enrich the knowledge base of intelligent decision-making support system for waterway transportation in the inland rivers.

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Optimization of Land Utilization and Distribution Based on Multi-Objective Ant Colony Algorithm

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Abstract
Aiming at promoting conservation and intensive use of land resources, optimized distribution and utilization of land is an important means to achieve sustainable development, and an important topic facing the current land science and management of land resources. How to formulate scientific and operable land utilization and distribution plans to avoid plans from becoming play of numbers and ensure them to be effectively implemented has become an urgent issue for optimized land distribution and optimization. Revolving around the core issue of optimized land distribution and utilization, this paper points out that most of the current model methods emphasize on optimization of quantitative structure, but lack scientific and reasonable space distribution methods. As a result, the concrete numbers in plans fail to be implemented in terms of the actual space. Concerning the problem, a new optimized land utilization and optimization model, ant colony algorithm, is put forward. The algorithm is combined with GIS to ensure the integration of quantitative structure optimization and space layout optimization.
Key words: MULTI-OBJECTIVE ANT COLONY ALGORITHM, LAND UTILIZATION, GIS COUPLING, PLANNING MODEL

1. Introduction

To ensure the reasonable utilization of a land cell is to achieve economic benefits, ecological benefits, social benefits and other multiple objectives of regional land utilization under the restrictions of certain land indexes [1]. During the optimized land distribution and optimization process, it is necessary to adhere to the principle of benefiting the organization of production space, scale operation and utilization of land [2], combination of various natural, social, economic status and other local conditions [3]. Therefore, optimized land utilization and distribution is a multi-objective optimization problem [4].

Digitally speaking, land utilization and distribution is in essence a multi-objective optimization issue under certain restrictions [5]. Land utilization and distribution is an integer programming problem containing “I×J” variables under certain restrictions [6]. Obviously, due to the characteristics of raster data, a cell stands for certain area [7]. Various land area zones can be obtained through simple accumulation. It can be seen that a land use partition map is a plan formed by corresponding functions of various land cells. The optimization goal is to seek a land utilization and distribution diagram, which can maximally meet various goals of decision-makers [8]. In fact, land utilization and distribution cannot achieve an optimized state. The planning and decision-making process of land utilization is in essence a continuous searching for a better optimization method of land utilization and distribution.

Theoretically speaking, the multi-objective optimization issue of land utilization and distribution can be solved through mathematical planning [9]. However, optimized land utilization and distribution is a complex multi-objective optimization issue [10]. Besides, the problem space is large. Conventional multi-objective planning and solutions can hardly cope with problems of land use areas with a large database [11]. Therefore, a new solution must be found.

2. Analysis of optimized land distribution and utilization through the ant colony algorithm

As a general global optimization algorithm with excellent performance, the ant colony optimization has found wide applications in various fields [12]. The inherent paralleled mechanism and global optimization property of the ant colony optimization can contribute to the solution of multi-objective optimization problems, especially occasions featuring many objective functions, nonlinearity of mathematical expressions, unclear objectives, many optimization variables and difficulty to be solved by conventional methods [13]. Besides, with the development of computer technology, scholars have also put forward some effective algorithms to solve optimization issues from the perspective of practical and engineering perspective instead of purely from the perspective of mathematical theories [14]. It is a necessity in response to the continuous development of model decision for the solution of optimized land utilization and distribution models transforming from seeking the optimal solution to obtaining a series of the satisfactory solutions (optimal solution of Pareto) [15]. Since traditional methods to solve multi-objective optimization problems are limited, the application of evolutionary algorithm will be a research trend [16].

This paper puts forward the multi-objective ant colony to solve optimized land distribution and utilization models so as to effectively alleviate the burdens of land utilization and planning personnel to plan land uses and provide some references for decision-makers’ analysis of differences of various plans and further optimization of design [17].

3. Basic idea and steps of solving structural optimization models with the ant colony algorithm

3.1. Basic idea of the planning model

The value range of various variants in the regional land resources planning model can be expressed below:

$$l_i \le x_i \le u_i, i = 1, 2, K, n. \quad (1)$$

Where, l_i is the lower limit of the decision-making variable, x_i; while u_i is the upper limit of x_i.

Define the step length between inter-zones. When $(u_i - l_i)$ can be exactly divided by the step length, it is assumed that $ki = \left[\frac{ui - li}{length}\right]$; when $(u_i - l_i)$ cannot be exactly divided by the step length, it is assumed that $ki = \left[\frac{ui - li}{length}\right] + 1$. In this way, Number "i" dimension of the n-dimension cube can be divided into "*ki*" sections. Among them, Number "*j*" section can be expressed as, $[li + (j-1).length, \min(ui, li + j.length)]$.

