Dynamic Urban Land-Use Change Management Using Multi-Objective Evolutionary Algorithms

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Abstract

Frequent land-use changes in urban areas requires an efficient and dynamic approach to reform and update detailed plans by re-arrangement of surrounding land-uses in case of change in one or several urban land-uses. However, re-arrangement of land-uses is problematic, since a variety of conflicting criteria must be considered and satisfied. This paper proposes and examines a two-step approach to resolve the issue. The first step adopts a multi-objective optimization technique to obtain an optimal arrangement of surrounding land-uses in case of change in one or several urban land-uses, whereas the second step uses clustering analysis to produce appropriate solutions for decision makers from the outputs of the first step. To present and assess the approach, a case study was conducted in Tehran, the capital of Iran. To satisfy the first step, four conflicting objective functions including maximization of consistency, maximization of dependency, maximization of suitability, and maximization of compactness were defined and optimized using NSGA-II (Non-dominated Sorting Genetic Algorithm). Per-capita demand was also employed as a constraint in the optimization process. Clustering analysis based on ACO (Ant Colony Optimization) was used to satisfy the second step. The results of the optimization were satisfactory both from a convergence and from a repeatability point of view. Furthermore, the objective functions of optimized arrangements were better than existing land-use arrangement in the area, with the per-capita demand deficiency significantly compensated. The approach was also communicated to urban planners in order to assess its usefulness. In conclusion, the proposed approach can extensively support and facilitate decision making of urban planners and policy makers in reforming and updating existing detailed plans after land-use changes.

Key words: *Dynamic Urban land-use change, Multi-objective Optimization, NSGA-II, Clustering, Decision support, Soft Computing*

1. Introduction

Urban land-use planning is both anticipatory and reactive. In a growing community, planners are often concerned with shaping the pattern of growth to achieve a sensible and attractive land-use pattern, avoiding both oppressively dense development and overly scattered, fragmentary development (Ullah & Mansourian, 2016; Levy, 2017). Different types of plans and strategies have been designed for urban land-use planning, from which the most common are master and detailed plans. Master plans cover an entire municipal area, usually designed land-use zone, road network, as well as general densities and so on. In contrast, detailed plans design land-use, densities, and site layout more specifically, reflecting the expected and acceptable use of every parcel (Allterman & Hill, 2007). A major issue with such plans is the lack of flexibility with given changes (Jacobsson & Soldem, 2016; Zecovic et al., 2015; Gang, 2014; Taiao, 2010), that is, when several land-uses change without following the detailed plan, the remaining land-uses may no longer have their original validity. Therefore, in urban dynamics, it is of great importance to know the effects of changing some land-uses on the arrangement of other land-uses in a spatial level to preserve the sustainable development (Hersperger, 2018; Handayanto, 2017). So, to satisfy a dynamic urban planning, one should address the question 'If one land-use changes, how should the other land-uses be changed in order to maintain the optimal equivalence of the quantitative and qualitative criteria of urban planning?' (Pasione, 2009).

According to urban planning researches and resources (Couch, 2016; He, 2015; Arndt, and Doge, 2015; Hall, 2011), and also the criteria which are employed in urban detailed plans in Iran (Iran's Supreme Council for Urbanization and Architecture, 2010), for urban planning, generally two types of criteria are considered: qualitative and quantitative. Quantitative criteria refer to per-capita demand which comes from a comparison between present per-capita demand and related standards, or by investigating the present and spatial needs of the region to be considered. Qualitative criteria are related to dependency, consistency and suitability in land-use sustainable arrangement (Iran's Supreme Council for Urbanization and Architecture, 2010; Maleki et al., 2017; Talei et al., 2007). In urban areas, dependency is defined as the need of some land-uses to others for more functionality (Maleki et al., 2017; Mansourian et al., 2011; Talei et al., 2007). For instance, residential land-use needs commercial and educational land-uses for more functionality. Consistency or Compatibility illustrates that the allocation of land to each land-use type should be designed to minimize undesirable impacts among adjacent land uses (Iran's Supreme Council for Urbanization and Architecture, 2010). For example, an industrial use adjacent to residential land uses will cause some negative externalities and they are not consistent. Lastly, Suitability means the appropriateness of a land with its land-use type which is defined using many different factors in urban planning (Ghavami et al., 2016).

In this research, socio-economic conditions have not been considered directly but these four criteria somehow model this issue and situations indirectly. In case of low consistency, dependency, suitability, and per-capita demand, this may give rise to other negative externalities in terms of economic, social, health aspects. For instance, a negative externality like the neighboring of an industrial and residential land-use may cause the property to lose value. In contrast, positive effects can cause gains in property values. In summary, for more accurate results, it would be better to consider socio-economic factors directly.

Consequently, if urban land-use changes at the parcel level, the balance between the quantitative and qualitative elements may be disturbed in the plans. This paper proposes a solution for dynamic updating of land-use plans to satisfy urban dynamics and compute the change in quantitative and qualitative elements. A multi-objective optimization mechanism based on NSGA-II (Non-dominated Sorting Genetic Algorithm) is suggested, in which both the quantitative and qualitative elements are considered and optimized simultaneously. This is presented by the optimization of the arrangement of land-uses. In the case of land-use change, the priorities of land-uses for a specific land unit can be re-assigned and the effect of changes can be studied. By dynamic, the authors mean that the planning using a multi-objective optimization algorithm is flexible rather than fixed.

Since the search space of the problem that we solve in this work is discrete, it was important for us to choose a multi-objective optimization algorithm which works efficiently in discrete spaces. NSGA-II is such an algorithm, since it can be adopted using binary encoding (Deb et al., 2002), it is very fast (Balling et al., 2000), effective (Jin, 2006) and easy to implement (Masoumi et al., 2017).

In multi-objective problems, there is a wide range of solutions that represent the best possible trade-offs among the objectives, so decision makers often have difficulties in selecting a single one from them based on their priorities. In this study, a clustering method based on ant colony optimization (ACO) was adopted and justified in classifying trade-off solutions to facilitate decision making. In total, this study considered 35 types of different land-uses in three levels: local, district, and urban. Based on the above description, the characteristics of the proposed model are the following:

• It measures the effect of the changes for each land-use in the arrangement of other land uses using multi-objective optimization algorithms.

• It suggests alternative land-use arrangements after changes in other land-uses, based upon quantitative and qualitative parameters in master and detailed urban plans using multi-objective optimization algorithms.

• It supports decision makers using a clustering algorithm to explore the effect of their decisions when a land-use changes and also aids them to select their own priorities among Pareto-optimal solutions.

• It uses a vector data format, which has its own difficulties, instead of adopting a raster format for modeling urban parcels that are more compatible with the boundaries of the urban area.

• It uses 35 types of urban land-uses with a different radius of effect to model the interactions between different urban land-use types in order to model actual environment of urban parcels.

The paper is organized as follows: Section 2 provides an overview of the literature. Section 3 discusses the methodology and employed data. Section 4 reports the experimental results of the model. Section 5 presents the evaluation and discussion, and finally, Section 6 outlines the conclusions.

2. Literature review

Most land-use planning studies using optimization techniques are only concerned with one particular aspect of optimized arrangements, e.g., traffic, social, or economic conditions (Kucukmehmetoglu & Geymen, 2016; Farkas, 2009; Moah & Kanaroglou, 2009; Chang et al., 2008; Chuvieco, 1993). There are also studies which have considered the effects of neighboring land-use arrangements and have suggested some changes (plans) based on these effects. The latter studies have not used optimization techniques, rather they focused on the external consequences of the land-use changes (i.e. Yang et al., 2016). Meanwhile, there are also studies in which multiple objective functions have been optimized for land-use arrangements. Shiffa et al. (2011) used particle swarm optimization (PSO) to optimize the arrangement of land-uses considering maximization of suitability and accessibility, while minimizing land-use change expense. They optimized a single objective function which had been defined as a function of the previously mentioned three other objective functions. The spatial unit of land-uses was considered as urban zones and since a single objective problem was solved the results were rather inflexible and dependent on the weight of the objectives.

Ligmann-Zielinska et al. (2009) used a multi-objective optimization model with a ‘hop-skip-jump’ (HSJ) method, an algorithm to generate diverse solutions. The objective functions were to minimize the inconsistency of the land-uses and the density of the buildings simultaneously. They did not place a special emphasis on choosing optimized solutions out of the Pareto-Front and did not interact with decision makers. Balling et al. (2000) used a heuristic multi-objective genetic algorithm to optimize three objective functions: minimization of traffic, minimization of transportation costs and minimization of land-use change. In their approach, the objective functions were not optimized simultaneously. A genetic algorithm was implemented on each individual objective function periodically, then the best individuals were selected for optimization of the next objective function. This, in turn, disregards some of the optimized solutions during the processes (Balling et al., 2000). Feng and Lin (1999) developed different alternatives for urban land-use management adopted by urban planners. A cumulative genetic algorithm (CGA) with multiple objectives was used. The spatial unit was city zones. The employed objective functions were land-use suitability for sustainable development and the consistency of neighboring zones. However, this disregarded all the related factors in the land-use arrangement and using urban zones spatial units. Cao et al. (2012) defined the objective functions and constraints of their studies based on maximization of economic productivity, environmental and ecological benefit, social factors, compatibility, and accessibility. The researchers tried to provide different scenarios of decision making about optimized arrangement of land-uses in a city. Thus, the arrangements were defined in areas with no defined land-use. Three types of land-use including residential, commercial and industrial were considered, using a boundary-based fast genetic algorithm (BFGA) to search for optimal solutions to the land allocation problem (Cao et al., 2012).

It is of note that the main goal of much of the above-mentioned research was to optimize land-use arrangement from one special aspect, for instance traffic, social, or economic conditions as an objective function or allocation of a particular land-use. Other studies have examined external effects resulting from land-use changes, regarding arrangement of land-uses in the neighborhood level without any optimization. Some studies have developed optimized arrangements on the basis of multi-objective problems without attention to dynamic planning and the usability of the results for decision makers. In this research, the main goal is to model and measure land-use changes in urban areas based on urban dynamics considering four objective functions simultaneously. Vector format has been used, which has its own complexities, but models urban behavior more naturally. The proposed model will help decision makers to select their own priorities from among Pareto-Front solutions using clustering solutions.

3. Materials and methods

3.1. Multi-objective optimization

A multi-objective problem can be defined mathematically as a minimizing or maximizing $f(x)$ vector, where x is a vector with n aspects of decision variables, $x = (x1, x2, \ldots, x_n)$ out of S set (Engelbrecht, 2007; Coello Coello & Lamont, 2004), in other words Equation.1 and Equation.2 show the definition of multi-objective problem:

minimize $f(x) = (f_1(x),\ldots, f_m(x))$ (1)

subject to $g_i(x) \leq 0,\ i = 1,\ldots,q, x \in S$ (2)

A multi-objective problem consists of n parameters, q constraints and m objective functions. In order to solve such a problem, different methods and algorithms have been suggested. In the algorithms based on mathematical methodologies, problem solving results in a precise and absolute answer. However, if the search space is large or the volume of calculations is high, then the problem solving is too ambitious and sometimes impossible. However, heuristic and meta-heuristic algorithms may produce some acceptable solutions in complex problems with a very large search space (Talbi, 2009; Gen & Cheng, 2000). The genetic algorithm, as an example of meta-heuristic and evolutionary algorithms, would be suitable to solve multi-objective problems, since it has the potential of working with a set of different solutions as an initial population (Deb et al., 2003). This potential would result in a set of Pareto-Front solutions in one algorithm's run, also producing acceptable solutions in an extended search space (Engelbrecht, 2007).

