# A Fast Particle Swarm Optimization Algorithm for Land-use Allocation

Liu YaoLin[1,2], Peng JinJin[1]

[1] School of Resource and Environment Science, Wuhan University, Wuhan 430079, China
[2] *Ministry of Education Key Laboratory of Geographic Information System, Wuhan University, Wuhan 430079, China*

## 1. Introduction

Land-use allocation is a process of allocating different activities or uses to specific units of area within a geospatial context(Kai, Bo et al. 2011). It is a complex resource allocation problem involving large data, complicated spatial operation and multi-objective balancing.

Some mathematic methods, such as linear programing (LP), integer programing (IP), have been introduced to solving land-use allocating problem. But land-use allocation is always a non-linear, multi-peak, geospatial related problem. In most cases, it is impossible to generating optimal solutions with these mathematic methods if the study area is large and the objectives are complex. So such complicated non-linear multi-objective optimization problems as a type of Non-deterministic Polynomial (NP) hard problem require heuristic methods for executing optimization processes(Kai, Bo et al. 2011).

Heuristic methods have the ability to solve the complicated spatial optimization problems including land-use allocation. And it hardly has any limitations to the form of objectives and constrains. Many land-use allocation models have been developed with the help of heuristic methods such as Simulated Annealing (SA)(Aerts, van Herwijnen et al. 2003), Genetic Algorithm (GA)(Cao, Batty et al. 2011), and Ant Colony Optimization (ACO)(Liu, Li et al. 2012). But these methods have too many parameters so that an appropriate configuration needs better priori knowledge. Also these models suffer from low efficiency, and that makes it inconvenient for decision makers to gain solutions at an acceptable time.

Particle Swarm Optimization (PSO), known as a type of heuristic methods, originated from the simulation of bird flocking by James Kennedy and Russell Eberhart (Kennedy and Eberhart 1995). PSO has good social science background to be understandable and little parameters to be configured. It is widely applied in power system, automatic control, pattern recognition and image processing. PSO is also can be used to solve land-use allocation problem. Hu Fuyu(2012) developed a Discrete Particle Swarm Optimization (DPSO) algorithm for optimal allocation of earthquake emergency shelters. But the allocation problem only involves one use and land-use allocation involves many more uses, which makes it much more complicated. Liu Yaolin(2011) used a PSO algorithm to solve the Multi-Objective of Land-use Allocation(MOLA) problem in a semiarid loess hilly area. However, the model has little constraints for the land-use transition of units, which make some local area with a fragment land-use pattern.

To develop a fast and effective land-use allocation model with PSO algorithm, two major modification have been made in this study. Firstly, a new concept called “combined position” is proposed refer to the traditional concept of “position” in PSO.

With the help of combined position, the model shows a better efficiency than the traditional PSO algorithm. Secondly, a transition rule system has been introduced in the optimization process. Transition rules make sure the land-use change of units to be reasonable and meet the requirements of constraint conditions. Finally, a Particle Swarm Optimization Land-use Allocation (PSOLA) model have been built to assist decision making in Land-use Planning.

## 2. Method

To apply PSO algorithm to optimal land-use allocation, some concepts in the original PSO should be mapped into the actual land-use allocation problem. Particle stands for a candidate solution, which means a land-use planning scheme in land-use allocation problem. Position stands for the current location of particle, which means the current land-use status of units. Velocity stands for the direction of particle, which means the land-use transition possibilities (equation 1) of units.

As shown in the framework of PSOLA (fig. 1), the model executes optimization process as below. An initialization step based on the land-use map executes first of all to generate a set of candidate solutions. Then the particle updates its velocity and position based on the equations (equation 2, 3). And a mutation operation is added additionally after updating to adjust the unreasonable land-use allocation area of the scheme. The particle is evaluated by a fitness function and the local best position of particle (Pbest) and the global best position of swarm (Gbest) are updated based on the fitness value of particle. Finally, if the land-use allocation scheme represented by the particle is good enough, then the algorithm output the best solution. Otherwise, the algorithm should continue iterate until a satisfied solution is generated.

$$v_d = (P_{arable}, P_{garden}, P_{forest}, P_{builtup}, \dots) \tag{1}$$

$$v_{i+1,d} = wv_{id} + c_1 rand()(p_{id} \ominus x_{id}) + c_2 Rand()(p_{gd} \ominus x_{id}) \tag{2}$$

$$x_{i+1,d} = x_{id} \oplus v_{i+1,d} \tag{3}$$

where *d* stands for the *d*th dimension of particle, *i* stands for *i*th generation of the iteration process; *v*, *x* represent the velocity and position of particle; w, c1, c2 are the momentum coefficient, recognise coefficient, social coefficient; rand(), Rand() are the functions that generate random numbers between 0 and 1; *pid*, *pgd* stand for the local best position of particle (Pbest) and the global best position of swarm (Gbest); Symbol $\ominus$ is a learning operator, which acts as the increase of transition possibility to Pbest and Gbest; Symbol $\oplus$ is a status update operator, which determinate a new status of unit.

