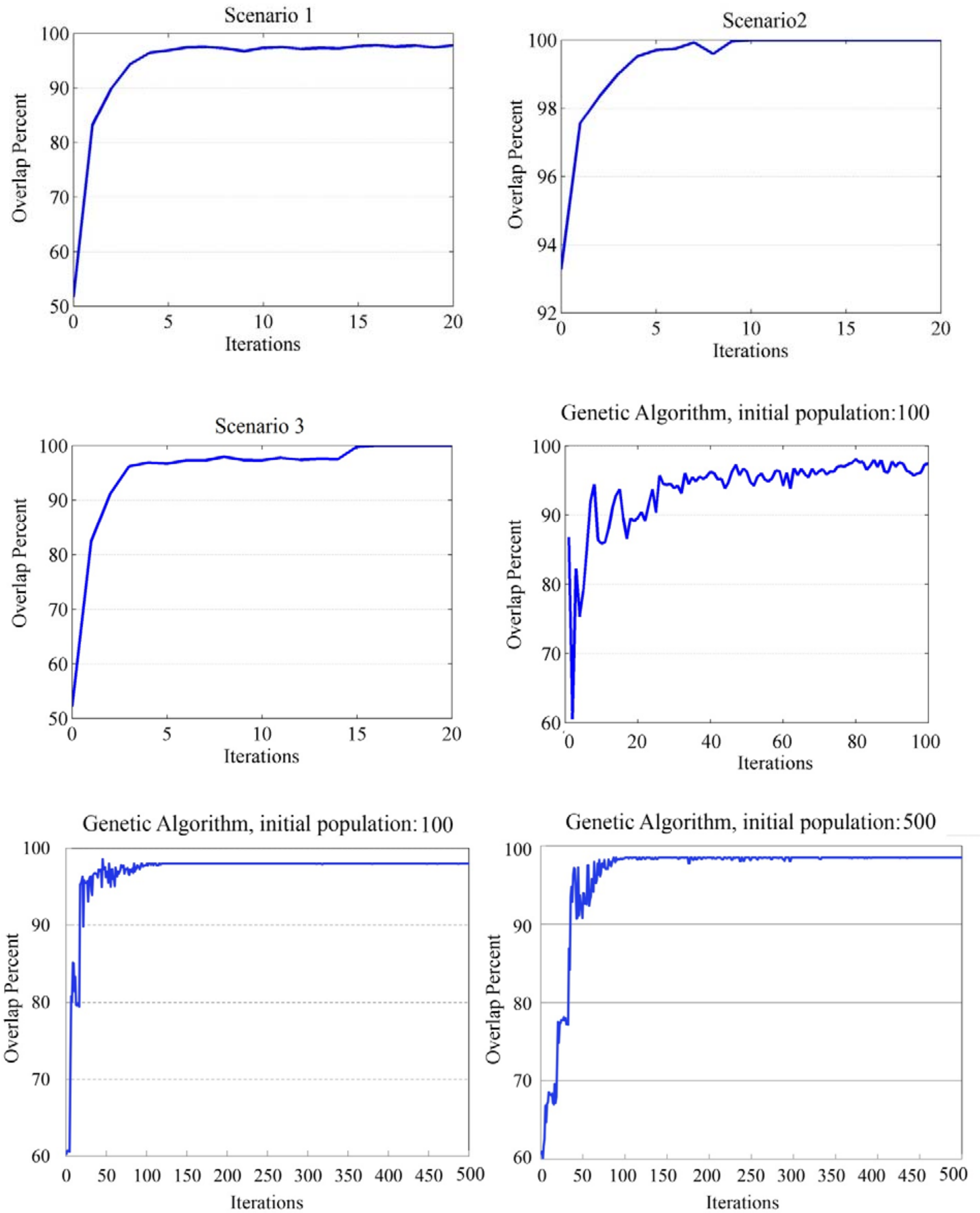


Figure 14. The overlap percent of solutions in different scenarios and the GA with different settings for itse population size and maximum number of iterations

Table 3 shows the overlap percentage of solutions of the three scenarios, and the GA with a population size of 100 and a maximum number of iterations of 100, and the current status of the land-uses with respect to each other. In other words, this table shows the percentage of changes required to reach a near-optimal layout. The results of the first scenario with respect to the third scenario are the most similar and the overlap percentage of their land-uses reaches 98.15%. The current status has approximately an 87% overlap with the results obtained by different approaches. The second scenario is different in terms of the overlap percentage with respect to the GA, given that it reached an NE very quickly and was far from the optimal state. While the result of the GA is more similar to scenarios 1 and 3, they have a greedier behavior in the competition.