The complexities in modeling each of the qualitative and quantitative elements (Ghavami et al, 2016; Cao et al., 2011; Zhang et al., 2010; Chang et al., 2008) and the existence of various alternatives in land-use arrangement, due to extended search area (i.e. different choices for land-use arrangements) (Cao et al., 2012; Aerts et al., 2003; Xiao, 2002), make it very difficult to model optimization problems. As a result, it can be considered as an NP-hard (Non-deterministic Polynomial-time) problem. In optimization sciences, a meta-heuristic is a higher-level heuristic designed to find, generate, or select a heuristic that may provide a sufficiently good solution to an optimization problem, especially with incomplete or imperfect information or NP-hard problems. So, meta-heuristic algorithms constitute an important alternative to solve NP-hard and multi-objective problems (Talbi, 2009), such as land-use arrangement optimization problems. NSGA-II, as a multi-objective optimization algorithm, is a common meta-heuristic algorithm used to solve such problems. Some meta-heuristic algorithms can only work in discrete sets, often a subset of integers, whereas other models contain variables that can take on any real value. In optimization problems, the type of problem based on its search space impacts on the quality of results and algorithm run-time (Elbeltagi, 2005). The problem in the present study is discrete (which is explained in the future sections), so NSGA-II was selected as our evolutionary search engine, since it can be adopted appropriately with discrete search spaces (Jansen, 2013; Bui & Alam, 2008). Also, its superiority (Shaygan et al., 2014; Jin, 2006) and relative ease of implementation (Masoumi et al., 2017; Deb, 2001) are well known.

3.2. NSGA-II

NSGA-II (Deb et al. 2002a) is a multi-objective evolutionary algorithm that uses non-dominated sorting and a crowded-comparison operator to find a set of evenly distributed solutions to a multi-objective optimization problem. NSGA-II was proposed to reduce computational complexity, improve diversity of the solutions and because of its superiority with respect to its ancestor, NSGA, which was proposed by Srinivas and Deb (1994). NSGA-II, by applying non-dominated sorting and crowding distance, selects the best individuals regarding non-domination and uniform distribution as follows:

- non-dominated sorting: a point is considered as a non-dominated solution only if there is no other point in the search space which is equal in all objectives and is better than that point in at least one objective function (Coello Coello et al., 2007).

- crowding distance: this factor is used to choose better solutions on a front from the distribution point of view.

Figure 1 shows population sorting in NSGA-II: the populations of P_t and Q_t (resulting from crossover and mutation) are first sorted based on domination and placed according to the order of the fronts. Then the last front, where the members should be omitted to gain more individuals for the population (Front 3 in Figure 1), should be sorted according to the crowding distance, and finally, the necessary number of individuals is selected to produce P_{t+1}.

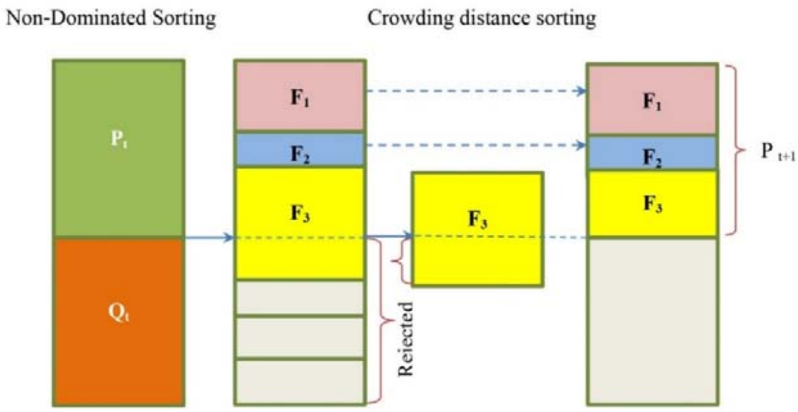

Figure 1. Population sorting in NSGA-II, where P is the initial population, Q is the resultant population from crossover and mutation operators, and F_i represents the fronts (Deb, 2001)

3.3. Mathematical expression for optimizing arrangements of urban land-uses responding to land-use changes

In order to express a multi-objective problem mathematically, the objective functions and its conditions should be defined precisely and according to the decision makers' criteria. In this part, objective functions and criteria of the problem will be explained. It is of note that in this research, 35 types of land-uses were considered in three urban areas, local, district, and regional, as shown in Table 1. The variety of considered land-uses is one of the issues which increases the level of complexity in the model.

3.3.1. Objective functions

Dependency, consistency, suitability and compactness of neighbor land-uses were the four objectives used in this study, as these four elements as well as the physical elements will change when land-use changes in an urban environment.

Table 1. The land-use types considered in this study

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

- Dependency

In urban areas, the functionality of some land-uses is dependent on others, for example, residential land-uses need commercial and educational land-uses in their neighborhood. This concept in land-use planning is defined as dependency (Batty, 2005).

In the land-use change problem, the effect of land-use change on the neighboring dependency can be a function of their distances. Therefore, total dependency is a function of the distance between the land-uses and their degree of dependency, as in Equation.3:

$$DEP_{ij} = f_1(d_{ij}, DEP_{cicj}) = DEP_{cicj} \times \alpha^1(d_{ij}) \quad (3)$$

where, DEP_{cicj} stands for the degree of dependency between two land-use classes (c_i and c_j), d_{ij} is the distance between land-use i and parcel j, and $\alpha^1(d_{ij})$ is the distance function that is presented in Equation.4:

$$\alpha^1(d_{ij}) = \begin{cases} 1 & d_{ij} \le d_{ij}^{\min} \\ \left(\dfrac{d_{ij}^{\max} - d_{ij}}{d_{ij}^{\max} - d_{ij}^{\min}}\right)^{\beta} & d_{ij}^{\min} \le d_{ij} \le d_{ij}^{\max} \\ 0 & d_{ij} \ge d_{ij}^{\max} \end{cases} \quad (4)$$

where, $d_{ij}^{\min}$ is the minimal distance between changed land-use i and parcel j which takes place in the neighborhood of two parcels and $d_{ij}^{\max}$ is the maximum effective distance of land-use i on parcel j. In this study, the minimum distance occurs in neighborhood parcels, the maximum distance is considered equal to the effect radius of changed land-use, and the area located out of effect radius of land-use is considered as unaffected area. Figure 2 shows graphically how the radius of effect is defined in the Dependency objective function.

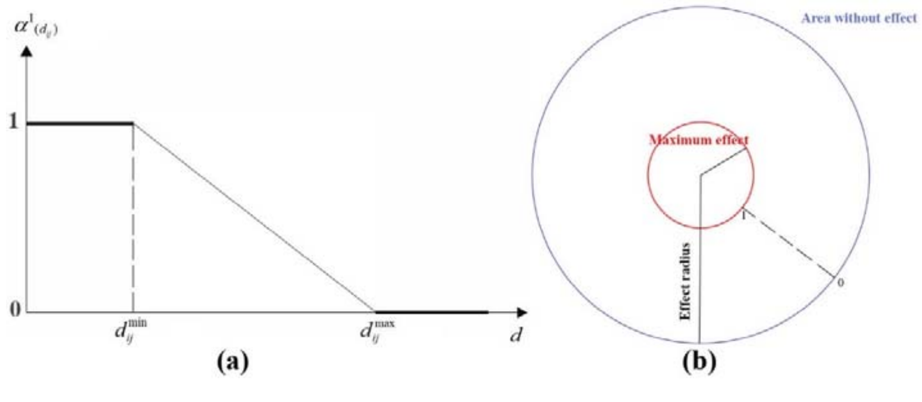

Figure 2- The definition of $\alpha^1(d_{ij})$ function using the effect radius in the Dependency objective function. Figure 2(a) shows the shape of $\alpha^1(d_{ij})$ function and Figure 2(b) describes when a parcel changes the maximum effect (1) occurs in neighbor parcels and the effect decreases linearly considering the radius of effect.

The Delphi method (Linstone & Turoff, 1975) was used to determine the degree of dependency of land-uses in the form of a matrix. According to the experts' opinion, dependency was divided into five levels including high dependency (HD), medium dependency (MD), low dependency (LD), medium independency (MI), and high independency (HI). The experts were also asked to consider the dependency element as independent from all other quantitative and qualitative elements, such as consistency and suitability. Table 2 shows the extracted dependency matrix from the Delphi model for two residential and commercial land-uses.

Since the algorithm uses numerical values for problem solving, the qualitative values extracted from the Delphi method in the dependency matrix were transformed into quantitative values using a structured pairwise comparison method in the analytical hierarchy process (AHP) (see Bhushan, 2004; Golden, 1989 for more information about the method). Coefficients of 0.43, 0.28, 0.18, 0.08, and 0.04 were obtained for the five levels, namely HD, MD, LD, MI, and HI, respectively. Finally, the objective function of dependency was defined as Equation.5:

$$F_1 : Maximize\,(\frac{1}{n}\sum_{i=1}^{n}(\frac{1}{n_i}\sum_{j=1}^{n_i}(Dep_{ij})) + \underset{ij}{Min}(Dep_{ij})) \qquad (5)$$

where, n_i is the number of neighbors of parcel i and n is the total number of parcels.

In some cases, very low dependencies can be compensated by very high dependencies in the average. For example, consider the set of Dep_{ij} in two various arrangements A and B as Equation.6.

$$\begin{aligned} A &= \{0.11, 0.75, 0.22, 0.53, 0.47, 0.63\}, \\ B &= \{0.37, 0.49, 0.32, 0.46, 0.38, 0.51\} \end{aligned} \qquad (6)$$

The average of Dep_{ij} in arrangements A and B is equal to 0.45 and 0.42, respectively. If the second term in Eq.5 is not considered, the algorithm will justify just based on the value of average which is better in arrangement A. But logically, arrangement A is not proper in comparison with arrangement B because it consists of 2 inappropriate Dep_{ij} functions (0.11 and 0.22) which are compensated in average with other high values in this set. Thus, the second part (the minimum value of the Dep_{ij} amounts) was added to the objective function to be maximized by the algorithm in the proposed arrangement to overcome this problem. Since, adding this term in the objective function will ignore solutions with the high average and low Dep_{ij} which are not our target.

Table 2. Extracted dependency matrix from the Delphi model, LD, MD, HD, MI and HI refer to low dependency, medium dependency, high dependency, medium independence and high independence, respectively.

