Journal of Urban and Environmental Engineering, v.10, n.1, p.42-49

ISSN 1982-3932
doi: 10.4090/juee.2016.v3n1.042049

Journal of Urban and Environmental Engineering

www.journal-uee.org

MULTI-OBJECTIVE LAND USE OPTIMIZATION THROUGH PARALLEL PARTICLE SWARM ALGORITHM: CASE STUDY BABOLDASHT DISTRICT OF ISFAHAN, IRAN

Alireza Sahebgharani*

Department of Urban Planning, Faculty of Architecture and Urban Planning, Art University of Isfahan

Received 26 November 2015; received in revised form 16 May 2016; accepted 18 June 2016

Abstract: Land use planning seeks to divide land, the most valuable resource in the hands of planners, among different land types. During this process, various conflicting objectives are emerged which land use planners should prepare land use plans satisfying these objectives and deal with a large set of data and variable. For this reason, land use allocation is a multi-objective NP-hard optimization problem which is not solvable by the current exact methods. Therefore, solving land use optimization problem relies on the application of meta-heuristics. In this paper, a novel meta-heuristic named parallel particle swarm is developed to allocate seven land types (residential, commercial, cultural, educational, medical, sportive and green space) to Baboldasht district of Isfahan covered by 200 allocation cells with size 1000 m^2 for maximizing compactness, compatibility and suitability objective functions. Afterwards, the outputs of the new developed algorithm are compared to the outputs of genetic algorithm. The results demonstrated that the parallel particle swarm is better than genetic algorithm in terms of both solution quality (1.35%) and algorithm efficiency (63.7%). The results also showed that the outputs achieved by both algorithms are better than the current state of land use distribution. Thus, the method represented in this paper can be used as a useful tool in the hands of urban planners and decision makers, and supports the land use planning process.

Keywords: Particle swarm algorithm; genetic algorithm; multi-objective optimization; land use allocation; Baboldasht district of Isfahan

* Correspondence to: Alireza Sahebgharani, Tel.: +98 91 3288 0336. E-mail: a.sahebgharani@aui.ac.ir

INTRODUCTION

All of land use planning processes contain allocation module which fosters distributing different land types between land units based on a wide range of conflicting objectives. In the allocation process, the task of planners is to make a consensus among these conflicts according to the allocation constraints (i.e. available land, minimum and maximum of land use requirement, etc.) and the priority of each. Therefore, land use allocation is a multi-objective optimization problem deals with a large set of data and variable which puts it into the category of NP-hard problems.

For the above reasons, solving land use optimization problem relies on the application of meta-heuristics and various researches had been assigned to adapt these algorithms with the framework of the land use optimization problem (Simulated Annealing: (Aerts & Heuvelink, 2002; Duh & Brown, 2007; Santé-Riveira *et al.,* 2008); Tabu-Search: (Qi *et al.,* 2008); Genetic Algorithm (GA): (Cao *et al.,* 2011; Cao *et al.,* 2012; Holzkämper & Seppelt, 2007; Janssen *et al.,* 2008; Karakostas & Economou, 2014; Matthews, 2001; Stewart *et al.,* 2004; Xiao *et al.,* 2002; Zhang *et al.,* 2010); Particle Swarm: (Liu, Lao, *et al.,* 2012; Masoomi *et al.,* 2013); Ant Colony: (Liu, Li, *et al.,* 2012); and Bee Colony (Yang *et al.,* 2015)). Reviewing these researches show that although various algorithms adapted and examined by scholars for land use allocation, a slight part of the literature was dedicated to develop particle swarm based algorithms (PSO), and parallelizing particle swarm algorithm (PPSO) has not yet been considered. Thus, the main objectives of this paper are to develop a new particle swarm based algorithm, and to examine its efficiency and quality in practice and in comparison to a common population-based meta-heuristic, GA.

Concisely, the main contributions of this paper in both theoretical and technical aspects are: developing a novel meta-heuristic for tackling the land use optimization problem, developing a new mutation operator and a termination criterion, applying the proposed algorithm in practice, and comparing the results of the new developed algorithm with the results of GA.

In this paper, firstly, the multi-objective land use optimization problem is modeled. Secondly, PSO and PPSO are completely described. Thirdly, model specifications including data requirements and assumptions are represented. Fourthly, the PPSO is performed on the study area and the results are represented and compared with GA. Finally, the conclusions are drawn.

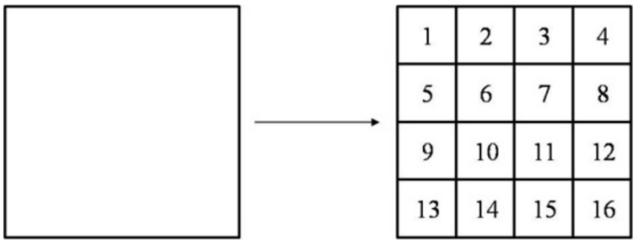


Fig. 1 Method for transforming continuous variable, land, to discrete variable.