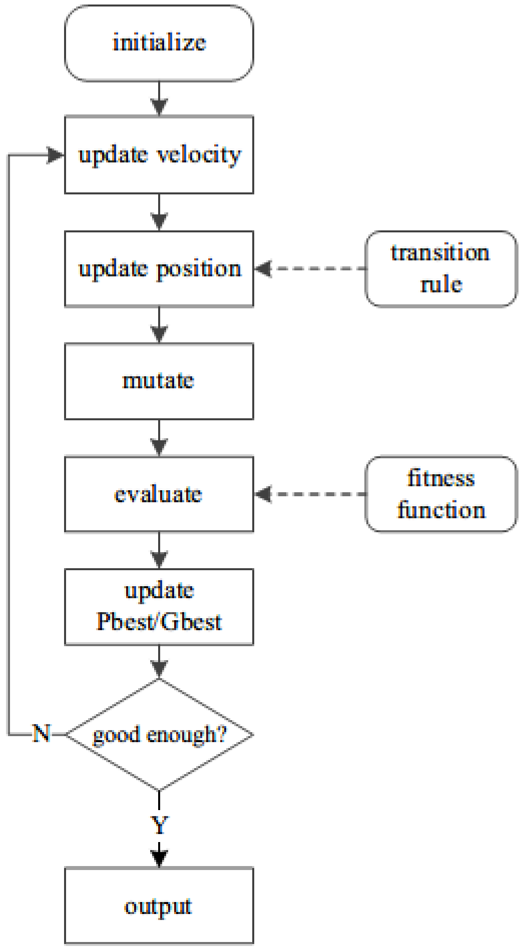

Figure 1. The framework of PSOLA model

### 2.1 Combined position

The position of particle stands for the land-use status of units in the land-use allocation problem. It is usually represented by a single grid cell. However, the single grid cell representation makes the optimization with low efficiency because the computing burden raise exponentially as the number of grid cell increase.

To raise the efficiency of the PSOLA model, the concept of combined position is proposed in this study. The combined position is a package of several single positions, which means a land-use patch (fig. 2) in the land-use allocation problem. With the modification to the position representation, the basic operation unit of the algorithm has become a patch instead of a single cell. And also PSOLA model only allow the boundary cells of the patch changing its land-use status and keep the internal cells unchanged. The combined position representation reduces the quantity of cells involved in computing in each generation of the optimization process. So the model needs less computation than the original PSO algorithm and shows an efficiency raise.

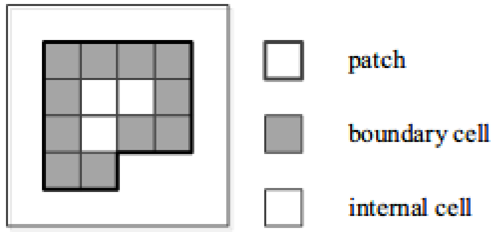

Figure 2. Patch, boundary cell and internal cell

### 2.2 Transition rule

The new location of a position is only determined by its velocity in PSO algorithm. But it is unreasonable to allow units to change its status without limitations because of the fact that the land-use allocation problem always has some constraints to specific units. So a transition rule system based on the constraints has been built in PSOLA model.

The constraint in land-use allocation problem can be classified as attribute constraint and spatial constraint. The attribute constraint is the attribute requirements to units such as slope and soil fertility. This constraint can be easily accomplished with attribute condition judgement in the transition rule system. But the other constraint, the spatial constraint, is more complicated because it involves many types of spatial operation. In the PSOLA model, a dynamic neighbour operation strategy has been introduced to accomplish the spatial constraints. A dynamic neighbour operation searches a variable range of neighbours of the focused cell to achieve distance measurement, buffer analysis, intersection and other types of spatial operation(Tong and Murray 2012).

## 3. Result

The model take a town located in Fuyang city, Zhejiang province in China as study area to verify its efficiency and effectiveness. The land-use map surveyed by the local bureau of land and resources in 2009 was rasterized with 25*25 square meters. The converted land-use raster map consisted of 281736 grid cells and was used as the base map to process other social, economic and natural data refer to the land-use planning. Suitability and compactness were the objectives and the fitness function was constructed by a weighted sum way. The transition rule system was built concerned with the grain for green policy, farming radius constrain, transportation limitation, soil and water conservation requirement. Four models with different strategy have run for 100 iteration with same parameter configuration. The results shows below (table 1, fig. 3).