Here, "n" components to be solved can be regarded as "n" peaks. ("n" decision-making variables constitute the solution of a model.) Number "*i*" peak stands for Number "*i*" component of the solution. There will be "*ki*" ligatures between Number "i" peak and Number "*i*+1" peak, meaning the value of Number "*i*" component might be on "*ki*" different sections. Assume that the number of pheromones at the moment of "t" is $\tau_{ij}(t)$ on Number "*j*" ligature.

In the system, "m" ants are initialized. During the solution of the planning model, every ant starts from the first peak, and reach the second peak by choosing certain ligature according to certain strategy. Then, it starts from the second peak and repeats the former step. After the ant reaches Number "n" peak, it should choose a ligature among *kn* ligatures so as to reach the finishing point. The path covered by every ant stands for a solution plan (namely a solution of the model). It points out the section where every component is located.

In order to ensure the concrete value of every component, several corresponding components with good fitness can be preserved among various sections of various components as the candidate groups of each section. In order to speed up the convergence speed of the optimization model, the author refers to the ant colony algorithm with variation features put forward by WU Qinghong, et al. Selection, intersection, variation and other genetic operations have been adopted to find the solutions to corresponding component in the candidate groups of various sections. First, randomly choose the individual value from the candidate groups of various sections. Then, conduct crossbar transition and variation transformation of them and adopt the newly-obtained value as the corresponding component of the solution. The value of the candidate groups is updated dynamically. Once a component with a better solution appears among the section, the value will replace the poorer one.

After one iteration, "*m*" ants obtain "*m*" solutions. It is necessary to conduct fitness calculation and evaluation of these solutions. The fitness evaluation function can be adopted to evaluate the advantages and disadvantages of solutions. The quantity of pheromones on every side (the section of every component) is updated according to the value of the fitness function value. The iteration keeps on repeating until conditions are met.

3.2. Steps of the planning model

The workflow and steps of the algorithm of the planning model are listed below:

(1) Initialize

Initialize that "m" ants can obtain "m" initial solutions. Calculate the fitness value of the "m" initial solutions, and the section of every component based on the component of the "m" initial solutions. After that, candidate groups of the corresponding component on every section are generated. Rank the fitness value of solutions of the candidate groups in order, and calculate the quantity of pheromones on every section (every side) of every component according to the fitness value.

(2) Iterative process

while not (end condition) do

{

(2.1)for k=l to m do (Conduct a loop of "m" ants in turn)

{

for i=l to n do (Conduct a loop of "n" components in turn)

{

(2.1.1)Decide the value of Number "i" component in Number "j" section according to q0 and probability, $P_{ij}^k(t)$;

(2.1.2)Partially update the quantity of pheromones, $\tau_{ij}(t)$, of Number "j" section of Number "i" component;

(2.1.3)Conduct selection, intersection, variation and other genetic operations among the candidate groups with the components of the solutions of Number "j" section of Number "i" component;

}

Work out the newly-obtained fitness function value ;

}

(2.2)Modify the quantity of pheromones on every side;

(2.3)Adopt "*num*" solutions (solution plans) with the best fitness and intersect the value of every component into candidate groups of the corresponding section of every component. Here, "*num*" is adjusted according to the practical situations. The component value with relatively poor fitness in every candidate group is eliminated.

Choose the section number, j, of Number "*i*" component in the above step of (2.1.1) according to the following equation:

$$j = \begin{cases} \arg\max\{\tau \text{ij}\} & q \le q_0 \\ j_0 & Others \end{cases} \qquad (2)$$

The value of q is evenly distributed among the section [0, 1] and can be randomly chosen. Parameter q_0 stands for the probability of sections of a component with the optimal solution to be chosen. For example, when q_0=0.8, the maximum section of pheromones is chosen at a high probability of 0.8. The remaining sections of the component are chosen at the probability of 0.2. $\arg\max\{\tau \text{ij}\}$ stands for the coding of the section with the maximum pheromones in "*i*" component. When $q > q_0$, the coding, j_0, of the section can be valued within [1, ki] according to the following probability:

$$P_{ij0}^{k}(t) = \tau_{ij0}^{(t)} / \sum_{k=l}^{ki} \tau_{lk}^{(t)} \qquad (3)$$

Where, $_{lk}^{(\ )}$ stands for the quantity of pheromones of Number "j" section of the "i" component. It is dynamically changed and updated during the calculation process of the optimization model.