MATERIALS AND METHODS

Formulation of multi-objective land use optimization problem

Formulating an optimization problem generally contains three main steps: defining decision variable(s), defining objective function(s) and defining problem constraint(s). According to these steps, formulation of the multi-objective land use optimization problem is represented as follows.

Land is a continuous variable, but land use allocation needs discrete variable. Thus, it is necessary to define a method in which the continuous variable transforms to discrete variable. A simple method is to cover the study area by a grid each part of which is a square with the same size. In this method, each square can be marked by indicating its location number in the grid **Fig. 1**.

Based on the above mentioned method, the decision variable is defined as x_{ij} where j is the land type allocated to cell i. It must also be noted that x_{ij} is a binary variable adopted value 1 if land type j allocated to cell i and 0 otherwise.

After defining decision variable, it is time to formulate objective functions. In the literature of land use optimization, context-based and suitability-related objectives were broadly indicated (Balling *et al.,* 1999; Cao *et al.,* 2012; Chandramouli *et al.,* 2009; Duh & Brown, 2007; Karakostas & Economou, 2014; Liu, Lao, *et al.,* 2012; Liu, Li, *et al.,* 2012; Liu *et al.,* 2013; Masoomi *et al.,* 2013; Santé-Riveira *et al.,* 2008; Stewart *et al.,* 2004; Wang *et al.,* 2004; Xiao *et al.,* 2002). These functions were often slope, elevation, land price and distance-related factors (e.g. distance from urban center, arterial roads, etc.). In this paper, three objectives: suitability maximization, compactness maximization and compatibility maximization are selected based on two criteria: data availability and repetition in previous researches. Suitability was formulated through **Eq. (1)** where $suit\_val_{ij}$ is the suitability value of cell i for land type j derived from suitability analysis for each land type, n is the number of allocation cells and m is the number of land types.

$$f_1 = \max\left(\sum_{i=1}^{n}\sum_{j=1}^{m} suit\_val_{ij} \times x_{ij}\right) \tag{1}$$

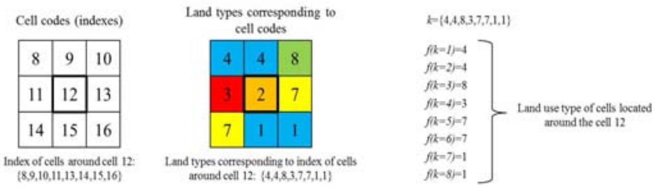


Fig. 2 Process of determining land types of surrounding cells.

Compatibility was modeled in **Eq. (2)** where k is the set including land type of cells around cell i (i.e. if $k=\{5,4,1,7,3,6,6\}$, $f(k=5)$ will be equal to 3 **Fig. 2**), and $compatibility\_val_{j,f(k)}$ derived from pre-defined compatibility matrix is compatibility value between land type j and land type $f(k)$.

$$f_2 = \max\left(\sum_{i=1}^{n}\sum_{j=1}^{m}\left(x_{ij}\times\sum_{k=1}^{8} compatibility\_val_{j,f(k)}\right)\right) \quad (2)$$

Compactness was formulated through **Eq. (3)** where $x_{f(k)}$ is a binary variable represented as: $\begin{cases} if, f(k=1:8)=j, x_{f(k)}=1 \\ otherwise, x_{f(k)}=0 \end{cases}$. $f(k)$ is calculated similar to the process shown in **Fig. 2**.

$$f_3 = \max\left(\sum_{i=1}^{n}\sum_{j=1}^{m}\left(x_{ij}\times\sum_{k=1}^{8} x_{f(k)}\right)\right) \quad (3)$$

It is blatant that land use optimization is a multi-objective problem in which the measurement scale of each objective is different from the others. Thus, it is necessary to standardize and combine values of objectives during the optimization process. There are various methods for this purpose (e.g. weighted sum method: (Porta *et al.,* 2013; Yang *et al.,* 2015), goal programming: (Cao *et al.,* 2012; Stewart *et al.,* 2004) and fuzzy goal programming: (Chang & Ko, 2014). In this paper, the goal programming method represented in **Eq. (4)** is applied.

$$f_{total} = \sum_{o=1}^{O}\left(w_o \times \left(1-\frac{f^{\max}-f^{o}}{f^{\max}}\right)\right) \quad (4)$$

Two constraints were considered in this research. The first constraint represented in **Eq. (5)** certitudes that the area of each land type does not breach the pre-defined maximum and minimum land requirement boundaries.

$$\min\_required_j \le \beta \times \sum_{i=1}^{n}\sum_{j=1}^{m} x_{ij} \le \max\_required_j \quad (5)$$

The second constraint represented in **Eq. (6)** certitudes that one and only one land type allocates to each allocation cell.

$$\sum_{j=1}^{m} x_{ij} = 1, x_{ij} \in [0,1], \forall j = 1,..,m; \forall i = 1,...,n \quad (6)$$