Land-use types		Residential			Commercial			Educational						Religious			Medical			Administration		Cultural			Sport			Urban Equipment			Industrial				Park		
		Low Density	Moderate Density	High Density	Daily	Regional level	District level	Kindergarden	Primary School	Secondary school	High School	Technical School	University/College	Local Level	Distrinct Level	Regional Level	Local Level	Distrinct Level	Regional Level	Distrinct Level	Regional Level	Local Level	Distrinct Level	Regional Level	Local Level	Distrinct Level	Regional Level	Local Level	Distrinct Level	Regional Level	Local Level	Distrinct Level	Regional Level	Industrial Complex	Local Level	Distrinct Level	Regional Level
Residential	Low-Dencity	MD	MD	LD	HD	MD	MD	HD	HD	MD	MI	MI	HI	HD	MD	MI	HD	MD	HI	MD	MI	MD	MD	LD	HD	MD	LD	HD	MD	LD	LD	HI	HI	HI	HD	MD	MD
	Moderate-Density		MD	MD	HD	MD	MD	HD	HD	MD	MI	MI	HI	HD	MD	MI	HD	MD	HI	MD	MI	MD	MD	LD	HD	MD	LD	HD	HD	LD	LD	HI	HI	HI	HD	MD	MD
	High-Density			MD	HD	MD	MI	HD	HD	MD	MD	MD	LD	HD	MD	MD	HD	MD	LD	MD	MI	MD	MD	LD	HD	MD	LD	HD	HD	LD	LD	HI	HI	HI	HD	MD	MD
Commercial	Daily				HI	MI	HD	MD	MD	MD	LD	LD	LD	MI	MI	MI	LD	HI	HI	MI	MI	MI	MI	MI	MD	MD	LD	HD	MD	LD	HI	HI	HI	HI	MD	MD	MD
	Regional Level					HI	HD	MD	MD	MD	MD	MD	LD	MI	MI	HI	MD	HI	HI	MI	HI	MI	MI	MI	MI	MI	MI	HD	HD	HD	HI	HI	HI	HI	MI	MI	MI
	District Level						HI	MI	HI	HI	HI	HI	MI	MI	MD	MD	HI	MI	MI	MI	MI	HI	MI	MI	HI	HI	HI	HD	HD	HD	HI	HI	HI	HI	MI	MI	MI
Educational	Kindergarden							HI	HI	HI	HI	HI	HI	HI	HI	HI	MD	MI	MI	HI	HI	HI	MI	MI	MI	HI	HI	HD	MD	MI	HI	HI	HI	HI	MD	MI	MI
	Elementry School								HI	HI	HI	HI	HI	MI	HI	HI	MD	MI	MI	HI	HI	MI	MI	MI	MD	HI	HI	HD	MD	MI	HI	HI	HI	HI	MD	MI	MI
	Secondary School									HI	HI	HI	HI	MI	HI	HI	MD	MI	MI	HI	HI	MI	MI	MI	MD	MI	MI	HD	MD	MI	HI	HI	HI	HI	MD	MI	MI
	High School										HI	HI	HI	MI	HI	HI	MD	MI	MI	HI	HI	MD	MD	MD	MD	MD	MD	HD	HD	MI	HI	HI	HI	HI	MD	MD	MD
	Technical School											HI	HI	MI	HI	HI	MD	MI	MI	HI	HI	MD	MD	MD	MD	MD	MD	HD	HD	MI	HI	HI	HI	HI	MD	MD	MD
	University/College												HI	MI	HI	HI	MD	MI	MI	MI	MI	MD	MD	MD	MD	MD	MD	HD	HD	MI	MI	HI	HI	HI	MD	MD	MD
Religious	Local Level													HI	HI	HI	HI	HI	HI	HI	HI	MI	HI	HI	HI	HI	HI	HD	HD	MI	HI	HI	HI	HI	MI	HI	HI
	District Level														HI	HI	HI	HI	HI	HI	HI	MI	HI	HI	HI	HI	HI	HD	HD	MI	HI	HI	HI	HI	MI	HI	HI
	Regional Level															HI	HI	HI	HI	HI	HI	MI	HI	HI	HI	HI	HI	HD	HD	MI	HI	HI	HI	HI	MI	HI	HI
Medical	Local Level																HI	HI	HI	HI	HI	HI	HI	HI	MI	MI	MI	HD	HD	MI	HI	HI	HI	HI	HI	HI	HI
	District Level																	HI	HI	HI	HI	HI	HI	HI	MI	MI	MI	HD	HD	MI	HI	HI	HI	HI	HI	HI	HI
	Regional Level																		HI	HI	HI	HI	HI	HI	MI	MI	MI	HD	HD	MI	HI	HI	HI	HI	HI	HI	HI
Administration	District Level																			HI	HI	HI	HI	HI	HI	HI	HI	HD	HD	MI	HI	HI	HI	HI	HI	HI	HI
	Regional Level																				HI	HI	HI	HI	HI	HI	HI	HD	HD	MI	HI	HI	HI	HI	HI	HI	HI
Cultural	Local Level																					HI	HI	HI	MI	MI	HI	HD	HD	MI	HI	HI	HI	HI	MI	MI	MI
	District Level																						HI	HI	MI	MI	HI	HD	HD	MI	HI	HI	HI	HI	MI	MI	MI
	Regional Level																							HI	MI	MI	HI	HD	HD	MI	HI	HI	HI	HI	MI	MI	MI
Sport	Local Level																								HI	HI	HI	HD	HD	MI	HI	HI	HI	HI	MI	MI	MI
	District Level																									HI	HI	HD	HD	MI	HI	HI	HI	HI	MI	MI	MI
	Regional Level																										HI	HD	HD	MI	HI	HI	HI	HI	MI	MI	MI
Urban Equipment	Local Level																											HI	HI	HI	HI	HI	HI	HI	HD	HD	HD
	District Level																												HI	HI	MI	MI	MI	MI	MD	MD	MD
	Regional Level																													HI	MI	MI	MI	MI	HI	HI	HI
Industrial	Local Level																														HI	MI	HI	HI	HI	HI	HI
	District Level																															HI	MI	HI	HI	HI	HI
	Regional Level																																HI	MI	HI	HI	HI
	Industrial complex																																	HI	HI	HI	HI
Park	Local Level																																		HI	HI	HI
	District Level																																			HI	HI
	Regional Level																																				HI

- Consistency

In urban areas, sometimes land with a specific use type may ‘repel’ certain neighboring land-use types due to the existence of a significant negative effect (Talei et al., 2007). For example, adjacent industrial and residential land-uses is not consistent. Ideally, the location and allocation of land to each land-use type should be designed to minimize any undesirable impact on adjacent land-uses.

To indicate consistency in a mathematical way, the consistency matrix in parcel level and the Delphi method were used for dependency. The objective function of dependency was defined as a function of distance, since the further apart the two land-uses, the less their consistency or inconsistency effect will be. Therefore, the consistency function can be defined as indicated in Equation.7.

$$CONS_{ij} = f_2(d_{ij}, C_iC_j) = CNS_{cicj} \times \alpha^2(d_{ij}) \tag{7}$$

where, d_{ij} is the distance of the center of mass between parcels i and j, CNS_{cicj} is the consistency of two land-use classes, C_i and C_j, in the consistency matrix, $\alpha^2(d_{ij})$ is the distance function related to consistency (The definition of $\alpha^2(d_{ij})$ is similar to $\alpha^1(d_{ij})$ in the dependency objective function, but here, the maximum effect values for consistency is different from maximum effect radius in the dependency objective function), and $CONS_{ij}$ is the consistency function of parcels i and j. Finally, the consistency objective function can be defined as indicated in Equation.8:

$$F_2 : Maximize\left(\frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{n_i}\sum_{j=1}^{n_i}(CONS_{ij})\right) + \underset{ij}{Min}(CONS_{ij})\right) \tag{8}$$

where, i is the parcel, j is the neighbor of the parcel, i, n_i the number of neighbors of parcel i, and n indicates the total number of parcels.

- 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. Therefore, it depends on many parameters such as physical, economical, etc. (Qui & Zhang, 2011; Koomen et al., 2007; Malczewski, 2004). The following parameters were selected based on the literature and experts' suggestions to model the physical suitability of land for a specific land-use. The flow chart of calculating suitability values for each parcel is presented in Figure 3.

- Area (A): the area of a land parcel is one of the most important factors to establish a suitable land-use for it (Malczewski, 2004). In this research, to extract the appropriate area for each land-use, where it was possible, existing standards were used, but where the suitable area for the land-uses was not mentioned in the sources, expert knowledge was used. Table 3 represents the extracted areas and their degrees of suitability for each land-use. According to the consistency and dependency matrix, the qualitative values in Table 3 were converted to quantitative values using the AHP method and by a pairwise comparison of like dependency and consistency objective functions. The final quantitative values are presented in Table 4.

- Accessibility (AC): accessibility means the access of land parcels to public transportation. To determine the accessibility of land-uses, Table 5 was created on the basis of the parcel distance to transportation and the proper suitability degree was determined based on it. Finally, these qualitative values were converted to quantitative values based on Table 4 and the structural AHP method.
- Air & voice pollution (AVP): this parameter was determined for all parcels by considering their distance from noise and air pollution sources in urban areas. These sources are considered as the transportation system, educational land-uses, and industrial land-uses. The effect of each source has been classified in the levels of local, regional and district. For instance, in the classification of the distance to the transportation system, the roads were classified into local roads, main roads and highways categories. In the next stages, the degrees of not suitable (NS), lowly suitable (LS), medium suitable (MS) and highly suitable (HS) are related to each parcel, considering its distance to these classes. As for the case of area, these values were converted to quantitative values by a pairwise comparison. Finally, each parcel in the study area has its own values based on one of each class. An overlay analyst was employed to obtain final values of suitability related to AVP for the transportation system, educational land-uses, and industrial land-uses.
- Restrict to change (R): rigidity to land-use changes was considered as highly, medium, lowly and not suitable. The resulted values were also transformed into quantitative values using pairwise comparisons and the AHP method similar to the above-mentioned factors.

Table 3. Extracted areas for each land-use type and their degree of suitability (the unit is square meter). To extract the appropriate area for each land-use, where it was possible, existing standards for Iran were used (Iran's Supreme Council for

Urbanization and Architecture, 2010; Afsharnia, 2014), but where the suitable area for the land-use was not mentioned in the sources, expert knowledge was used.

Land-use type/ Suitability			High suitability	Medium suitability	Low suitability	Not suitable
	Residential	Low-Density	>250	150-250	50-150	<50
		Moderate-Density	>250	150-250	100-150	<100
		High-Density	>500	450-500	450-400	<400
Services Land-use Types	Commercial	Neighborhood shop	65-100	50-65	50-35	<35
		Convenience retail	400-500	400-350	350-250	<250
		Regional/City shop	>600	500-600	450-500	<450
	Educational	Kindergarten	>500	400-500	300-400	<300
		Elementary School	>2500	1500-2500	1000-1500	<1000
		Secondary School	>2500	1500-2500	1000-1500	<1000
		High School	>7000	5000-7000	4000-5000	<4000
		Technical School	>7000	5000-7000	4000-5000	<4000
		University/College	>7000	5000-7000	4000-5000	<4000
	Religious	Local Level	300-500	200-300	<200	<200
		District Level	700-1000	700-500	500-400	<400
		Regional Level	1500-2500	1000-1500	500-1000	<500
	Medical	Local Level	750-1000	500-750	<500	<500
		District Level	2000-2500	1500-2000	1000-1500	<1000
		Regional Level	>25000	20000-25000	<20000	<20000
	Administration	District Level	750-1000	500-750	<500	<500
		Regional Level	4000-5000	3000-4000	2000-3000	<2000
	Cultural	Local Level	1500-2000	1200-1500	1200-1000	<1000
		District Level	3500-4000	3000-3500	2000-3000	<2000
		Regional Level	4500-5000	4000-4500	3500-4000	<3500
	Sport	Local Level	4500-5000	4000-4500	3500-4000	<3500
		District Level	14000-15000	13000-14000	12000-13000	<12000
		Regional Level	25000-30000	20000-25000	15000-20000	<15000
	Urban Equipment	Local Level	200-250	150-200	100-150	<100
		District Level	450-500	400-450	350-400	<350
		Regional Level	1750-2000	1500-1750	1250-1500	<1250
	Industrial	Local Level	80-100	60-80	50-60	<60
		District Level	750-1000	500-750	250-500	<250
		Regional Level	2500-3000	2000-2500	1500-2000	<1500
	Park	Local Level	2500-3000	2000-2500	1500-2000	<1500
		District Level	9000-10000	8000-9000	7000-8000	<7000
		Regional Level	24000-25000	23000-24000	22000-23000	<22000

Table 4. Quantitative values extracted by the pairwise comparison method

The degree of suitability	HS	MS	LS	NS	Geometric Average	Standardized value
HS (High Suitability)	1	2	3	5	2.3403	0.47

MS (Medium Suitability)	0.5	1	2	5	1.4142	0.29
LS (Low Suitability)	0.33	0.5	1	3	0.8387	0.17
NS(Not Suitable)	0.2	0.25	0.33	1	0.3584	0.07

Table 5. Suitability degrees of parcels accessibility for residential land-use with medium density according to the distance and the type of road: highly suitable (HS), medium suitable (MS), lowly suitable (LS) and not suitable (NS), respectively.