Since the algorithm chooses the maximum section of the quantity of pheromones of "ki" sections among ever component at the probability of q_0. Therefore, section with the maximum quantity of pheromones is often chosen. (If q_0 =0.8, the probability of the section with the maximum pheromones is 80%.) In this way, the component value of the newly-obtained solution is almost concentrated in the section, and the optimization algorithm might be easily stagnated. In order to avoid the stagnation of the algorithm, the quantity of pheromones in the chosen section can be partially updated according to the step of (2.1.2). Among the chosen sections, the quantity of pheromones should be properly cut down so as to reduce the probability of the section to be chosen by the other ants to certain extent.

Assuming that Number "i" component of Number "k" individual chooses Number "j" section. The quantity of pheromones in the "j" section is partially updated according to the following equation:

$$\tau_{ij}^{(t)} = (1-\rho)\cdot\tau_{ij}^{(t)} + \rho\cdot\min\left\{\tau_{ir}^{(t)}\right\} \qquad (4)$$

Where, 0≤*r*≤k_i, ρ stands for the parameter whose quantity of pheromones is reduced.

In this way, the quantity of pheromones in the partially updated section is the convex combination of the quantity of original pheromones and the quantity of minimum pheromones of every section in Number "i" component. When the section with the maximum quantity of pheromones is chosen for several times, the quantity of pheromones will be reduced to or get close to the average level of the quantity of pheromones among "ki" sections. In this way, the probability for ants to choose the other sections during path-finding will be correspondingly increased. This will increase the diversity of solutions built during the calculation process of the optimization model, and also decrease the occurrence of the stagnation phenomena.

In the step of (2.1.3), selection, intersection, variation and other genetic operations can be conducted among the candidate groups of Number "j" section of the "i" component to generated the value of the "*i*" component. The algorithm is listed below:

Selection, intersection, variation and other genetic operations of the candidate groups:

(1)When the number of candidate value in a candidate group is g_i=0,namely when there is no candidate value among the candidate group, the random number during the section of $[li+(j-1)\cdot length, \min(ui, li+j\cdot length)]$ as the value of the component is directly chosen to skip the genetic operations of selection, intersection, variation and so on;

(2)When the number of candidate value in a candidate group is g_i=1, namely when there is only one candidate value among the candidate group, the variation is conducted of the candidate value by skipping the genetic operations of selection, intersection and so on;

(3)When the number of candidate value in a candidate group is g_i =2, when the candidate group has two candidate value, the two candidate value directly undergo intersection, variation and other genetic operations by skipping selection and manipulation;

(4)When the number of candidate value in a candidate group is g_i≥3, namely when the candidate group has three or more than three candidate value, two candidate value are chosen from them to go through intersection, variation and other genetic operations;

1)The operation is chosen according to the value of fitness of every candidate value in the candidate group. Two candidate value is chosen according to large fitness and probability.

Assuming that the fitness of the solution of Number "*j*" value is "f_j" the probability of it to be chosen is:

$$fj / \sum_{k=1}^{gi} fk \qquad (5)$$

Where, gi stands for the number of candidate value in the candidate group of the section.

2)During the intersection operation, it is assumed that the two value chosen in the candidate group of the section are, $X_t(1)$ and $X_t(2)$, and their fitness value is f_1 and f_2, respectively. Parameter p_{cross} stands for the probability of whether to conduct crossover operation of the two candidate value.

$p \in [0,1]$ is randomly generated. If $p<p_{cross}$, conduct crossover operation. Set the random number, $\gamma \in [0,1]$, the end value after crossover operation is:

$$X_{cross} = xi(1) + \gamma \cdot [xi(2) - xi(1)] \quad (6)$$

If $p> p_{cross}$, the crossover operation is not necessary. The end value after the operation is:

$$X_{cross} = xi(1) \quad (7)$$

3)During the variation operation, conduct variation operation of the end value, $X_{cross,}$ of the crossover operation at the probability of p_{mutate} to obtain X_{mutate}. Define the upper and lower limit of Number "k" section of Number "i" component as u_{ik} and l_{ik}, and assume that:

$$d_i = \max\{u_{ik} - x_{cross}, x_{cross} - l_{ik}\} \quad (8)$$

After the variation operation, the end value of the randomly-generated number, $\delta \in [-1,1]$, is:

$$x_{mutate} = \begin{cases} x_{cross} + \delta d_i & x_{cross} - l_{ik} \le \delta d_i \le u_{ik} - x_{cross} \\ x_{cross} - \delta d_i & Others \end{cases} \quad (9)$$

This can ensure the result after the genetic operation still stays in the section.