Development of PSO and PPSO algorithms

PSO algorithm has developed by Kennedy and Eberhart in 1995 (Eberhart & Kennedy, 1995). The main concept of this algorithm was derived from the behavior of animal groups such as swarms and fishes. In PSO, solution space is randomly searched by the position vector of some particles. Movement of the particles consists of a random and a deterministic component. Although particles tend to move randomly, they attract to the best global position. In the process of particle's movement, if a particle finds a better solution than its previous positions, the new position will be updated as the best position of the particle. This process iterates for all particles until a pre-defined termination criterion is met. Then, the best position of each particle is determined, the best position between the best positions of particles is selected, and all particles try to reach to this selected position. During this process, more parts of the solution space will be searched and the probability of finding the global optima will be increased. All of these steps iterates until the meeting of the termination criterion. The general structure of PSO is represented in **Table 1**.

The general structure of PSO is not appropriate for solving land use optimization problem. Therefore, in this paper, this structure is modified before developing PPSO algorithm. In single PSO algorithm, at first, an initial solution (also called land use plan and land use layout) satisfying the problem constraints is generated.

Table 1. General structure of PSO algorithm (Bashiri & Karimi, 2010)

Begin
Objective function $f(x)$, $x = (x_1,\ldots,x_p)^T$
Initialize locations x_i and velocity v_i of n particles.
Initialize maximum $f_{max}^{t=0} = max(f(x_1),\ldots,f(x_n))$ (at $t = 0$)
while (criterion)
$t = t + 1$
  for loop over all n particles and all p dimensions
    Generate new velocity v_i^{t+1} using $v_i^{t+1} = v_i + \alpha\varepsilon_1 \otimes [g^* - x_i^t] + \beta\varepsilon_2 \otimes [x^* - x_i^t]$
    Calculate new locations $x_i^{t+1} = x_i^t + v_i^{t+1}$
    Evaluate objective function at new locations x_i^{t+1}
    Find current maximum f_{max}^{t+1}
  end for
  Find the current best x_i^* and current global best g^*
end while
Output the results x_i^* and g^*
End

At second, several particles, various layouts of initial solution, are developed. At third, for each particle two different land uses are randomly selected and swapped and the value of f_{total} is calculated. It should be indicated that the swapping process, which performs like a local search algorithm, iterates according to the criterion defined by the planner. At third, the best position of each particle, the layout which has the best value of f_{total}, is determined and the best of the best positions is selected. Then, all of particles try to have the similar position with the position of the best particle. In land use allocation case, it means that in each particle the land use(s) of some allocation cells became similar to the land use(s) of the allocation cells in the best particle determined in the previous step. This process iterates until the termination criterion is met. **Figure 3** shows the modified process of single PSO algorithm.

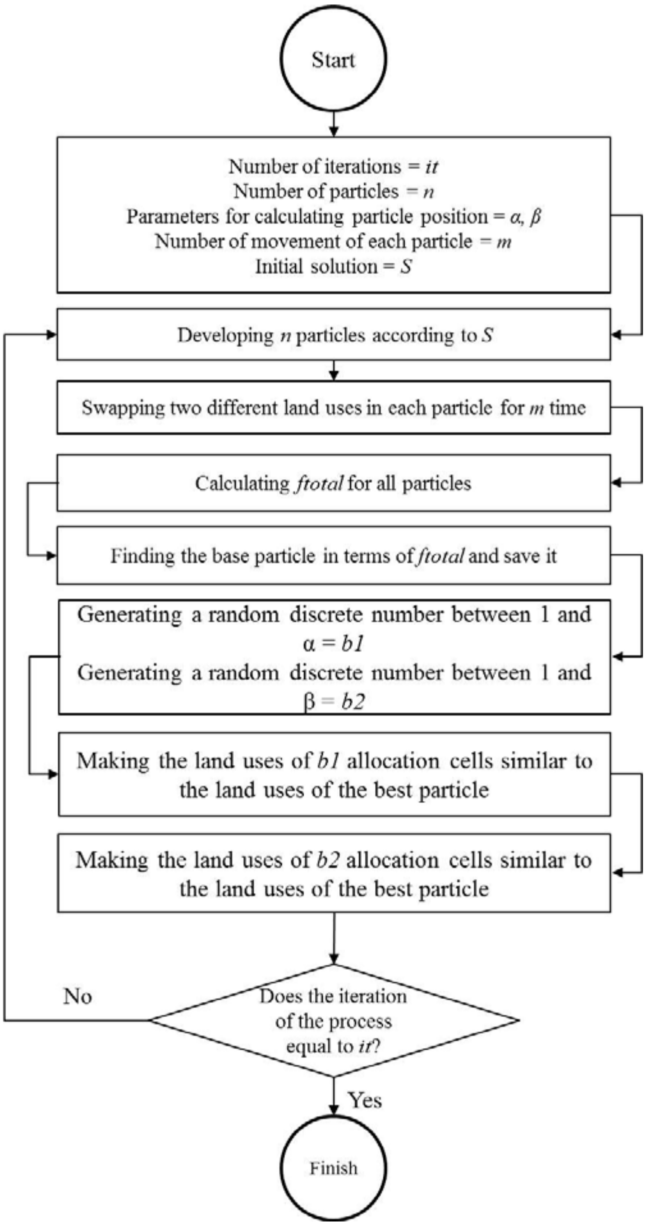


Fig. 3 Modified single PSO algorithm.