Road type/ Distance	0-100	100-300	300-500	<500
Local Street	HS	MS	LS	NS
Collector Street	HS	MS	LS	NS
Second degree street	NS	MS	MS	NS
First degree street	NS	LS	LS	NS
Highway and Freeway	NS	LS	LS	NS

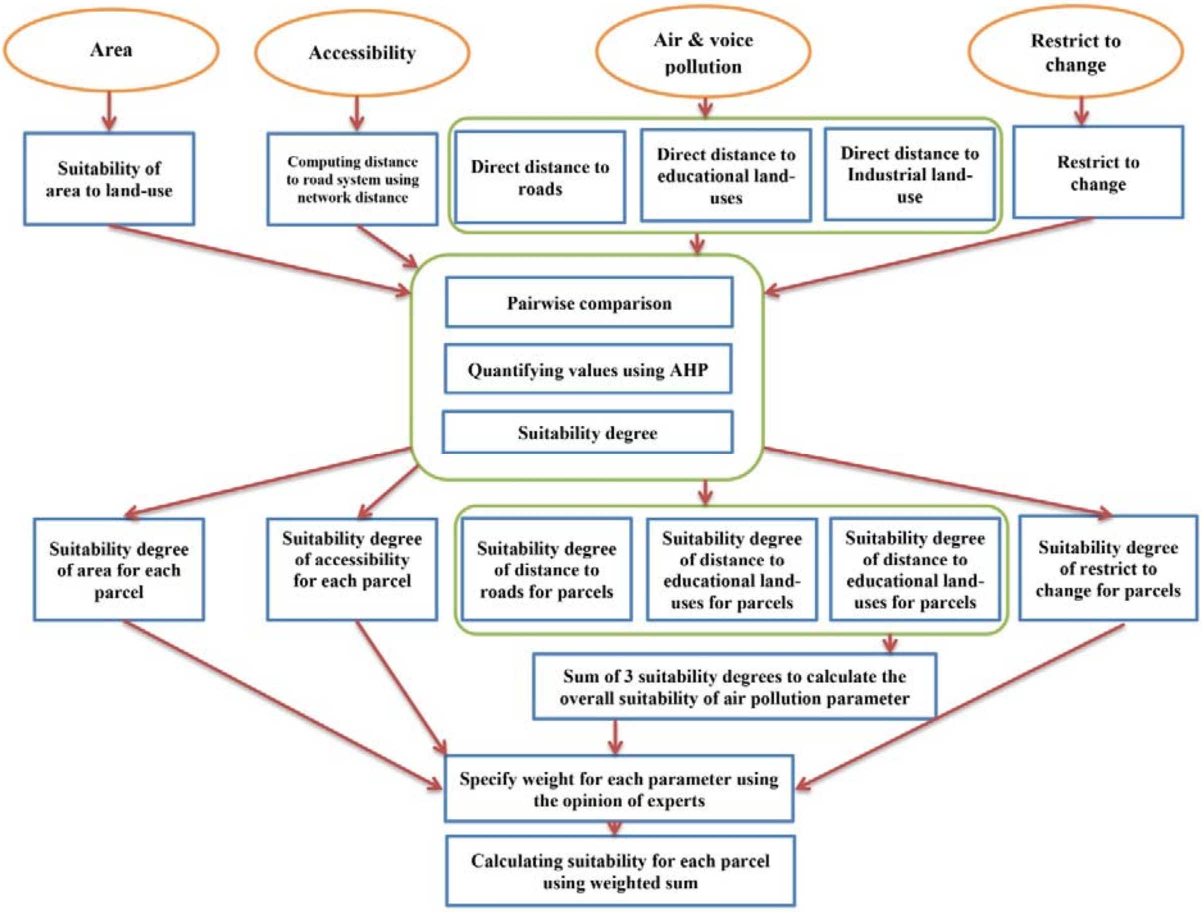

Figure 3. The process of calculating suitability values for each parcel considering area, accessibility, air & voice pollution, and restrict to change

To calculate the suitability of each parcel, considering their area, accessibility, air pollution and restrictions to change, for the given land-use classes, the MCA[2] method was employed. MCA was developed for complex multi-criteria problems that include qualitative and/or quantitative aspects of the problem in the decision making process (Mendoza et al., 1999). To evaluate suitability for each parcel using MCA, first, the weight of each factor according to the survey filled by the urban planning experts, was extracted. The suitability for the parameters of area (A), accessibility (AC), air and voice pollution (AVP) and restriction to change (R) were considered as 0.30, 0.30, 0.25, and 0.15, respectively according to the experts' opinion. Total suitability of land-use class of C_i for parcel j was extracted from Equation.9.

[2] Multi-Criteria Analysis

$$S_{j,Ci} = w_1 A_{j,Ci} + w_2 Ac_{j,\,Ci} + w_3 AVP_{j,\,Ci} + w_4 R_{j,\,C} \tag{9}$$

in which, w_1, w_2, w_3, w_4 are the weights given to area, accessibility, AVP, and restriction to change respectively considering the expert's opinion to calculate suitability for each parcel.

Finally, the third objective function (suitability) was defined as follows (Equation.10).

$$F_3 : Maximize\ (\frac{1}{n}\sum_{i=1}^{n} S_{i,Ci} + Minimmum\ (S_{i,C_i})) \tag{10}$$

where, $S_j\ c_i$ is the suitability of C_i land-use with parcel j and n is the number of parcels in the arrangement. As can be seen from equation 9, in this function, the second part was added to the objective function to prevent a compensation state in total suitability as described for the dependency and consistency objective functions.

- Compactness of neighboring land-uses

Compact land-use is desired in various planning domains. Promoting compactness/controlling fragmentation has been a common and important goal of land-use planning toward sustainability (Cao & Huang, 2010). In summary, in the compact cities, the land-use of neighbors considered the same as possible.

To create compactness of neighboring land-uses in this research, the following actions were taken. First, the neighbors of each parcel were indicated in the program, then a counter was defined to be added one unit in case the neighboring land-uses are the same in the arrangement. Therefore, the related objective function was defined as Equation.11.

$$F_4 : Maximize \sum_{i} Compactnes\ s_i \tag{11}$$

where the *compactness* is the above-mentioned counter.

3.3.2. Constraint of the problem

The needs of each person for a certain space of land is defined as per-capita demand in urban land-use planning. When the land-use of some parcels changes to another type, the balance of per-capita demand is not maintained, so, to manage the per-capita demand, some procedure is required. To achieve a balanced per-capita demand after a land-use change, the constraint of the problem in this research was defined as providing desired per-capita demand of the land-uses in suggested arrangements after a change.

Different methods have been suggested to deal with constraints in multi-objective optimization problems (Coello Coello, 2002; Deb, 2001), from which the most common approach is to use a penalty function (Coello Coello, 2002). This method transforms a constrained optimization problem into an unconstrained one by adding a certain value to the objective function based on the amount of constraint violation present in a certain solution. Per-capita demand was introduced into the problem with the following constraint (Equation.12).

$$P_C^{\min} \leq P_c \leq P_C^{\max} \qquad (12)$$

where, P_c is existing per-capita demand of the land-use class of C, $P_C^{\min}$ is the minimum per-capita of the land-use class C, and $P_C^{\max}$ is the optimized per-capita of the land-use class C. $P_C^{\min}$ and $P_C^{\max}$ were extracted from the standards of the Supreme Council of Iran Architecture and Urban Planning in 2011. The violation function was also defined as Equation.13.

$$\begin{cases} P_{C_i} < P_{Ci}^{\min} \rightarrow v_i = 1 - \dfrac{P_{C_i}}{P_{Ci}^{\min}} \\ P_{C_i} > P_{Ci}^{\max} \rightarrow v_i' = \dfrac{P_{C_i}}{P_{Ci}^{\max}} - 1 \\ P_{Ci}^{\min} \leq P_{Ci} \leq P_{Ci}^{\max} \rightarrow v_i = v_i' = 0 \end{cases} \qquad (13)$$

where, v_i, v_i' are the values of the violations normalized in intervals 0 and 1 by defining the above fractions. Therefore, the mean of the violations can be calculated using Equation.14.

$$\begin{cases} \bar{v} = < v_i > = \dfrac{1}{n}\sum_{i=1}^{n} v_i \\ \bar{v}' = < v_i' > = \dfrac{1}{n}\sum_{i=1}^{n} v_i' \end{cases} \qquad (14)$$

where, n is the number of land-use classes, which is 35 in this study, and v', v are the mean of negative and positive violations existing in the given arrangement. The total value of violation can also be calculated using a weighted mean (Equation.15):

$$\bar{V} = \frac{w_1\bar{v} + w_2\bar{v}'}{w_1 + w_2} \qquad (15)$$

where, w_1, w_2 are the values of the given weights for the negative and positive violations. Taking these weights into consideration, the weight of the violations can be changed if necessary. Since the objective of this problem is maximizing the objective functions, the magnitude of the violation was applied to the objective functions as a reductive variable, that is, a reduction coefficient is applied when there is violation to the constraints, in order to reduce the corresponding objective function value. Therefore, the total value of the violation was computed in the objective functions according to Equation.16.

$$\hat{F} = \frac{F}{1+\overline{V}} \quad (16)$$

where, F is the value of the objective function and $\hat{F}$ is the modified value of the same function (in terms of the per-capita demand penalty).

3.4. Defining the elements of NSGA-II in the case study

In this section, the specifies of NSGA-II adopted for our problem are discussed.

3.4.1. Definition of gene and chromosome

In this research, a chromosome is defined as a set of cells, any of which is a gene, indicating the land-use in the problem. In other words, a chromosome is a list of assigned land-uses to all the parcels as shown in Figure 4. This method has been widely used (Butcher et al., 1996; Stewart et al., 2004; Seixas et al., 2005) and with this type of chromosome definition, the search space is discrete, so the optimization problem is also a discrete problem.

C_1	C_2	...	C_k	...	C_n

Figure 4. Defined chromosome in this research (C_k means that the land-use of parcel C is k)

3.4.2. Creating an initial population

The initial population was created randomly, resulting in a long run-time because of the divergence of the algorithm and long run-time. To solve this problem, an alteration of 30% was made in existing land-uses arrangement, so that 30% of the initial population obtains a pattern of current arrangement of land-uses, reducing the run-time. In fact, the initial population was a combination of randomly created solutions and as a result of changes in the existing state. This method is called 'problem based initial population' (PBI) (Shiffa et al., 2011), and has been used in many studies of land-use management (Shiffa et al., 2011; Cao et al., 2012).

3.4.3. Crossover

Genetic algorithms produce new chromosomes for a better search of possible solutions by using crossover (Haupt & Haupt, 2004). Different crossover operators have been proposed in the literature (Coello Coello, 2007). For simplicity, a single and double pointed linear crossover operator was used in this research. If the crossover operator is applied randomly, the created children may have some problems in the arrangement. As shown in Figure 5, the arrangement of parents is appropriate, but in the children, the industrial land-use is set as a residential land-use neighbor as a result of this process. To prevent this, first, the algorithm searches two neighbor residential land-uses in two selected parents. Then, if we conduct the crossover from one of these positions, in the produced children we will have residential land-uses as neighbors in the crossover position, but other parts are replaced. In addition, the crossover rate in the population was set as 0.9 in this research.