After all ants obtain the solution through one iteration, (2.2) of the algorithm can undergo the following equations:

$$\tau_{ij}^{(t+1)} = \rho \cdot \tau_{ij}^{(t)} + \Delta\tau_{ij}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \quad (10)$$

The quantity of pheromones of every section, $\tau_{ij}^{(t)}$, is correspondingly updated and undergoes the following equation:

$$\Delta\tau_{ij}^{k} = \begin{cases} W \cdot f_k & If \text{ "Number "} j \text{" section" of Number "} i \text{" component of ant "} k \text{" is chosen} \\ 0 & Others \end{cases} \quad (11)$$

Where, W stands for a constant, f_k stands for the value of the fitness function of the solution of ant "k."

4. Combination of the multi-objective algorithm and the optimized land utilization and distribution

4.1. About the optimal solution of Pareto

In terms of the multi-objective optimization issue of optimized land utilization and distribution, any two solutions, $X^{(1)}$ and $X^{(2)}$, is half possible that one of the solution dominate the other solution or has no solution to dominate it. If the following conditions are met, Solution $X^{(1)}$ can be said to dominate Solution $X^{(2)}$:

(1)Among all objective functions, Solution $X^{(1)}$ is not inferior to Solution $X^{(2)}$. In other words, among all objective functions, $f_s(X^{(1)}) \lhd f_s(X^{(2)})$;

(2)Solution $X^{(1)}$ should be superior to $X^{(2)}$ at least in one objective function. In other words, $f_s(X^{(1)}) \succ f_s(X^{(2)})$ at least in one objective function.

If any of the above conditions is violated, Solution $X^{(1)}$ cannot dominate Solution $X^{(2)}$. If Solution $X^{(1)}$ dominates Solution $X^{(2)}$ or Solution $X^{(2)}$ is dominated by Solution $X^{(1)}$, Solution $X^{(1)}$ is the one not to be dominated;

The above concept can guide the searching for a series of solutions not to be dominated. Assuming that there are "N" solutions. Every solution is corresponding to "M" objective function value. Through the following operation steps, a series of solutions not to be dominated can be found out:

Step 1: Start from the first solution, i, and choose it;

Step two, controllably compare Solution $X^{(i)}$ and Solution $X^{(j)}$ ($j \ne i$) among all objective functions according to the above stated two rules;

Step 4, if all solutions in the set are considered, or in other words, when $i = N$, it will move to the next step; otherwise, $i+1$, and return to the second step:

Step 5, find out solutions not marked as "to be dominated," and these solutions are the target solutions.

A group of solutions can be divided into different groups according to their non-dominating degree. When the above operation steps are implemented for the first time among a group of solutions, the end result is the initial non-dominating solution. To achieve further classification, these non-dominating solutions in the original solution set can be first calculated. Then, calculation can be conducted for a second time according to the above operation procedure. Such calculation results belong to the non-dominating solutions of the second category. These newly-obtained non-dominating solutions can be worked out. If the above operations are conducted for a second time, non-dominating solutions of the third category can be found out. The above operations can be repeated until all solutions are classified as the same non-dominating solution. It is very important to learn how many non-dominating solution categories a set containing "N" solutions can be divided into. In a solution set, if there are no solutions which can dominate the other solutions, a minimum non-dominating solution ca- tegory is formed. In other words, all solutions in the original set are classified as the non-dominating category. When any solution of a set is dominated by the other solutions, the set has the maximum non-dominating solution category. As to the multi-objective optimization problem studied in this paper, there is mutual conflict between objective functions, but the major objective is to find the optimal non-dominating solution.