In contradiction to PSO which focuses on searching the solution space by a single algorithm, PPSO divides the solution space into several parts, searches each part separately by a single algorithm, and share the outputs between single PSOs for reaching better solutions. The PPSO developed in this paper starts with generating n solutions satisfying the problem constraints. Then, each solution is improved by a single PSO with pre-defined parameters (i.e. number of iterations, number of particles, etc.). These solutions constitute a new solution set which is applied for making the next generation, a set including n solutions. For making new solution set, at first, two different random solutions are selected from the set of improved solutions. There are different methods such as tournament selection and Baltzman coefficient (Fattahi, 2011) for solution selection. In this paper, a well-known method called roulette wheel is adopted and its working process is shown in **Fig. 4**.

Afterwards, the selected solutions are combined by crossover operator to increase the diversity of solutions. There are various crossover operators in the literature of optimization (one point, two points, uniform, three parents and ordered crossovers (Fattahi, 2011). In this research, the uniform crossover operator shown in **Fig. 5** was considered.

As the outputs of the uniform crossover operator may not satisfy the problem constraints, a mutation operator called constraint modifier mutation operator (CMO) was defined. **Table 2** shows the process of CMO.

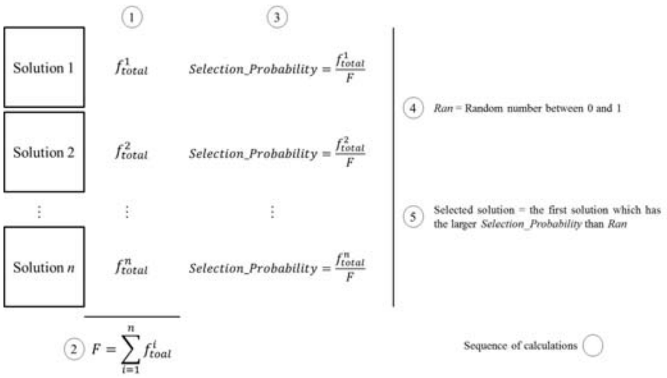


Fig. 4 Roulette wheel method.

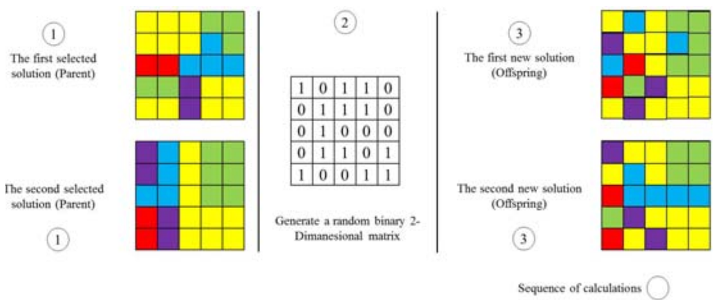


Fig. 5 Uniform crossover.

Table 2. Process of constraint modifier mutation operator

Begin
set *constraint*_set = $\begin{pmatrix} 1 & 2 & \cdots & n \\ nt_{21} & nt_{22} & \cdots & nt_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ nt_{i1} & nt_{i2} & \cdots & nt_{in} \end{pmatrix}$; (*n* is the land types and nt_{in} is the number of cells in type *n* in existing acceptable constraint *i* in constraint set.
set *land_use_plan* = solution outputted from crossover process
set *counted_land_types_in_solution* = $\begin{pmatrix} 1 & 2 & \cdots & n \\ nlt_1 & nlt_2 & \cdots & nlt_n \end{pmatrix}$; (*n* represents all land types and nlt_n is the counted number of land uses in the land use plan)
set *j = 0*
Calculate:
for *k = 1:i*
  set *j = j+1*
  set *minus_constrain_set* = set *minus_constrain_set* = $(nt_{k1} \;\; nt_{k2} \;\; \cdots \;\; nt_{kn}) - (nlt_1 \;\; nlt_2 \;\; \cdots \;\; nlt_n)$
  set *new_solution(k,j)*= $|minus\_constrain\_set|$ (|| is absolute value of all arrays of the *minus_constrain_set*)
end for
set *summation* = sum(*new_solution*) (summation will be done for each column of *new_solution*)
set *min_summation = min(summation)*
set *min_constraint_index* = find(*summation* == *min_summation*)
if members of *min_constraint_index > 1*
  selected_constraint = random(*min_constraint_index*)
end if
shortage_extra_land_type = all arrays in row *selected_constraint* in *new_solution* (i.e. $\begin{pmatrix} 1 & 2 & \cdots & n \\ nt_{s1} & nt_{s2} & \cdots & nt_{sn} \end{pmatrix}$)
while all arrays in *shortage_extra_land_type* matrix will be equal to 0 **do**
  a1 = select a random array from second row of *shortage_extra_land_type* matrix with value larger than 0
  b1 = shortage_extra_land_type(1,a1)
  a2 = select a random array from second row of *shortage_extra_land_type* matrix with value smaller than 0
  b2 = shortage_extra_land_type(1,a2)
  change_index = find a random array in *land_use_plan* with type *b1*
  set land use type of *change_index* equal to *b2*
  set *a1 = a1-1*
  set *a2 = a2+1*
end while