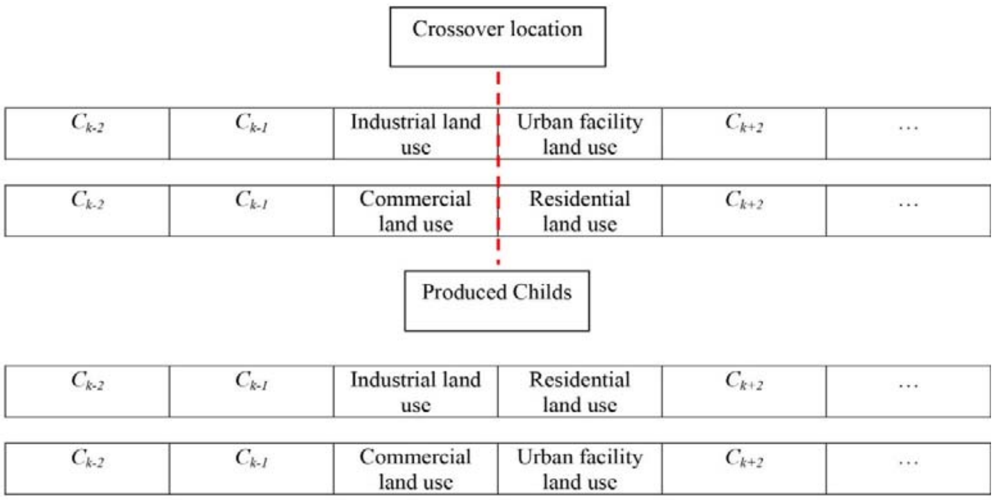

Figure 5. A sample of random crossover operator

3.4.4. Mutation

Mutation makes it possible for a genetic algorithm to explore better and to reach new regions of the search space (Coello Coello, 1999). For the mutation operator adopted in this paper, a proportion of parcels was selected and their land-uses were transformed randomly into one land-use with a high or medium suitability. By doing this, the algorithm may not select a land-use with low suitability or improper for parcels. It should be noted that the mutation rate was set as 0.1.

3.5. Data preparation in the case study area

District 3 of region 7 in Tehran, extending approximately 1 square kilometer, was used as the case study area and 1:2000 urban maps which included parcel level data were used for the analysis.

This district is noticeable for its various land-uses in different levels of urban management. The main attribute data required to create the spatial database were the classification of individuals' age, along with the land-use of parcels. Figure 6 shows the case study area representing the main land-use classes.

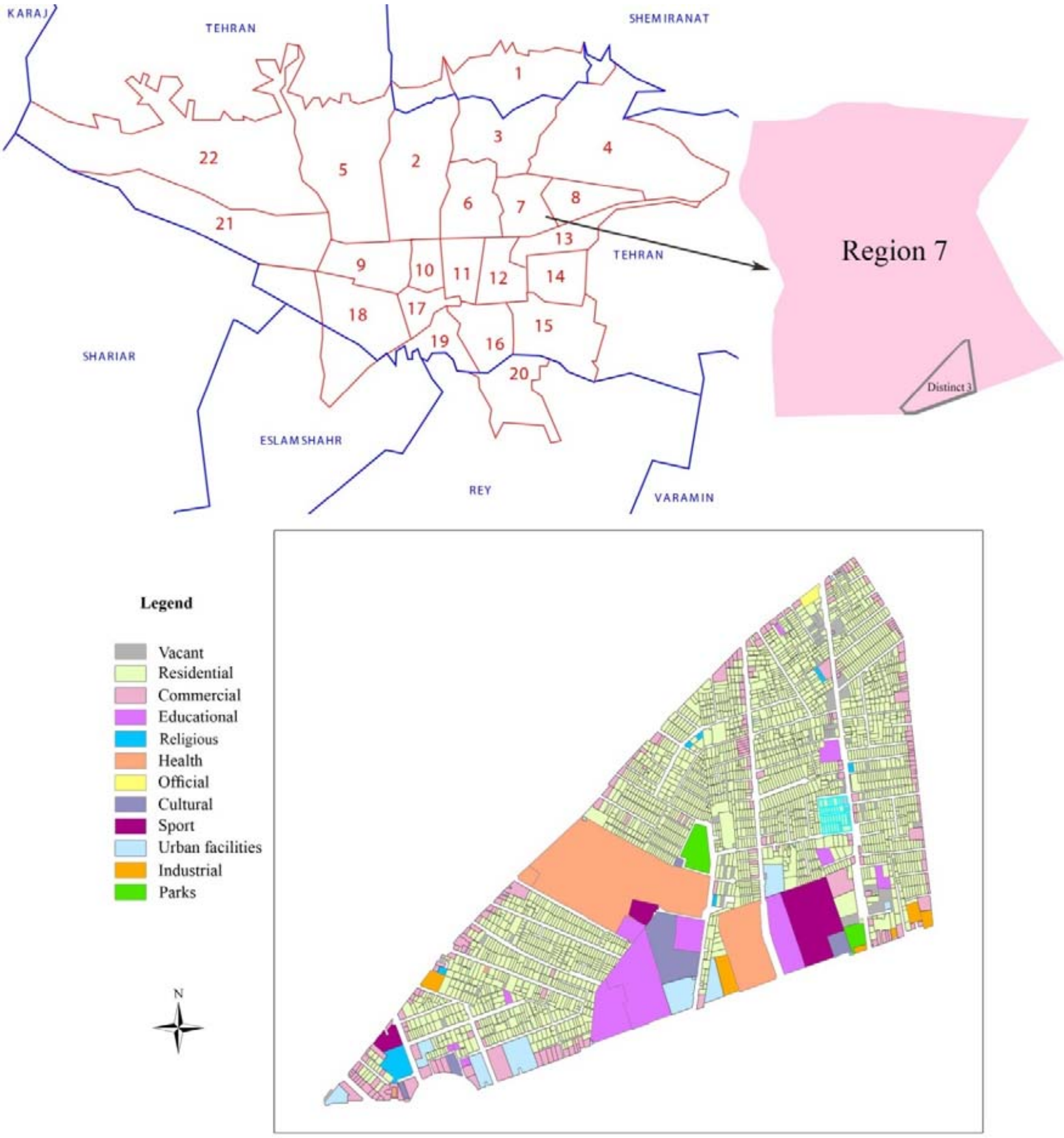

Figure 6. Study area of the research along with the main classes of parcel land-use and their sub classes as described in Table 1

3.6. Comparison of MOPSO and NSGA-II

To evaluate the results and compare the solution with other multi-objective optimization algorithms, MOPSO (Multi-Objective Particle Swarm Optimization) has been used. In this research a version of MOPSO which was proposed by Coello Coello et al. (2004) has been used because of its low computational complexity and fast convergence. Additionally, its source code is available in the public domain. So, in this section, the definition of parameters for MOPSO and the measures employed to compare these two algorithms will be discussed and the results will be introduced in the evaluation section. Readers can be referred to Coello Coello et al. (2004) for more details about how MOPSO works.

3.6.1. Defining the elements of MOPSO for modelling land-use change

Assuming that we have *i* parcels in the study area, a particle is considered as a structure consisting of *i* cells, in which every cell represents a land-use type (*m* land-use types). Actually, every cell *i* is filled by a land-use type C_i. similar to the definition of a chromosome in NSGA-II.

As mentioned before, the space of the problem is discrete, whereas MOPSO is designed to work with continuous spaces and real numbers. In order to transform the problem's search space into a continuous space, it is necessary to define a conversion function, as described by Equation 26. In the discrete space of the problem, every cell *i* is filled by a land-use type C_i (which is the code related to each land-use type) while in the continuous space of MOPSO *(X)*, x_i is the converted content of the i^{th} cell, which is a real number between 0 and 1. Here, *m* is the number of land-use types. Equation.17 shows the relation between these two spaces.

$$\begin{aligned}
&0 \le x_i < \frac{1}{m} \rightarrow C_i = 1 \\
&\frac{1}{m} \le x_i < \frac{2}{m} \rightarrow C_i = 2 \\
&\dots \\
&\frac{k}{m} \le x_i < \frac{k+1}{m} \rightarrow C_i = k+1 \\
&\dots \\
&\frac{m-1}{m} \le x_i < \frac{m}{m} \rightarrow C_i = m
\end{aligned} \qquad (17)$$

The objective functions and constraints are considered the same as in NSGA-II.

3.6.2. Comparing MOPSO and NSGA-II

There are variety of quality indicators to compare multi-objective algorithms (Riquelme, et al., 2015). In this research, the comparison has been conducted using three performance measures based on other studies (Zitzler et al., 2000; Lili and Wenhua, 2008; Coello Coello et al., 2007;

Bajestani et al., 2009; Grosan et al., 2003): Spacing, Diversity and Quality which are defined as follows:

- Spacing Measure (SM)

This performance measure evaluates the diversity of solutions in the Pareto-Front. Equation.18 shows the definition of this measure (Lili and Wenhua, 2008).

$$SM = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(d_i - \bar{d})^2} \qquad (18)$$

in which, n refers to the number of solutions on the Pareto-Front, $\bar{d}$ is the average of all d_i .A lower value of *SM* indicates a better distribution of solutions.

- Diversity Measure (DM)

This performance measure assesses the diversity of solutions in the Pareto-Front. Consider f^{min} and f^{max} are the minimum and maximum values of objective function f respectively. For every objective function, Δf is defined as Equation.19 (Bajestani et al., 2009).

$$\Delta f_j = f_j^{\max} - f_j^{\min}, j = 1,2,\dots,m \qquad (19)$$

Where m shows the number of objective functions. The diversity measure (*DM*) is defined by Equation.20.

$$DM = \sqrt{(\sum_{j=1}^{m}\Delta f_j)^2}, j = 1,2,\dots,m \qquad (20)$$

Considering Eq.20, the higher the diversity measure value, the better will be the spread of the solutions is in the solution space.

- Quality Measure

Using this measure, two sets of non-dominated solutions can be compared to each other (this is a binary performance measure). If *A* and *B* considered as two Pareto-Front approximations, *C(A,B)* and *C(B,A)* are defined as Equation.21.

$$C(A,B) = \frac{\left|\{b \mid b \in B, \exists a \in A, a \succ b\}\right|}{|B|} \quad , \quad C(B,A) = \frac{\left|\{a \mid a \in A, \exists b \in B, b \succ a\}\right|}{|A|} \qquad (21)$$

in which, a and b are the members of A and B sets, the sign $|\,|$ indicates the number of members in the set, and $\succ$ shows the domination concept. Finally, the quality measure is defined by Equation.22 (Ziztler et al., 2000).

$$Q(B,A)=\frac{C(A,B)}{C(A,B)+C(B,A)}$$
$$Q(A,B)=\frac{C(B,A)}{C(A,B)+C(B,A)} \quad (22)$$

So, the quality measure is a relative criterion in the comparison of two Pareto-Front approximations.

3.6. Support decision making in choosing scenarios by adopting clustering methods

The Pareto-Front of a multi-objective optimization algorithm includes a variety of optimum solutions from which decision makers should select one. However, it is not generally easy for decision makers to make a selection. In this study, the results were categorized using clustering analyses to address the issue. In this approach, fuzzy linguistic parameters are taken from the decision maker about an objective function, e.g., consistency, in the form of very high consistency, high consistency, medium consistency, low consistency, and very low consistency. Then, a representative of each group is shown to the decision maker using five corresponding centers of clusters. In this way, the decision maker will be able to see the plan of the corresponding land-use arrangement along with each representative parameter.

3.6.1. Clustering

Clustering analysis is defined as assigning a set of objects to the groups in a way that each object is more similar to members of its group than the others. There are different algorithms for clustering, the selection of which depends on the type of data (for more details see Gan et al., 2007).

In some common clustering algorithms, such as k-means and subtractive, the mass points are calculated and updated through several iterations, then the nearest point in the cluster to the mass is introduced as the cluster center. Since the solutions in the Pareto-Front of this study were close to each other, it is more appropriate to use a method in which cluster centers are selected from a subset of points, so the ACO (Ant Colony Optimization) algorithm was adopted. The operational steps for ACO are not described in this paper, only its application (for operational details of ACO see (Dorigo, 2005 and Clerc, 2006)).

3.6.2. Clustering Pareto-Front using ACO

For the clustering of the solutions in the present study, it was assumed that the goal is to select the K center (and then K clusters) of the data set with a size of n. Therefore, the number of possible permutations can be calculated from Equation.23.

$$\binom{k}{n} = \frac{n!}{k!(n-k)!} \qquad (23)$$

Figure 7 illustrates this process. According to this encoding, K of the first layers of the ants' movement is taken as the centers of the clusters and the other points are assumed as the points of the cluster according to their minimal distance from the center. Thus, among the ants' movements, only the ones in the centers of the clusters are of importance.