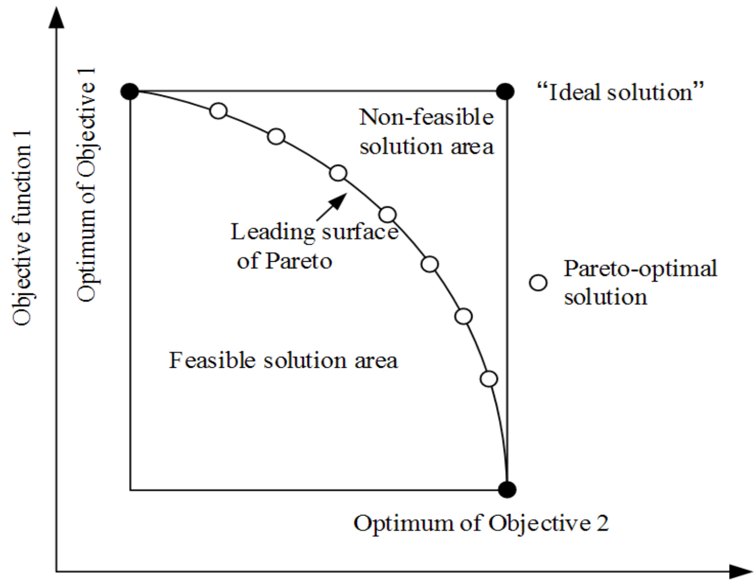

Figure 1. Schematic diagram of Pareto optimal solution of two maximized objective functions

4.2 Combination of the ant colony algorithm and optimized land utilization and distribution

At present, the ant colony algorithm has been a publically-acknowledged hot research issue. The application of the ant colony algorithm to solving multi-objective function optimization issues has become a development trend in the field. Land utilization and optimization is a complex multi-objective planning issue and the problem space is huge, so it has no optimal state. The process of planners' optimized distribution decision-making is in essence a continuous searching for relatively good distribution methods. Therefore, it is well-reasoned to apply the ant colony algorithm to the optimized land distribution and optimization:

(1) The ant colony algorithm can help find the plan close to the optimal solution of the model. It is hard for conventional methods to achieve the optimal solution;

(2) The ant colony is a self-organizing system. The self-organizing system achieves the self-update of the system through a combination of the positive feedback and the negative feedback so as to ensure the algorithm to achieve a satisfactory solution. However, conventional methods are often regarded as a "black-box" operation, which is influenced by subjectivity more or less;

(3) The utilization of the ant colony algorithm can help obtain many distribution plans. Decision-makers can choose according to their practical needs.

Zilzler E. pointed out that the whole Pareto optimal solution set cannot be accurately obtained in terms of a practical and complex system. In order to obtain a similar Pareto optimal set, the multi-objective optimization searching method should meet the following conditions (Zitzler E., 1999):

(1) The distance between the approximate Pareto optimal front and the genuine Pareto optimal front should be small as much as possible;

(2) Various approximate Pareto optimal solutions obtained should distribute evenly on the approximate Pareto front as much as possible;

(3) The approximate Pareto optimal front should have an extensive distribution. Various objectives should be covered by various approximate Pareto optimal solutions within an extensive value range.

The conventional ACO might make the population converge on a single solution, thus cannot meet the favorable distribution and distributing goal of Pareto optimal solution. Thus, it is a must to introduce a specialized multi-objective treatment mechanism to ACO. The requirement of multi-objective optimization about ACO is reflected in the following two aspects:

(1) How to choose the individual distribution fitness and implementation so as to lead the searching process to move the colony to converge on the Pareto optimal set;

(2) How to maintain the diversity of the colony to avoid premature convergence and colony missing so as to obtain a favorable distribution and approximate Pareto optimal front.

In order to achieve three objectives of multi-objective searching, scholars have studied two major problems revolving multi-objective ant colony ant algorithm, and put forward several treatment strategies to form many feasible multi-objective evolution algorithm. Therefore, how to design and implement relevant evolution and operation, and improve the convergence property of the algorithm to ensure the searching to be directed at the Pareto optimal solution set; how to maintain colony diversity to avoid premature convergence and obtain even distribution and extensive range of non-inferior solutions; how to increase the solution efficiency of multi-objective evolution algorithm—all these problems have become the focus of the multi-objective ant colony algorithm research field.

5. Improvement of the ant colony algorithm and the GIS-coupled optimized land utilization and distribution

From the perspective of the data model, ACO is based on the coding string. As a kind of space data, land utilization data feature a faceted distribution. Therefore, it is necessary to treat the land use data so as to meet ACO's requirements of the colony. Generally speaking, every GIS-based land use cell is the only internal coding. Either the data are of the vector format or the grid format, they can be coded through these internal codes according to certain order. As to data of the grid format, they can get their grid coded from the left to the right and from the bottom to the top. The code combination thus formed constitutes the code of every ant in the ACO. After the code structure at every position and of every ant is determined, every dimension of the ant is endowed with certain code according to the initialization method, which will generate an initial ant colony of certain scale. Later, iterative computation is repeated according to the operation steps of the ant colony algorithm until all conditions are met. During the process, GIS provides data for the generation of the initial ant colony with its strong space data treatment capacity, and is also used to conduct visual representation of the continuously evolving and generated colonies for the convenience of model verification and decision-making support.