The above steps iterate until the size of the new generation will be equal to *n*. All of these processes iterate while the termination criterion is met. Termination criterion considered in this paper is represented in **Table 3**. **Figure 6** shows the process of PPSO.

Study area

Baboldasht district of Isfahan is located at the southern part of the Isfahan's 7th municipality zone. It has 20 hectares, 928 lots, 873 residential units and 3492 population respectively (**Fig. 7**).

Table 3. Termination criterion

Iterate the PPSO for q times
If the best value of generations does not improve after 4q/5
  for k (k is equal to the n/2)
    select two random solutions by roulette wheel
    perform uniform crossover to generate two new solutions
    perform CMO operator
    save solutions
  end for
end if
if the best value of the new generation is better than the best value of the other previous generations
  iterate PPSO for q times
else
  stop the algorithm
end if

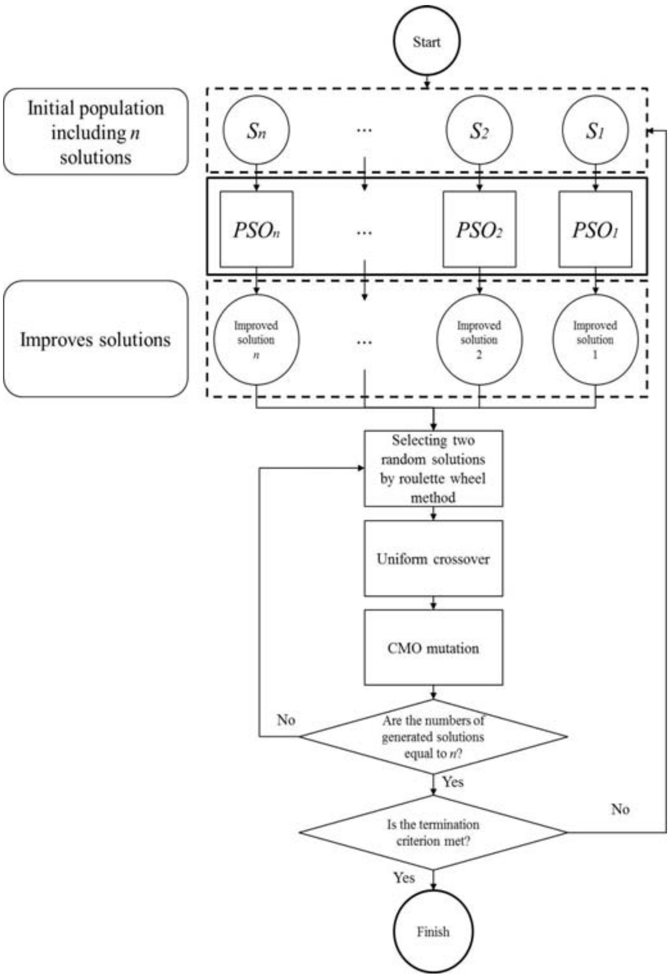


Fig. 6 Process of PPSO.

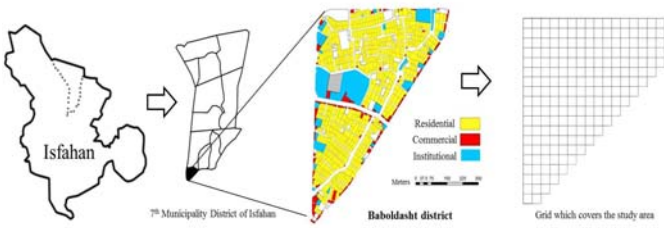


Fig. 7 Study area.

Baboldasht is one the unsustainable districts of Isfahan and suffers from the physical, economical and infrastructural shortages (Nastaran *et al.,* 2014), and also suboptimal distribution of land uses (Mohammadi *et al.,* 2015). Besides of these issues, because of the logical number of allocation cells covering this district, Baboldasht was selected as the context of implementing the developed algorithm.

Data and assumptions

Data and assumptions are as follows. Seven land types: Residential, commercial, medical, educational, cultural, sportive and green spaces were considered for allocation in the study area.

The area of each allocation cell was defined equal to 1000 m^2. Therefore, the study area was covered by 200 allocation cells.

Land use requirements were calculated according to **Table 4**.