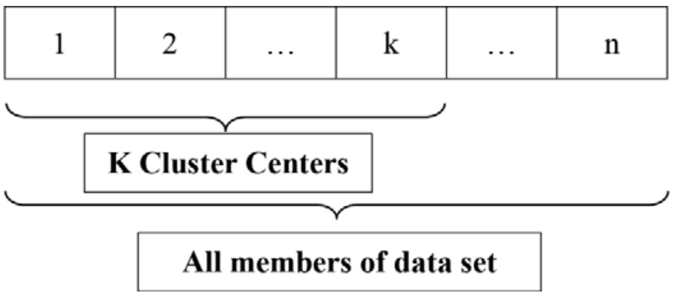

Figure 7. Encoding process in this research to solve the clustering problem using ant colony optimization algorithm

In the proposed algorithm, ant colony optimization was applied as follows. Figure 8 shows the Pseudocode of the clustering algorithm used in this research.

- Step 1: n number of ants was placed at each point as the initial population.
- Step 2: movement K began at the center of the cluster and Pheremone's behavior and the probability of choosing the next point was calculated using Equation.24.

$$P_{ij}^{l} = \frac{(\tau_{ij})^{\alpha}}{\sum_{m}(\tau_{im})^{\alpha}} \qquad (24)$$

where τ_{ij} is the value for the Pheremone which is poured into each arc in every layer of the cluster, α is the constant coefficient assumed as 1 here, and τ_{im} is the value of the Pheremone in the remaining arcs. As mentioned, here, the tour of ants is just between the center of the clusters. In this case the distance between ants is not important so the heuristic information (η) which depends on distance between ants and is commonly used in ACO, is not considered here.

- Step 3: reminder points were attributed to the center of the clusters.
- Step 4: cost function for any movement was defined as in Equation.25.

Cost_function = ∑(distance of each point from the center of the related cluster) (25)

- Step 5: the rule for Pheremone updating was defined as Equation.26.

$$\tau_{ij} \longleftarrow \tau_{ij} + \frac{Q}{Cost\_Function} \qquad (26)$$

- Step 6: calculation of Pheremone's evaporation using Equation.27.

$$\tau_{ij} = \tau_{ij}(1-\rho) \qquad (27)$$

where, ρ is the evaporation coefficient of the Pheremone.

- Step 7: after moving all ants and calculating the final Pheremone, the best movement was stored.
- Step 8: the algorithm was repeated from step 2 until it reached the final constraint.

```
Algorithm 1: Psedocode of using ACO for clustering Pareto-Front
nAnt : The number of Ants
τ : Pheromone value
ρ : Pheromone Evaporation coefficient
nData : The number of pareto-front solutions
nCluster : The number of cluster centers
Ant.Tour(i) : The tour of an ant(i)
Ant.Cost(i) : Cost function of the tour of ant (i)
Input: nAnt, τ, ρ, nCluster
Output: Cluster centers
for i=1 to nData
  for j=1 to nData
    Compute Distance matrix between all points in Pareto-Front
  end j
end i
while ~Stop Condition do
  for i=1 to nAnt
    for k=1 to nCluster
      for j=1 to nData
        if node(j) ~is member (j, Ant(i).Tour) then
          Compute the probability of selection (P(j)) using Equation.24
        end if
          Select next point using roulette wheel selection based on P(j)
          Add next point to Ant.Tour
      end j
    end k
  Compute Ant(i).Cost using Algorithm 2
  end i
Compute evaporation of Pheromone using Equation.27
Sort Costs
if Ant(1).Cost<Best Ant.Cost then
  Best Ant=Ant(1)
end if
End
```

```
Algorithm 2: Psedocode of Computing cost function
Input: Distance Matrix (D)
Output: Cost function of Ant(i).Tour
for i=1 to nData
  if i ~is member (Cluster Centers) then
    let D(:,i)=inf
  end if
end i
find the minimum distances in each rows of D → [d]
Cost= sum(d)
End
```

Figure 8. Pseudocode of ACO for clustering the Pareto-Front

4. Results

In this section, the results of simulation and their evaluation are discussed in two different parts.

4.1. Model Implementation

In this section, results from modeling the effect of urban land-use change using the NSGA-II will be discussed in detail and then the results from clustering the solutions in five clusters will be developed along with the solutions.

Investigation of the detailed plan in the selected study area showed that the commercial land-use is in short supply. Therefore, a number of areas were assigned to this land-use to test the efficiency of the model to study the effect of their change on the arrangements of other land-uses. This is shown in Figure 8 as changed parcels.

Figure 9 shows the resultant Pareto-Front of NSGA-II and the clustering solutions with five clusters from the ant colony optimization algorithm in a three- dimensional space. As discussed before, each point on this Pareto-Front may indicate one land-use arrangement and the representative of the middle cluster is the solution with the same weight as the objective function.

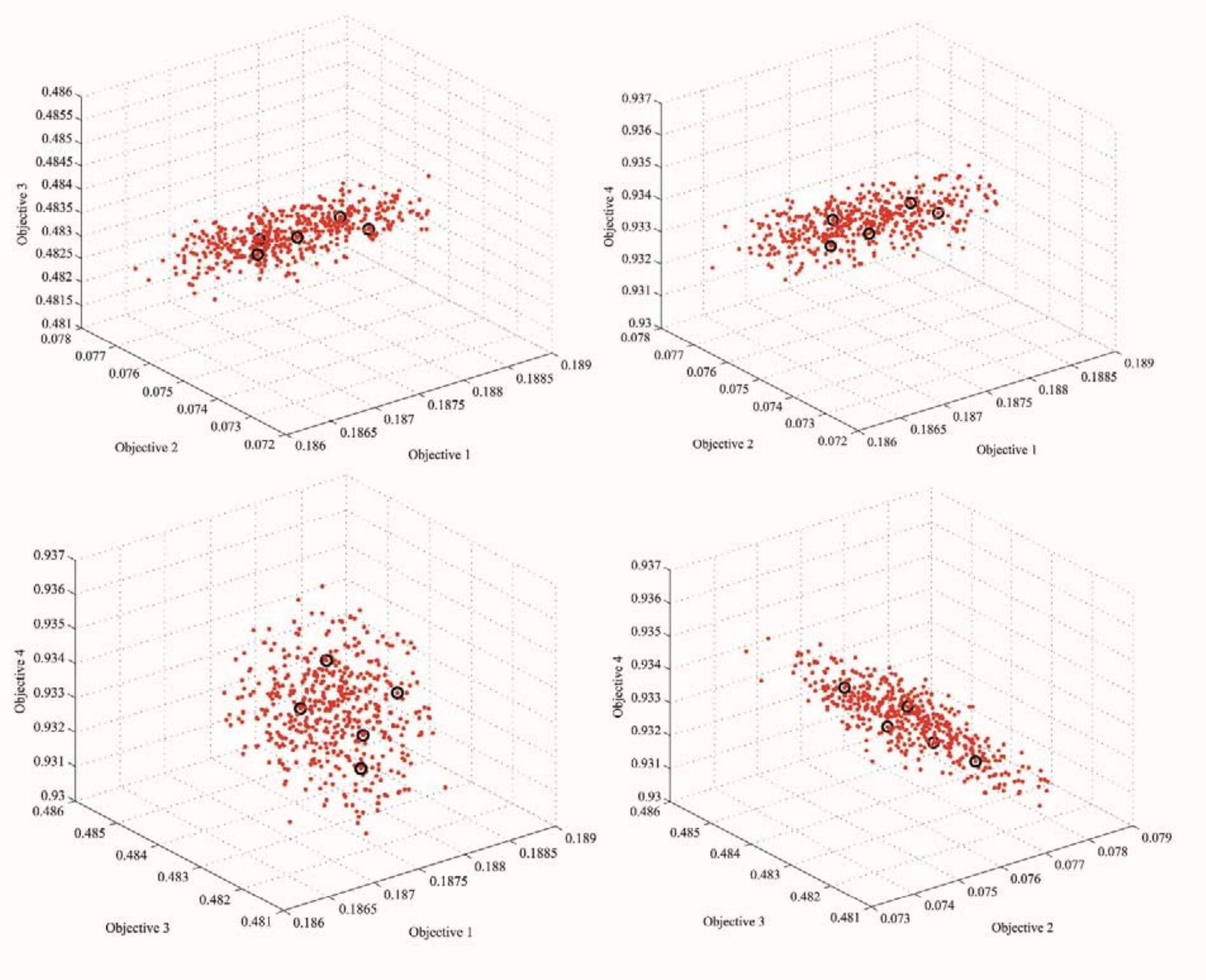

Figure 9. The Pareto-Front solutions produced by the NSGA-II and by clustering the solutions using an ant colony optimization algorithm in a three-dimensional space concerning each objective function (the red points indicate the optimized solutions and the points with black circles indicate the center of the clusters)

Table 6 shows the values of the objective functions in which they have maximum values. As mentioned before, the decision makers usually search the balanced values for all the objective functions. For this reason, a column, the so called 'solution with the same weight of objective functions' was created, which indicates the solution with the median value of any of the four objective functions. As can be seen in Table 6, the solution with the same weight of the objective functions has the highest fractional compensation per-capita (20.2%). This may be because the arrangement is balanced with respect to all the objective functions, so there is no excess in satisfying an individual function.

Table 6. Values of objective functions for cluster centers using the NSGA-II

Objective Function/ Solutions	Cluster center with maximum of the objective function 1	Cluster center with maximum of the objective function 2	Cluster center with maximum of the objective function 3	Cluster center with maximum of the objective function 4	Cluster center with balance value in all objective functions
F_1	0.188	0.185	0.187	0.187	0.187
F_2	0.075	0.078	0.073	0.073	0.076
F_3	0.484	0.482	0.485	0.484	0.482
F_4	0.932	0.932	0.935	0.936	0.934
Percentage of Per-capita demand Compensation	18.8	18.9	19.3	16.5	20.2

Figure 10 also shows the optimized arrangement corresponding to the balanced state of the objective functions (middle cluster) and the changed parcels in the district suggested by the algorithm according to the changes. For ease of understanding, the influence radius of the changed land-uses is also shown in this figure. The number of suggestions to change the land-use in this arrangement was 184, which was less than the other arrangements and 124 solutions among them were in the changed land-use influence radius.