Through the coupled integration of ACO and GIS, a brand-new complementary system is formed to conduct modeling analysis of the complex space phenomena, behaviors and processes. The framework of the coupling of the two is generally shown below:

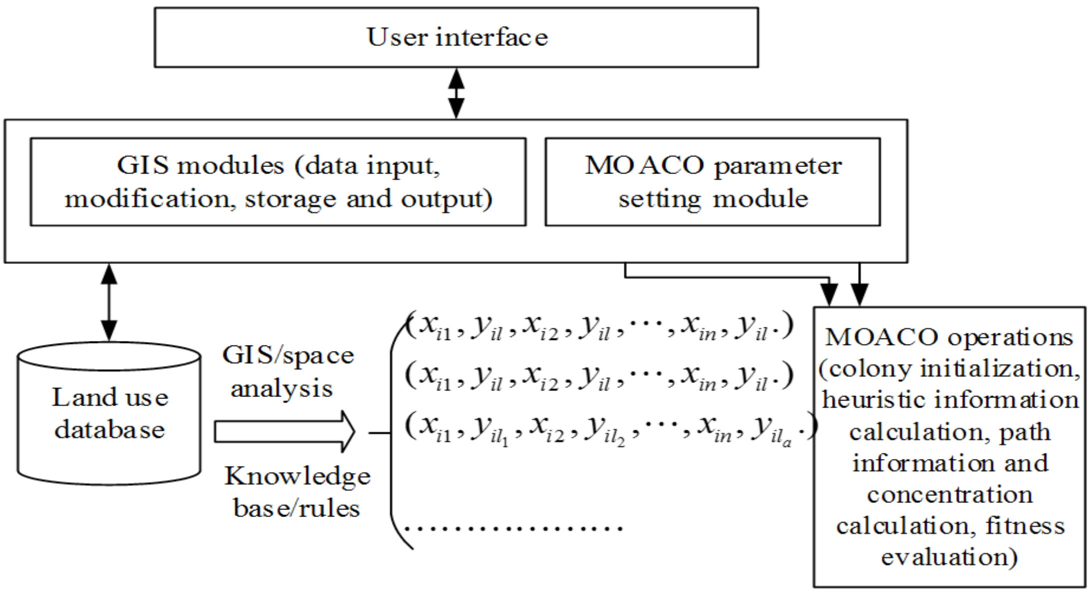

Figure.2 Coupled integration framework of ACO and GIS

5.1. Ant colony coding framework

Optimized land utilization and distribution is the goal of the ant colony algorithm. The employment of the integer quantity to code the land category is direct and easy to understand. An ant is almost one vector, which stands for a plan of the land utilization layout. Assuming that there are "n" plots to be laid out; the length of ants is "n;" every component stands for the position and land category of a plot. Ensure land of various uses to correspond to various components of ants so as to form an initial distribution plan.

For the sake of simplification, this paper assumes that there are eight land use categories in the practical model. Land use category can be expressed by the serial number ranging from 0 to 8. A code set of the land use category is {1, 2, 3, 4, 5, 6, 7, 8, 0}. The corresponding relation between the serial number and the land use category is: 1-arable land; 2-garden; 3-forest land; 4-other agricultural land; 5-land for transportation; 6-housing estate and industrial and mining areas, 7-waters and water conservancy facilities, 8-unutilized land and 0-non-calculated objective. The individual adopted by the ant colony algorithm in this paper is an objective made up of the two-dimensional grid. The grid stands for the space distribution of the land. For example, Table. 1 stands for the distribution plan of land utilization, namely a land utilization and distribution chart or a 6*6 grid. The number of the practical corresponding land utilization cells is 29. Where, "0" stands for the fixed cells for purposes other than space optimization. First, the grid chart is named by natural numbers to for serial number from the left to the right and from the top to the bottom. Table 2 stands for the coded-decimal notation, which every dimension of the ant is corresponding to. The serial number corresponding to every dimension of the ant in the ACO is (0,3,2,……,5,5,1).