Table 4. Minimum and maximum of land use requirements

Land type	Minimum required cells	Maximum required cells
Residential	103	204
Commercial	10	18
Educational	15	20
Medical	1	2
Green space	41	41
Cultural	4	6
Sportive	5	9

In the study area, the only physical factor which affects land suitability is distance from street network and the map of this factor was shown in **Fig. 8**.

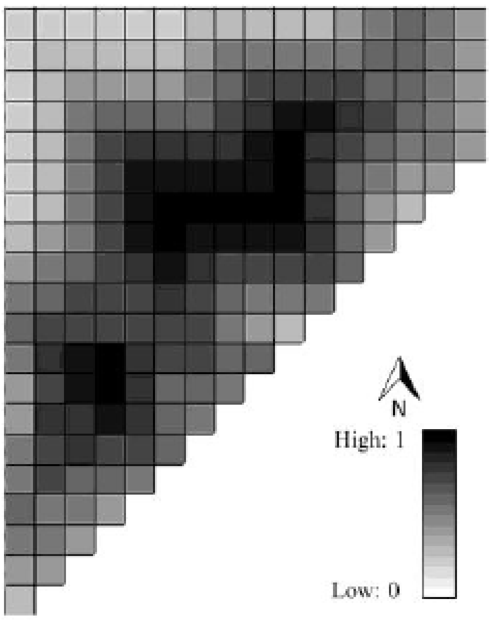


Fig. 8 Distance from street network.

Suitability of each land type was measured by Delphi method (see: Adler & Ziglio, 1996; Skulmoski *et al.,* 2007) with 15 participants. The results were shown in **Table 5**. The parameters of the PPSO was set based on **Table 8**. Compatibility of land uses calculated also by Delphi method is shown in **Table 6**. Weight of objectives used for calculating f_{total} is shown in **Table 7**.

Table 5. Suitability of land types vs. distance from street network

		Suitability value						
		Residential	Commercial	Medical	Educational	Sportive	Green space	Cultural
Distance	0-0.33	1	0.25	0.25	0.5	0.5	0.5	0.5
	0.33-0.66	0.75	0.75	0.5	0.5	0.75	0.75	0.75
	0.66-1	0.5	1	1	1	0.75	1	0.75

Table 6. Compatibility value of land types

Types	Residential	Commercial	Medical	Educational	Sportive	Green space	Cultural
Residential	1	0.5	0.25	0.25	0.5	0.75	0.5
Commercial	0.5	1	0.5	0.75	0.75	1	0.75
Medical	0.25	0.5	1	0.25	0.25	0.75	0.25
Educational	0.25	0.75	0.25	1	0.75	1	1
Sportive	0.5	0.75	0.25	0.75	1	1	0.25
Green space	0.75	1	0.75	1	1	1	1
Cultural	0.5	0.75	0.25	1	0.25	1	1

Table 7. Calculated weights of objective functions

Objective	Compactness	Compatibility	Suitability
Weight	0.717	0.088	0.195

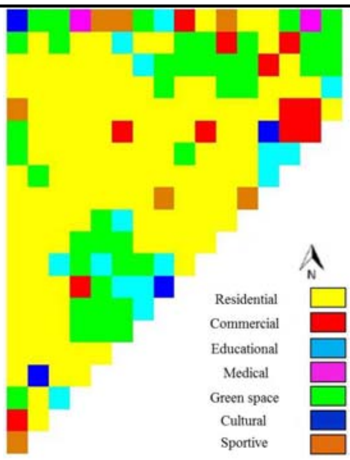
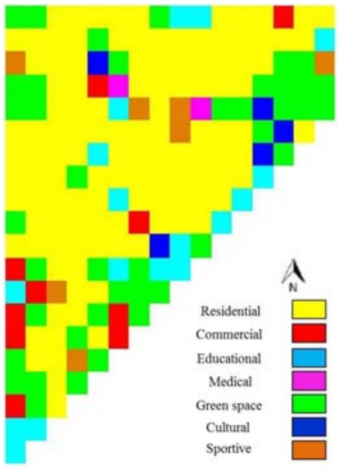
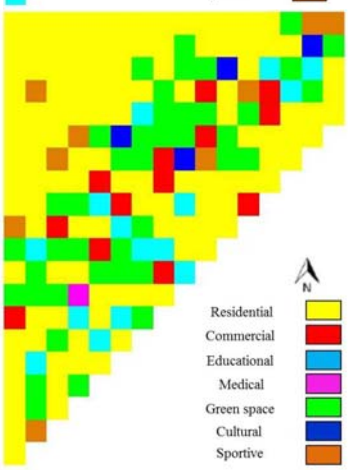
Table 8. Parameters of PPSO

General parameters	Size of population	100
	Number of single PSOs	100
PSO parameters	Number of particles	50
	Number of dual swapping	1
	b1	20
	b2	30
Termination parameters	Q	100
	4q/5	20
	K	50

RESULTS AND DISCUSSION

After data preparation, PPSO was performed on the study area. PPSO was programmed in MATLAB software, and a laptop with CoreTM 2 Duo T9550 @ 2.66 GHz CPU was used to implement it. The algorithm was firstly applied to optimize single objectives for preparing the ground of calculating f_{total} (**Table 9**).