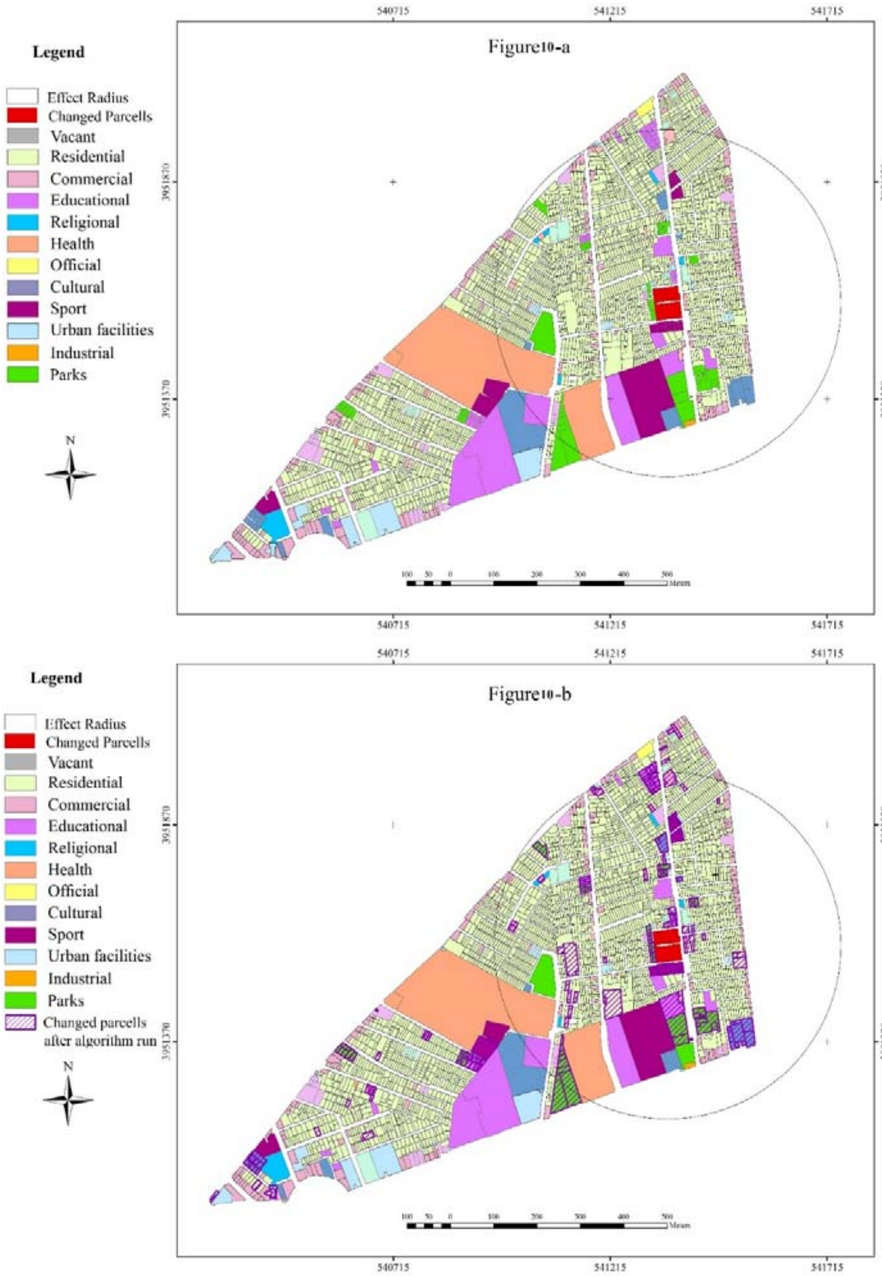

Figure 10. (10-a) Optimized arrangement corresponding to the balanced state of objective functions, and (10-b) changed parcels in the district suggested by NSGA-II, according to the resultant changes and corresponding to the balanced state of the objective functions (changed parcels marked by red color)

Furthermore, two common methods of clustering (i.e., Fuzzy k-means and k-means) were applied to compare the clustering results using the ant colony optimization algorithm. The results were then compared from two points of view, namely, the points of the cluster centers and the speed of implementation. The results showed a complete compliance of cluster centers in the ant colony optimization method with Fuzzy k-Means and discrepancy in one center with respect to the *k*-means method. Nonetheless, the operational speed of the ant colony optimization algorithm was higher than the two mentioned methods. The results of the clustering methods are shown in Figure 9. The fourth cluster center of the ACO method is different from the other two methods, as highlighted in Figure 11 by a green ring.

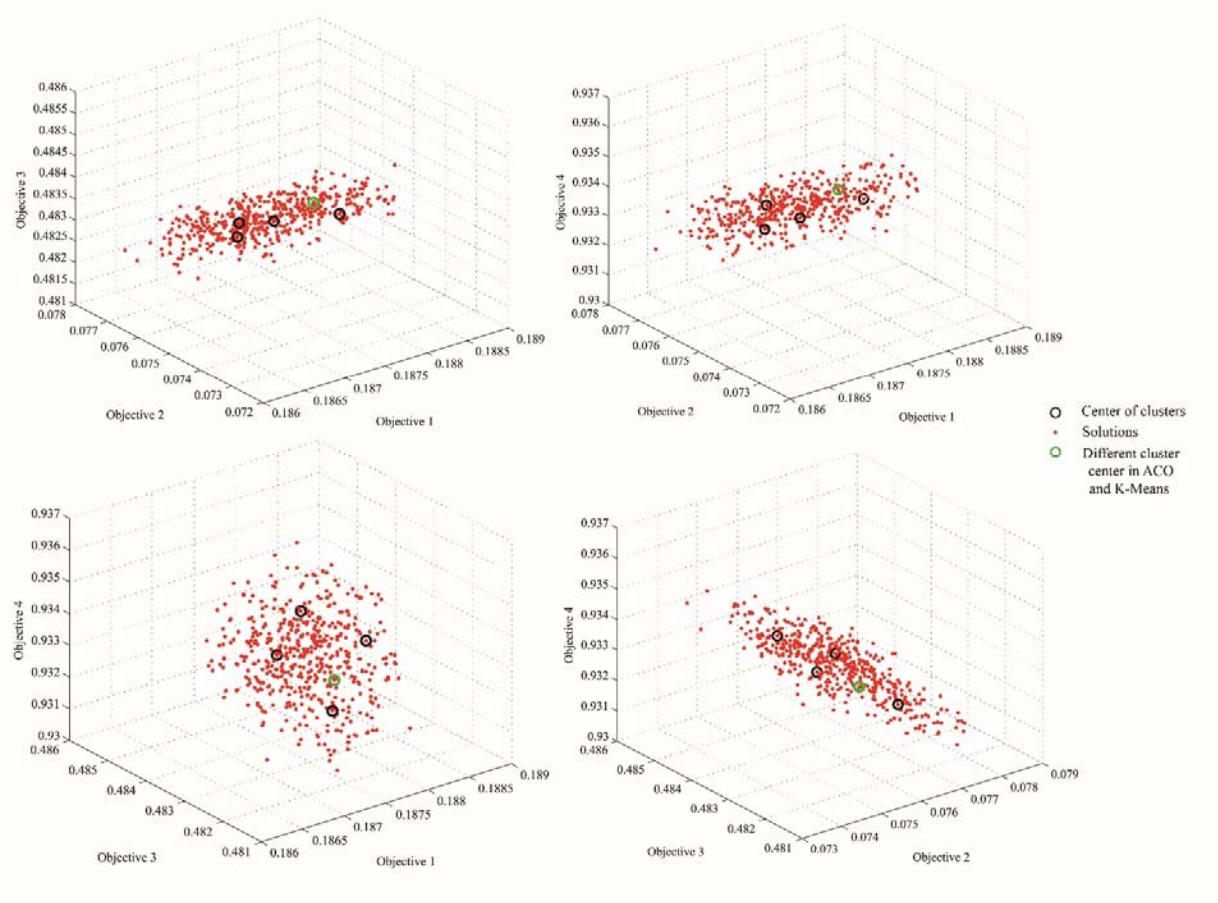

Figure 11. The results of the clustering methods in Pareto-Front solutions. The green ring indicates the cluster center which is different in the ACO method in comparison with other methods

5. Evaluation and Discussion

In the algorithms where the initial population is selected randomly, the results may vary with different runs. Therefore, it is necessary to conduct some tests to determine the stability of these algorithms (Saadatseresht et al., 2009). In this section, the results of the algorithm repeatability test and the algorithm convergence test will be discussed.

5.1. Algorithm repeatability test

To perform this test, the algorithm with an initial population and the same number of iterations was run several times. If the parameter tuning in the algorithm is defined and well-regulated, then in different runs it should produce approximately the same solutions (about 70%). In the present research, the algorithm was tested five times with the initial population of 500 and 500 iterations. Table 7 was produced to study the problem precisely, which shows the percentage of overlap in each run. It can be seen that the percentage of algorithm repetition within five runs was acceptable. The per-capita constraint plays an important role as the dispersion of its solutions can significantly affect the results.

Table 7. Comparison of overlap of the solutions in the five NSGA-II runs

Number of run	Number of compared run	Percentage of overlapping at the solutions
1	2	72
	2	78
	4	84
	5	82
2	3	86
	4	83
	5	85
3	4	73
	5	79
4	5	81

5.2. The algorithm convergence test

The algorithm convergence can be studied from multiple aspects. The most important factor indicating convergence of the algorithm is the consistency of the objective functions, that is, no significant change after a certain number of iterations. While testing the convergence of the model, the maximum change in the values of the objective functions was studied at every 50 iterations. Figure 10 shows the change of the values of every four objective functions at every 50 iterations.

The values of the four objective functions can be improved by increasing the number of iterations as shown in Figure 12. Furthermore, no significant change occurs after nearly 400 iterations. Therefore, it can be assumed that the algorithm reaches sufficient convergence after 400 iterations. Nevertheless, in order to confirm this, 500 iterations were conducted in this research.

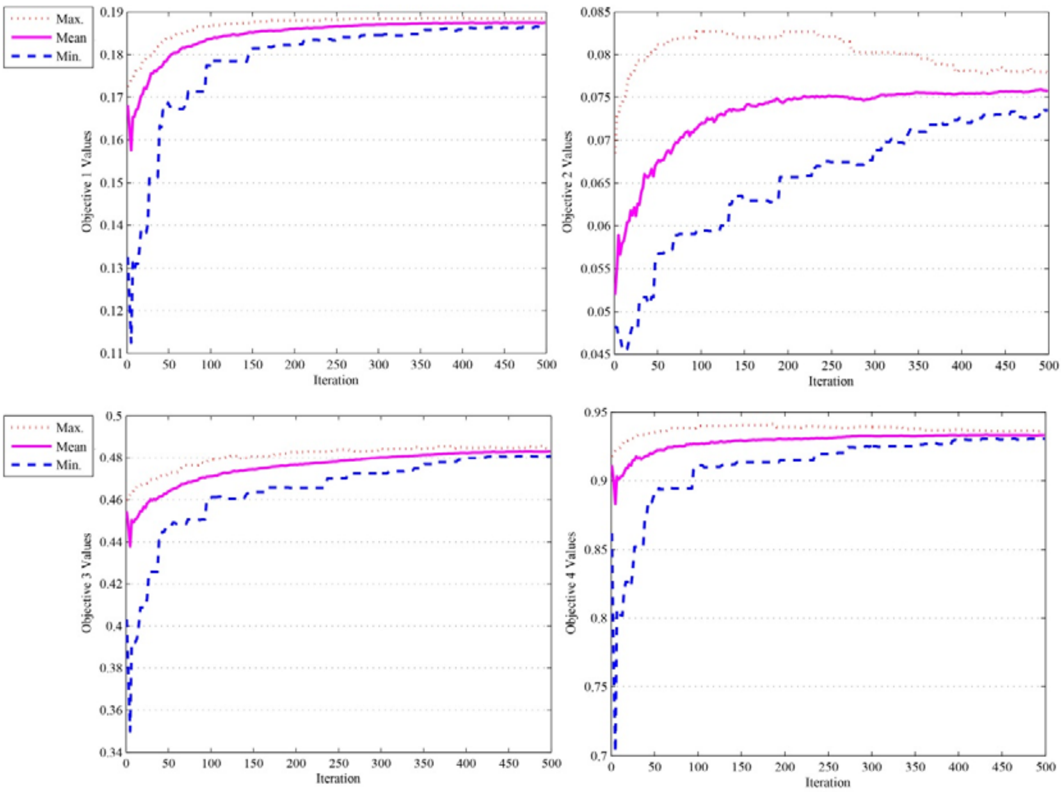

Figure 12. Changing the maximum, mean and minimum values of the four objective functions at every 50 iterations with the NSGA-II

5.3. Comparing the optimized arrangement with the current status

In this part, to evaluate the results, the optimized arrangements after some changes in land-uses were compared with the current arrangement (without any optimization after changes).