Table 1. Land use category distribution based on the grid net

0	3	2	3	5	1
0	3	3	4	5	5
1	1	1	3	3	2
1	1	2	3	4	0
0	2	6	3	4	0
0	0	2	5	5	1

Table 2. Comparison table between the cell serial number and the ant coding

Cell serial number (fractal dimension)	1	2	3	4	……
Coding	0	3	2	3	…….

5.2. Determination of the initial ant colony

There have been some optimized ant colony algorithms targeted at optimization of some mathematical functions, which, however, are free of the complex restrictions and limits. Most of them adopt the completely random generation of the ant colony, while optimal layout of land space is mostly based on the status utilization. Besides, most are faced with many rigid limitations, such as waters and water conservancy land use. Under general conditions, these land uses will not be easily changed. Before initializing the particle swarm, the author should ensure them to have certain prior knowledge. The research idea is based on that adopted by ZHOU Qiao (2007) in GA optimized distribution.

5.2.1. Treatment of settled cells

The cells whose uses have been clarified and allowing for no changes will not be considered during the optimization process. Besides, they will not be coded. In this way, the problem scale can be narrowed down and the algorithm efficiency can be improved. However, since the space relationship between different cells is involved in the space optimization goals of land utilization. These coding strings must contain these codes. Therefore, in terms of individual generation, a clear coding, namely a certain land use category, should be distributed to the land category coding that these cells are corresponding to. Since the land use category coding of all these individuals is the same, the code valuing of these cells remains unchanged. Besides, an integer array, Fix [N], is defined to store cell serial numbers whose land use categories remain unchanged. If the land use category serial number which the ant component is corresponding to is included in the array, Fix, the information of the dimension will not be operated. Maintain the value of these components unchanged so as to meet the requirement of maintaining the land use category of the fixed cells unchanged.

5.2.2. Treatment of the other cells

Various variables are defined below: The minimum size of the cluster of every category "1" is η_l^M ; u_{ij} stands for the current land use category of cell, $Cell_{ij}$; S_{ijl} stands for the suitability degree of the cell, $Cell_{ij}$, as Category l (namely u_{ij}=l): the integer array is $AllocatedCell[K]$ and various components are stores in cell numbers with the serial number of "1" respectively; λ_l stands for the minimum of the number of cells whose land use category is "1;" μ_l stands for the maximum of the number of cells whose land use category is "1:" the integer array is $ToperedCell[]$ and the temporary storage number units which have been calculated in the cluster neighboring domain with $Cell_{ij}$ as the initial and starting point.

The implementation will be carried out in the following way:

1)Randomly select an initial cell, $Cell_{ij}$. (All the undistributed units have the same probability to be chosen.) Distribute a serial number, l . The serial number distribution rule is shown below: According to the status quo of units and suitability index, S_{ijl} and u_{ij} , if the current purpose is l_0 and the suitability index, S_{ijl} , value that it corresponds to is the maximum, the use category distributed to the cell is l_0 ;

otherwise, a randomly-chosen use category, l_1, will be distributed to it:

if($u_{ij} = l_0$ and $S_{ijl} = \max\{S_{ijl} \mid l = 1,2,\ldots,8\}$)then

$$u_{ij} = l_0 \quad (12)$$

else

$$l = u_{ij} = l_1 \quad (13)$$

Then, judge whether the number of cells with the code of "1" has reached the maximum. If so, another use category, l', will be randomly distributed to the cell. The following conditions should be met. If the number of cells with the coding of l' is smaller than the maximum, the serial number of the cell will be added to $AllocatedCell[l]$ and the step will turn to (2);

2)Calculate the l type cluster formed by the unit, $Cell_{ij}$, and judge whether the value of the cluster has met the minimum requirement of η_l^M. If yes, turn to (4); if no, turn to (3);

3)Choose the units without the distribution coding from the cluster neighboring domain according to the value of S_{ijl}, generate a number P_{rand} randomly in the form of roulette, (P_{rand}, $_{ToperedCell[}$), and decide whether it has been distributed to use type "1." If the use type of "1" is distributed, turn to (5); otherwise, the next cell in the cluster neighboring domain will be repeatedly implemented until that the neighboring domain has no undistributed cells. Then turn to (1);

The undistributed codes in the cluster neighboring domain are chosen at the same probability. Judge whether the current cell has $ToperedCell[]$. If yes, the cell should be chosen again. Otherwise, the serial number of the current unit will be stored in $ToperedCell[]$, and a probability, P_{rand}, will be randomly generated and appear in the form of roulette, (P_{rand}, S_{ijl}). (It should be clarified whether the use type of "1" is distributed. If yes, turn to (5). Repeatedly implement (4) in terms of the newly-formed clusters until that the neighboring cells have all existed in $ToperedCell[]$. Or if there is no cell undistributed with the code, turn to (1)):

Here: Due to continuous operation of the neighboring units, when new cells are added into the current cluster, a new cluster will be generated; otherwise, the new cluster here is actually the original one.