Table 3. The overlap percentage of solutions of the three scenarios, the GA and the current status of the land-uses with respect to each other.

	Current Status	Scenario 1	Scenario 2	Scenario 3	GA
Current Status	100	87.78	83.34	87.71	86.97
Scenario 1	87.78	100	91.16	98.15	95.83
Scenario 2	83.34	91.16	100	90.23	89.16
Scenario 3	87.71	98.15	90.23	100	95.79
GA (pop:100, it:100)	86.97	95.83	89.16	95.79	100

It is worth noting that the running time required to find the best layout is not so imprtant in this problem, since our goal is to propose an aproach that can provide different options and scenarios to decision makers and, therefore, the optimization process can be done off-line. By providing different scenarios, decision makers can see and decide to choose their priorities. In other words, the algorithm can be used as a land use planning support system. The execution time of the proposed model in the three different scenarios has a significant improvement compared to the different settings of the GA; furthermore, the results were better in comparison to those obtained by the GA runs. Table 4 shows the average running time of each method in 10 executions. It is worth noting that all three scenarios, as well as the GA, were executed in the same computer system with a RAM of 4 GB and an Intel Core i5-4200U processor.

Table 4. The average runtime time of each method in ten independent executions

Method	Execution Time (Seconds)
Scenario 1	124
Scenario 2	23
Scenario 3	37.5
GA (pop:100, it:100)	1844
GA (pop:500, it:100)	29779
GA (pop:500, it:500)	61128

Table 5. The values of 4 objective functions in two different initial population types (current status and random layout) along with the overlap percentage between land-uses in the results

Initial population	Current status				Random layout				
Objectives	Consistency	Dependency	Suitability	Compactness	Consistency	Dependency	Suitability	Compactness	Overlap
Scenario 1	0.16986	0.04	0.46948	0.7151	0.1783	0.0409	0.3951	0.6871	97.16
Scenario 2	0.1618	0.04	0.4524	0.6121	0.1514	0.0408	0.3713	0.3755	94.5
Scenario 3	0.1701	0.0399	0.4667	0.7313	0.1783	0.0408	0.4062	0.7008	97.12

Table 5 shows the values of 4 objective functions in 3 scenarios along with the overlap between the resultant optimized arrangement employing two different initial populations (current status arrangement and random layout). As seen in this table, the second scenario has the worst results. Also, the overlap percentage is acceptable in two different situations which indicates that the results of game theory (specially the first and the third scenarios) are not so sensitive to the initial population.

4. Conclusions

Land-use planning is a process that properly combines the required land-uses in an area. Common approaches usually examine the appropriateness of the layouts in general and do not consider the local competition of parcels' land-use advocates as landowners of the process. Meanwhile, in land-use planning, in addition to the general mode, while considering local aspects we can achieve solutions which are more likely to reflect the reality of urban systems. Modeling local competitiveness among advocates of parcels can improve the generated solutions for land-use planning. In this study, in order to simulate the urban landscape in a near-real mode, the format of the spatial data was considered in vector form and all required urban land-uses in the study area were considered in the model in 36 classes. To investigate the results of the model's implementation, three scenarios were defined. The results of the first scenario showed that there may never be an equilibrium among them if the players are considered rigorous. The results of the second scenario indicated that lowering the expectations of the players would not lead to appropriate results. The results of the third scenario presented that while taking into account the level of expectations of the players with respect to being changeable during the game, appropriate results could be achieved; furthermore, an equilibrium between the players was obtained, i.e., all players had a relatively good level of satisfaction with the results. An evaluation of the results of the three scenarios, using the results of the GA with different settings, also showed that the proposed model could properly generate a result close to the one produced by this optimization method.

The proposed model has some limitations. One of them is that it does not consider mixed land-uses in a parcel. Furthermore, landowners, here, are regarded as advocates of parcels and are virtual. Therefore, some issues, such as policies, municipalities' acts, and socioeconomic states in urban systems, are not considered directly but they are explicitly considered in the criteria. If these matters were explicitly considered, the results would be more accurate.

As part of our future work, we will try to add some more issues into the modeling process in order to better approximate the complexities that occur in real urban areas. For instance, policymakers' goals should be reflected in a model or some other local effects could be considered.