The result from model A shows the highest fitness value than the other three models. It reveals that the new PSOLA model is capable of solving the land-use allocation problem. Model A with combined position strategy needs less 4.5% time consumption than model C without it, and it reveals that combined position strategy can raise the efficiency of PSO algorithm. A same conclusion can be drawn by comparing the time consumption in model B and model D. Compared with model B without transition rule strategy, model A with it shows a better fitness as well as suitability and compactness. It means that the transition rule strategy is an effective way to guide the algorithm to generate a better solution. This conclusion also recovered from the compare with model C and model D.

From the analysis of the results, it is found that the new PSOLA model is able to solve the land-use allocation problem in a more efficient and effective way. The model can be applied in land-use planning to help decision makers generate various land-use allocation schemes according to different development scenarios.

| Model | Strategy | Suitability | Compactness | Fitness | Time |
|---|---|---|---|---|---|
| A | Combined position Transition rule | 0.479676 | 0.923821 | 0.705299 | 2186 |
| B | Combined position | 0.476910 | 0.915635 | 0.686433 | 2030 |
| C | Transition rule | 0.479201 | 0.923017 | 0.703360 | 2290 |
| D | Basic | 0.476994 | 0.914359 | 0.685167 | 2157 |

Table 1. Results from different models.

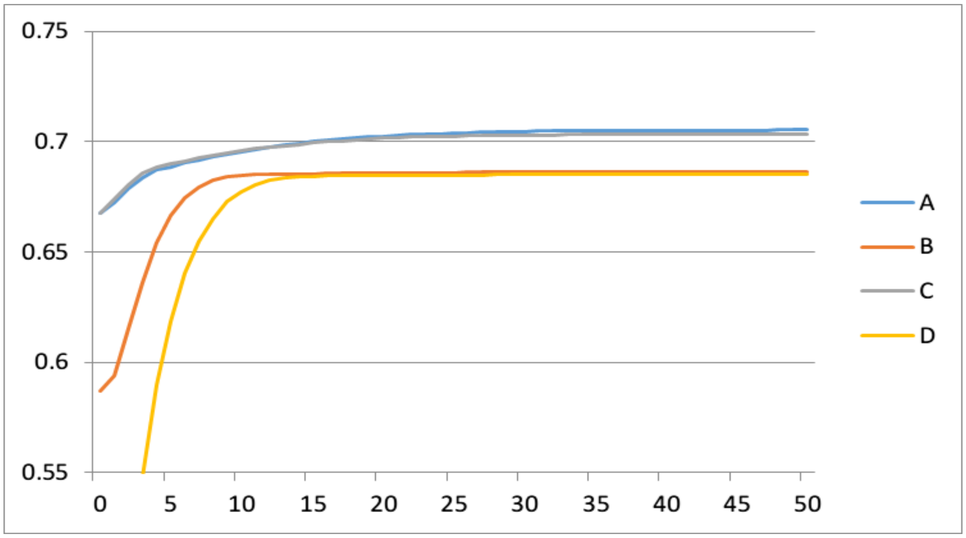


Figure 3. The convergence curves of different model

## 4. References


Aerts, J. C. J. H., M. van Herwijnen and T. J. Stewart (2003). "Using simulated annealing and spatial goal programming for solving a multi site land use allocation problem." Evolutionary Multi-Criterion Optimization, Proceedings **2632**: 448-463.

Cao, K., M. Batty, B. Huang, Y. Liu, L. Yu and J. F. Chen (2011). "Spatial multi-objective land use optimization: extensions to the non-dominated sorting genetic algorithm-II." International Journal of Geographical Information Science **25**(12): 1949-1969.

Hu, F., W. Xu and X. Li (2012). "A modified particle swarm optimization algorithm for optimal allocation of earthquake emergency shelters." International Journal of Geographical Information Science **26**(9): 1643-1666.

Kai, C., H. Bo, W. Shaowen and L. Hui (2011). "Sustainable land use optimization using Boundary-based Fast Genetic Algorithm." Computers, Environment and Urban Systems.

Kennedy, J. and R. Eberhart (1995). Particle swarm optimization. Neural Networks, 1995. Proceedings., IEEE International Conference on, IEEE.

Liu, X. P., X. Li, X. Shi, K. N. Huang and Y. L. Liu (2012). "A multi-type ant colony optimization (MACO) method for optimal land use allocation in large areas." International Journal of Geographical Information Science **26**(7): 1325-1343.

Liu, Y. L., D. F. Liu, Y. F. Liu, J. H. He, L. M. Jiao, Y. Y. Chen and X. F. Hong (2011). "Rural land use spatial allocation in the semiarid loess hilly area in China: Using a Particle Swarm Optimization model equipped with multi-objective optimization techniques." SCIENCE CHINA Earth Sciences: 1-12.

Tong, D. and A. T. Murray (2012). "Spatial Optimization in Geography." Annals of the Association of American Geographers **102**(6): 1290-1309.