Figure 13 shows the values of compensation in per-capita demand after running the optimization algorithm; there is an acceptable level of per-capita demand compensation in these selected solutions. Moreover, Figure 14 shows the changes of main land-use classes for the solution with maximum consistency. The maximum rate of changes is related to parks and vacant places land-use due to the current low per-capita demand in the region for parks. Also, the algorithm has used vacant places land-use for compensation of per-capita demands in some cases, such as parks and sports areas. Furthermore, the resistance to change in the suitability objective function for vacant land-uses is considered low. In addition, regarding the number of changed parcels in the whole case study area and in the effect radius (see Figure 15), most changes occur in the effect radius, illustrating the effect of distance in the algorithmic process.

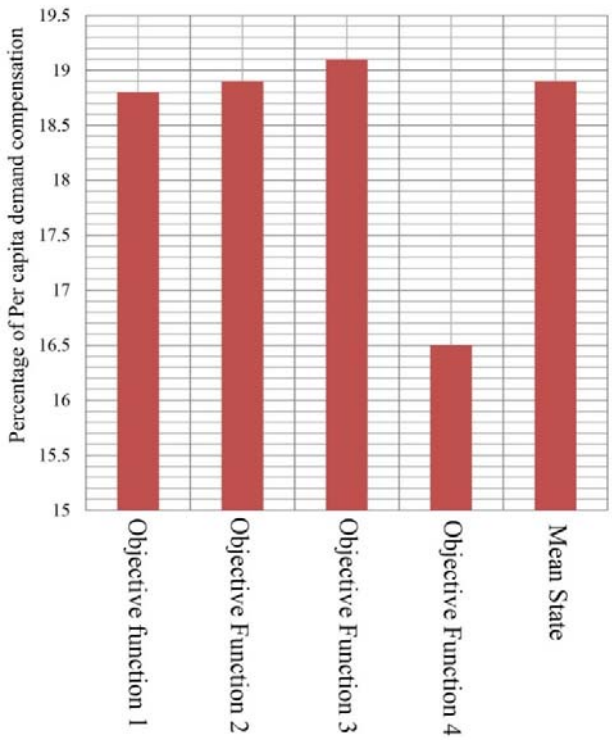

Figure 13. Compensation in per-capita demand after running the optimization algorithm

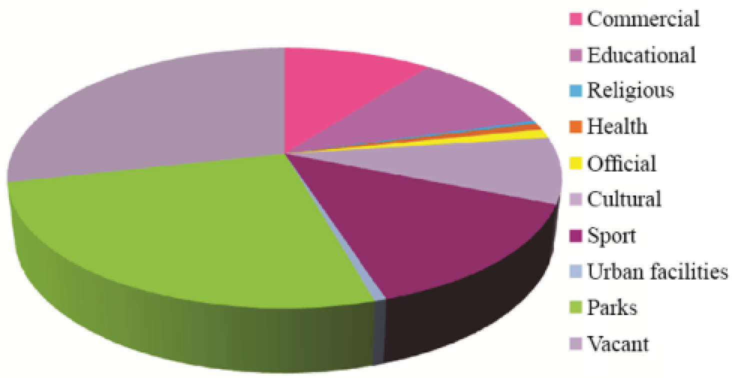

Figure 14. Changes in main land-use classes for the solution with maximum consistency

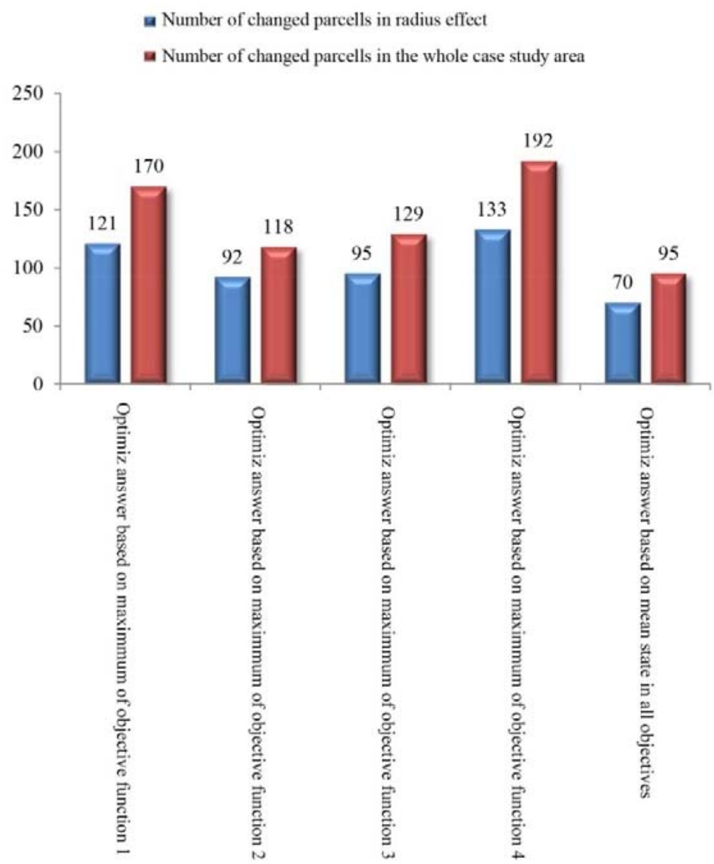

Figure 15. Number of changed parcels in the whole area and in the effect radius

5.4. Comparing NSGA-II and MOPSO

We present here the comparison of the results produced by NSGA-II and MOPSO. Figure 16 shows the Pareto-Front of 5 objective functions for MOPSO in 3D mode. It is important to say that the initial population and its size as well as also the number of iterations for this figure are the same as those used for the NSGA-II.

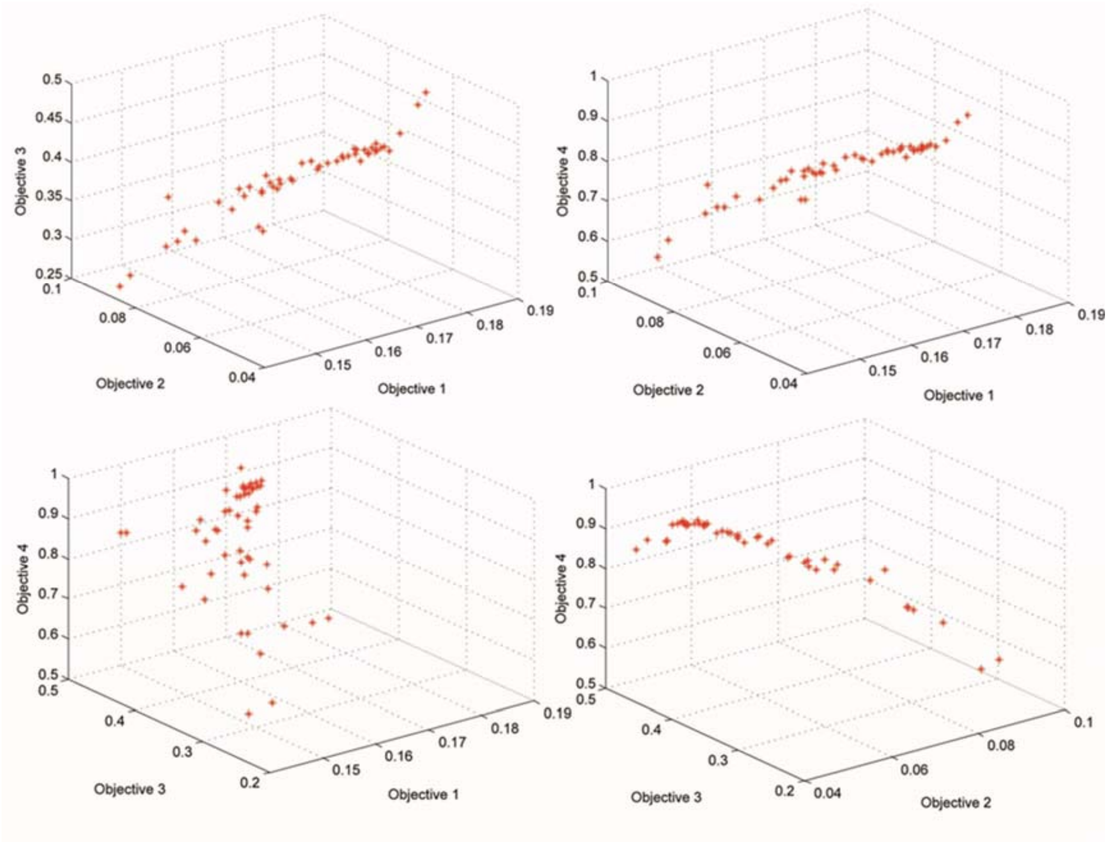

Figure 16 -Three-dimensional visualizations of Pareto-front for MOPSO related to 5 objective functions

Table 8 shows the comparison of results between NSGA-II and MOPSO adopting the performance measures previously indicated.

As seen in Table 8, The *SM* in NSGA-II is better than that of MOPSO. This can show the effect of using the crowding distance concept and the high number of solutions in the Pareto-Front of NSGA-II. In contrast, *DM* in MOPSO has better results. It means that MOPSO searched the space better than NSGA-II.

Table 8 - Comparison of NSGA-II and MOPSO using Spread and Diversity Measures.

Algorithm	The number of solutions in the Pareto-Front	SM	DM
NSGA-II	500	0.00933	0.64507
MOPSO	48	0.99303	0.81494

Additionally, the Quality Measure of NSGA-II is better than that of MOPSO (the ratio is 0.81394). This may be due to the use of a discretizing procedure in MOPSO rather than handling the problem as a discrete one (as done with NSGA-II).

5.4. Urban planner's evaluation of the proposed method

The main users of urban plans are urban designers and planners, so, five experts who work in the municipality were consulted to assess the advantages and disadvantages of the proposed method and to compare it with the current workflow in the study of parcel changes. Currently, the workflow to make decisions about parcel changes in municipalities in Iran is as follows: first, the possibility of change is checked considering current rules and some physical properties of land, including area, and accessibility in local scale. Then, quantified criteria, such as per-capita demand and density, are computed after change, correspondingly qualified criteria, like traffic, social and economic conditions, consistency, as well as dependency are approximated on the neighborhood scale. If the change of land-use is considered to make an acceptable level of alteration in criteria, then the change would be accepted.

The experts' opinions regarding the advantages and disadvantages of the proposed model are outlined below:

Advantages

- Possibility of calculating if the required parameters exist, for instance, the negative or positive effect of consistency, dependency and suitability.
- It is feasible to see the results of change in the arrangement of other land-uses and the number of affected parcels.
- Investigation of changes in criteria in the influence radius is accessible.
- Allows the real shape of land parcels to be considered.

Disadvantages

- Social and economic parameters are ignored as direct parameters. It is obvious that some social parameters are considered in the dependency parameter, but some analyses are necessary to evaluate economic and social concerns.
- Modeling is conducted in a region and some local interactions are missing.

6. Conclusion

Considering the dynamic nature of urban areas and, consequently, urban land-uses, this study proposes a novel approach for dynamic optimization of urban land-use plans when some changes occur in land-uses. This model has the ability to compute changes in physical criteria, such as consistency, dependency, suitability and compactness, suggesting arrangements using an optimization algorithm.

NSGA-II as a multi-objective optimization algorithm is also capable of modeling the complexity of optimizing an urban land-use management problem. The problem is solved using vector data, which is associated with some difficulties in the implementation, but it is near to the reality of an urban structure. After all, since a multi-objective evolutionary algorithm generates several solutions, the selection and clustering of these solutions by employing an ACO algorithm allows decision makers to select those that best match their priorities from the many produced by the multi-objective optimization algorithm. The performance of the proposed model could be improved by a further study of the dynamics of land-use assignment and the effects of land-use change.

Acknowledgments

The second author gratefully acknowledges support from CONACyT grant no. 2016-01-1920 (Investigación en Fronteras de la Ciencia 2016)..

Compliance with ethical standards

Conflict of interest Authors declare that they have no conflict of interest.

Human and animal rights This article does not contain any studies with human participants or animals performed by the authors.

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