Table 9. Results of PPSO for optimizing single objectives

Objective	Objective's value	Land use plan
Compactness	826	
Compatibility	1097	
Suitability	162.5	

The final output which represents the optimum spatial land use distribution with considering all objectives was shown in **Table 10**.

Table 11 represents the comparison between the results of GA, PPSO and the current state of land use distribution in the study area.

As **Table 11** shows, the best results were generated by PPSO algorithm. Deviation from the ideal value of the f_{total} (f_{total} = 1) was equal to 11.64, 34.6 and 63.5 percent for PPSO, GA and the current state respectively. Comparing the results also showed that the quality of solution and convergence time of PPSO were 1.35% and 63.7% better than the outputs of GA. In addition, the quality of solution achieved from GA was 79.9% better than the current state.

Table 10. Final result of PPSO

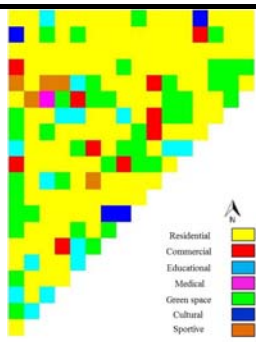
Land use plan	
Value of f_{total}	0.8836
Convergence time (h)	1.92

Table 11. Comparison between GA, PPSO and the current state of land use distribution in the study area

	PPSO	GA	Current state
Convergence time (h)	1.92	5.3	—
Value of f_{total}	0.8826	0.6541	0.364

CONCLUSION

In this paper, a new algorithm is developed based on parallelizing PSO algorithm for solving the multi-objective land use optimization problem with three objectives, seven land types and two constraints. The developed algorithm was performed on a real study area and the outputs were compared with GA, a common population-based meta-heuristic. The innovations of this research were developing a novel algorithm for facilitating the process of land use planning, developing a new mutation operator, and defining a new termination criterion. The main conclusions are:

(i) Both quality and convergence time of PPSO is better than GA.
(ii) The results of PPSO and GA are better than the spatial land use distribution of the current state.
(iii) The algorithm and method represented in this paper can be used for land use prescription and analysis.

(iv) The algorithm proposed in this paper can develop and analyze numerous and various land use plans and support the land use planning process.

REFERENCES

Adler, M. & Ziglio, E. (1996) *Gazing into the oracle: The Delphi method and its application to social policy and public health*: Jessica Kingsley Publishers.

Aerts, J. C. & Heuvelink, G. B. (2002) Using simulated annealing for resource allocation. *Int. J. Geogr. Infor. Sci.,* **16**(6), 571–587. doi: 10.1080/13658810210138751

Balling, R.J., Taber, J. T., Brown, M. R. & Day, K. (1999) Multiobjective urban planning using genetic algorithm. *J. Urb. Plan. Develop.,* **125**(2), 86–99. doi: 10.1061/(ASCE)0733-9488(1999)125:2(86)

Bashiri, M. & Karimi, H. (2010) *An analytical comparison to heuristic and meta-heuristic solution methods for quadratic assignment problem.* Paper presented at the Computers and Industrial Engineering (CIE), 2010 40th International Conference on.

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. *Int. J. Geogr. Infor. Sci.,* **25**(12), 1949–1969. doi: 10.1080/13658816.2011.570269

Cao, K., Huang, B., Wang, S. & Lin, H. (2012) Sustainable land use optimization using Boundary-based Fast Genetic Algorithm. *Comp. Envir. Urban Sys.,* **36**(3), 257–269. doi: 10.1016/j.compenvurbsys.2011.08.001

Chandramouli, M., Huang, B. & Xue, L. (2009) Spatial change optimization: integrating GA with visualization for 3D scenario generation. *Photog. Engin. Remote Sens.,* **75**(8), 1015-1022.

Chang, Y.-C. & Ko, T.-T. (2014) An interactive dynamic multi-objective programming model to support better land use planning. *Land Use Policy,* **36**(1), 13–22. doi: 10.1016/j.landusepol.2013.06.009

Duh, J.-D. & Brown, D.G. (2007) Knowledge-informed Pareto simulated annealing for multi-objective spatial allocation. *Comp. Envir. Urban Sys.,* **31**(3), 253–281. doi: 10.1016/j.compenvurbsys.2006.08.002

Eberhart, R. C. & Kennedy, J. (1995) *A new optimizer using particle swarm theory.* Paper presented at the Proceedings of the sixth international symposium on micro machine and human science.

Fattahi, P. (2011) *Metaheuristic Algorithms*. Bu-Ali Sina University.