Acknowledgements

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References

Abolhasani, S., Taleai, M., Karimi, M., & Rezaee Node, A. (2016). Simulating urban growth under planning policies through parcel-based cellular automata (ParCA) model. *International Journal of Geographical Information Science*, 1-26

Afsharnia, A. (2014). Assessing the Act of Iran's Supreme Council of Urbanization and Architecture about Land Use per Capita. *International Journal of Architecture and Urban Development, 4*, 53-66

architecture, I.s.s.c.o.u.a. (2010). Collection of ratification of Iran's supreme council of urbanization and architecture. In. Tehran

Arentze, T.A., Borgers, A.W., Ma, L., & Timmermans, H.J. (2010). An agent-based heuristic method for generating land-use plans in urban planning. *Environment and planning. B, Planning & design, 37*, 463

Batty, M. (2018). Artificial intelligence and smart cities. In: SAGE Publications Sage UK: London, England

Batty, M., & Xie, Y. (1994). From Cells to Cities. *Environment and Planning B: Planning and Design, 21*, S31-S48

Cao, K., Batty, M., Huang, B., Liu, Y., Yu, L., & Chen, J. (2011). Spatial multi-objective land use optimization: extensions to the non-dominated sorting genetic algorithm-II. *International Journal of Geographical Information Science, 25*, 1949-1969

Cao, K., Huang, B., Wang, S., & Lin, H. (2012). Sustainable land use optimization using Boundary-based Fast Genetic Algorithm. *Computers, Environment and Urban Systems, 36*, 257-269

Couch, C. (2016). *Urban planning: An introduction*. Macmillan International Higher Education

Farnahad, C.E. (2005). Development pattern of district 7 of Tehran (In Persian). In. Orderd by Tehran municipality

Feng, Y., & Liu, Y. (2013). A heuristic cellular automata approach for modelling urban land-use change based on simulated annealing. *International Journal of Geographical Information Science, 27*, 449-466

Ghavami, S.M., Taleai, M., & Arentze, T. (2016a). An intelligent spatial land use planning support system using socially rational agents. *International Journal of Geographical Information Science*, 1-20

Ghavami, S.M., Taleai, M., & Arentze, T. (2016b). Socially rational agents in spatial land use planning: A heuristic proposal based negotiation mechanism. *Computers, Environment and Urban Systems, 60*, 67-78

Guoxin, T., Shibasaki, R., & Matsumura, K. (2004). Development of a GIS-based decision support system for assessing land use status. *Geo-spatial Information Science, 7*, 72-78
Habibi, M., & Masaeli, S. (1999). *Urban land uses per capita (In Persian)*. Tehran: National Land and Housing Organization
Hall, P., & Tewdwr-Jones, M. (2010). *Urban and regional planning*. Routledge
Haque, A., & Asami, Y. (2014). Optimizing urban land use allocation for planners and real estate developers. *Computers, Environment and Urban Systems, 46*, 57-69
Kaiser, E.J., Godschalk, D.R., & Chapin, F.S. (1995). *Urban land use planning*. University of Illinois Press Urbana, IL
Li, X., & Parrott, L. (2016). An improved Genetic Algorithm for spatial optimization of multi-objective and multi-site land use allocation. *Computers, Environment and Urban Systems, 59*, 184-194
Li, X., & Yeh, A.G.-O. (2000). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science, 14*, 131-152
Liao, J., Tang, L., Shao, G., Su, X., Chen, D., & Xu, T. (2016). Incorporation of extended neighborhood mechanisms and its impact on urban land-use cellular automata simulations. *Environmental Modelling & Software, 75*, 163-175
Ligmann-Zielinska, A., Church, R.L., & Jankowski, P. (2008). Spatial optimization as a generative technique for sustainable multiobjective land-use allocation. *International Journal of Geographical Information Science, 22*, 601-622
Ligtenberg, A., Bregt, A.K., & van Lammeren, R. (2001). Multi-actor-based land use modelling: spatial planning using agents. *Landscape and Urban Planning, 56*, 21-33
Liu, X., Li, X., Shi, X., Zhang, X., & Chen, Y. (2010). Simulating land-use dynamics under planning policies by integrating artificial immune systems with cellular automata. *International Journal of Geographical Information Science, 24*, 783-802
Liu, Y., Tang, W., He, J., Liu, Y., Ai, T., & Liu, D. (2015). A land-use spatial optimization model based on genetic optimization and game theory. *Computers, Environment and Urban Systems, 49*, 1-14
Ma, S., He, J., Liu, F., & Yu, Y. (2011). Land-use spatial optimization based on PSO algorithm. *Geo-spatial Information Science, 14*, 54-61
Maab-Consulting-Engineers (2010). *Definitions and concepts of urban land-uses and determining the per capita (In Persian)*. Iran's Supreme Council for Planning and Architecture
Malczewski, J. (1999). *GIS and multicriteria decision analysis*. John Wiley & Sons
Maleki, J., Hakimpour, F., & Masoumi, Z. (2017). A Parcel-Level Model for Ranking and Allocating Urban Land-Uses. *ISPRS International Journal of Geo-Information, 6*, 273
Masoomi, Z., Mesgari, M.S., & Hamrah, M. (2013). Allocation of urban land uses by Multi-Objective Particle Swarm Optimization algorithm. *International Journal of Geographical Information Science, 27*, 542-566
Masoumi, Z., Coello Coello, C.A., & Mansourian, A. (2019a). Dynamic urban land-use change management using multi-objective evolutionary algorithms. *Soft Computing*
Masoumi, Z., Maleki, J., Mesgari, M.S., & Mansourian, A. (2016). Using an Evolutionary Algorithm in Multiobjective Geographic Analysis for Land Use Allocation and Decision Supporting. *Geographical Analysis*
Masoumi, Z., van L Genderen, J., & Maleki, J. (2019b). Fire Risk Assessment in Dense Urban Areas Using Information Fusion Techniques. *ISPRS International Journal of Geo-Information, 8*, 579
Osborne, M.J. (2004). *An introduction to game theory*. Oxford University Press New York
Porta, J., Parapar, J., Doallo, R., Rivera, F.F., Santé, I., & Crecente, R. (2013). High performance genetic algorithm for land use planning. *Computers, Environment and Urban Systems, 37*, 45-58
Saaty, T.L., & Vargas, L.G. (2012). *Models, methods, concepts & applications of the analytic hierarchy process*. Springer Science & Business Media
Schwaab, J., Deb, K., Goodman, E., Lautenbach, S., van Strien, M.J., & Grêt-Regamey, A. (2017). Improving the performance of genetic algorithms for land-use allocation problems. *International Journal of Geographical Information Science*, 1-24