Holzkämper, A. & Seppelt, R. (2007) A generic tool for optimising land-use patterns and landscape structures. *Environ. Model. Soft.,* **22**(12), 1801–1804. doi: 10.1016/j.envsoft.2007.02.008

Janssen, R., van Herwijnen, M., Stewart, T. J. & Aerts, J. (2008) Multiobjective decision support for land-use planning. *Envir. Plan. B, Plan.Design,* **35**(4), 740–756. doi: 10.1068/b33071

Karakostas, S. & Economou, D. (2014) Enhanced multi-objective optimization algorithm for renewable energy sources: optimal spatial development of wind farms. *Int. J. Geogr. Infor. Sci.,* **28**(1), 83–103. doi: 10.1080/13658816.2013.820829

Liu, X., Lao, C., Li, X., Liu, Y. & Chen, Y. (2012) An integrated approach of remote sensing, GIS and swarm intelligence for zoning protected ecological areas. *Lands. Ecol.,* **27**(3), 447–463. doi: 10.1007/s10980-011-9684-1

Liu, X., Li, X., Shi, X., Huang, K. & Liu, Y. (2012) A multi-type ant colony optimization (MACO) method for optimal land use allocation in large areas. *Int. J. Geogr. Infor. Sci.,* **26**(7), 1325–1343. doi: 10.1080/13658816.2011.635594

Liu, X., Ou, J., Li, X. & Ai, B. (2013) Combining system dynamics and hybrid particle swarm optimization for land use allocation. *Ecol. Model.,* **257**(1), 11–24. doi: 10.1016/j.ecolmodel.2013.02.027

Masoomi, Z., Mesgari, M. S. & Hamrah, M. (2013) Allocation of urban land uses by Multi-Objective Particle Swarm Optimization algorithm. *Int. J. Geog. Inf. Sc.,* **27**(3), 542–566. doi: 10.1080/13658816.2012.698016

Matthews, K. B. (2001) *Applying genetic algorithms to multi-objective land-use planning.* The Robert Gordon University.

Mohammadi, M., Nastaran, M. & Sahebgharani, A. (2015) Sustainable Spatial Land Use Optimization through Non-Dominated Sorting Genetic Algorithm-II (NSGA-II):(Case Study: Baboldasht District of Isfahan) *Ind. J. Sci. Techn.,* **8**(S3), 118–129. doi: 10.17485/ijst/2015/v8iS3/60700

Nastaran, M., Ghalehnoee, M. & Sahebgharani, A. (2014) Ranking Sustainability of Urban Districts through Factor and Cluster Analyses, Case Study: Municipal Districts of Isfahan *ARMANSHAHR Archit. Urban Develop.,* **12**(2), 177–189.

Porta, J., Parapar, J., Doallo, R., Rivera, F. F., Santé, I. & Crecente, R. (2013) High performance genetic algorithm for land use planning. *Comp. Envir. Urban Sys.,* **37**(1), 45–58. doi: 10.1016/j.compenvurbsys.2012.05.003

Qi, H., Altinakar, M. S., Vieira, D. A. & Alidaee, B. (2008) Application of Tabu Search Algorithm With a Coupled AnnAGNPS-CCHE1D Model to Optimize Agricultural Land Use. *J. Amer. Water Resour. Assoc.,* **44**(4), 866–878. doi: 10.1111/j.1752-1688.2008.00209.x

Santé-Riveira, I., Boullón-Magán, M., Crecente-Maseda, R. & Miranda-Barrós, D. (2008) Algorithm based on simulated annealing for land-use allocation. *Comp. Geosci.,* **34**(3), 259–268. doi: 10.1016/j.cageo.2007.03.014

Skulmoski, G., Hartman, F. & Krahn, J. (2007) The Delphi method for graduate research. *J. Inf. Tech. Educ.: Res,* **6**(1), 1–21.

Stewart, T.J., Janssen, R. & van Herwijnen, M. (2004) A genetic algorithm approach to multiobjective land use planning. *Comp. Operat. Res.,* **31**(14), 2293–2313. doi: 10.1016/S0305-0548(03)00188-6

Wang, X., Yu, S. & Huang, G. (2004) Land allocation based on integrated GIS-optimization modeling at a watershed level. *Land. Urban Plan.,* **66**(2), 61–74. doi: 10.1016/S0169-2046(03)00095-1

Xiao, N., Bennett, D. A. & Armstrong, M. P. (2002) Using evolutionary algorithms to generate alternatives for multiobjective site-search problems. *Envir. Plan. A,* **34**(4), 639–656. doi: 10.1068/a34109

Yang, L., Sun, X., Peng, L., Shao, J. & Chi, T. (2015) An improved artificial bee colony algorithm for optimal land-use allocation. *Int. J. Geogr. Infor. Sci.,* **29**(8), 1470–1489. doi: 10.1080/13658816.2015.1012512

Zhang, H., Zeng, Y. & Bian, L. (2010) Simulating multi-objective spatial optimization allocation of land use based on the integration of multi-agent system and genetic algorithm. *Int. J. Envir. Res,* **4**(4), 765–776.