Song, M., & Chen, D. (2018). An improved knowledge-informed NSGA-II for multi-objective land allocation (MOLA). *Geo-spatial Information Science, 21*, 273-287
Stevens, D., Dragicevic, S., & Rothley, K. (2007). iCity: A GIS–CA modelling tool for urban planning and decision making. *Environmental Modelling & Software, 22*, 761-773
Stewart, T.J., & Janssen, R. (2014). A multiobjective GIS-based land use planning algorithm. *Computers, Environment and Urban Systems, 46*, 25-34
Stewart, T.J., Janssen, R., & van Herwijnen, M. (2004). A genetic algorithm approach to multiobjective land use planning. *Computers & Operations Research, 31*, 2293-2313
Taleai, M., Sharifi, A., Sliuzas, R., & Mesgari, M. (2007). Evaluating the compatibility of multi-functional and intensive urban land uses. *International Journal of Applied Earth Observation and Geoinformation, 9*, 375-391
Tan, R., Liu, Y., Zhou, K., Jiao, L., & Tang, W. (2015). A game-theory based agent-cellular model for use in urban growth simulation: A case study of the rapidly urbanizing Wuhan area of central China. *Computers, Environment and Urban Systems, 49*, 15-29
Yanfang, L., & Liang, H. (2002). Land use structure optimization under systematic framework. *Geo-spatial Information Science, 5*, 46-52
Yang, J., Su, J., Chen, F., Xie, P., & Ge, Q. (2016). A Local Land Use Competition Cellular Automata Model and Its Application. *ISPRS International Journal of Geo-Information, 5*, 106
Yang, Q., Li, X., & Shi, X. (2008). Cellular automata for simulating land use changes based on support vector machines. *Computers & geosciences, 34*, 592-602

Appendix 1

land-use type/ Status		
Residential		Low-Density
		Moderate-Density
		High-Density
Services land-use types	Commercial	Neighborhood shop
		Convenience retail
		Regional/City shop
	Educational	Kindergarten
		Elementary School
		Secondary School
		High School
		Technical School
		University/College
	Religious	Local Level
		District Level
		Regional Level
	Medical	Local Level
		District Level
		Regional Level
	Administration	District Level
		Regional Level
	Cultural	Local Level
		District Level
		Regional Level
	Sport	Local Level
		District Level
		Regional Level
	Urban Equipment	Local Level
		District Level
		Regional Level
	Industrial	Local Level
		District Level
		Regional Level
	Park	Local Level
		District Level
		Regional Level