5)Add the serial number of cells to $AllocatedCell[K]$, and judge whether the number of units whose use type is "1" exceed the maximum, μ_l, of the "i" category. If yes, turn to (1); otherwise, turn to (2);

All the above steps will be kept on implementing until all units are distributed with a serial number of the land use

5.3. The ant colony algorithm and the GIS-coupled optimized land utilization and distribution steps

(1)Transform the vector graph into the grid graph, and extract GIS data. Use VB6.0 and other high-level language to export the graphic data and property data in GIS, and solve coordinates of the grid net, (x_i, y_i);

(2)Handle the raster data, and code the fixed land units and other land units;

(3)Set various parameters in the self-adaption ant colony algorithm. These parameters include ant colony scale, Q; heuristic factor, α; pheromone evaporation factor, ρ; the number of iterations, $t_{\max}$, the small positive parameter, δ and the optimal pheromone concentration, τ_0.

(4)Initialize the position of every ant, heuristic information and total pheromone concentration. The position of the status particle and the distribution of land use categories are:

$$\begin{cases} x_{kj} = Rnd * W.H + x_{\min} \\ y_{kjl} = l(l \in 1,2,3,\ldots.8) \end{cases} \quad (14)$$

The natural serial number of the grid cell can be found according to the coordinate value of x_{kj}. The natural serial number should be corresponding to the ant's fractal dimension. Where, x_{kj} and y_{kjl} stand for the value of the position coding and the land use category coding of Number "k" ant and Number "j" grid net. Rnd stands for the random number within the section of [0,1]; $x_{\min}$ is the minimum of the coordinate value of x; W and H stands for the width ad height of the two-dimensional space.

Since the very beginning of the algorithm, there are none ants passing every path. Thus, the initial pheromone concentration set on every path is the same. In this way, the randomness of transforming from one land use category to the other land use category can be enhanced from the perspective of the information pheromone concentration. Under the condition of not considering heuristic information, various land use categories have the same probability to be chosen. In other words, in the beginning, the probability of various paths to be chosen is the same. When certain use is chosen as the use category of the current land unit, Eq. (8) can be applied to the calculation of the remaining information pheromones.

(5) Number "k" ant distributes the uses of land units within the research area according to the parameter settings and Eq. (11). When all land units are distributed to one use, a solution is formed. Then, according to the set objective function, the solution of Number "k" ant can be evaluated. When all ants finish the first solution-seeking process, solutions

obtained by all ants in the colony will be evaluated in terms of their fitness so as to seek the optimal solution. Then, Eq. (9) and Eq. (5) will be employed to update the information concentration.

(6) Judge whether solutions generated by Number "N" iteration and by the previous iteration show any changes. If no, the pheromone evaporation factors will be adjusted according to Eq. (1). Then, keep on seeking, evaluating and updating solutions.

(7)Judge whether the end conditions have been met. If yes, the next round of ant colony evolution calculation starts until that the iteration results tend to be stable.

6. Conclusions

As a new-type intelligent algorithm, the ant colony algorithm has achieved some remarkable results while solving some optimization issues. Compared with the other colony algorithms, it is simple in terms of its operation. However, there are few researchers applying the ant colony algorithm to the study on complex multi-objective and multi-restriction optimization issues. This paper first expounds on the basic principles of ant colony algorithm and its defects, finding out a perfect combination point between the ant colony algorithm and the optimized land utilization and distribution. Targeted at some problems facing the ant colony algorithm, the author puts forward a self-adaption ant colony algorithm based on the self-adaptive evaporation mechanism of pheromones, which can ensure the rapid convergence of the colony and avoid being stuck in the local optimal solution. The algorithm serves as a major framework and to be coupled with GIS to be applied to the multi-objective optimized land utilization and distribution. Some critical problems are deeply studied. The heuristic functions and pheromone concentration update rules influencing the efficiency of the ant colony algorithm are designed and improved in details.

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Influence of the Surfactant on the Coupling Force between the Object Surface and the Particles

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Abstract
Based on the DOLV theory about the coupling and expansion between the object surface and the particles, this paper studies the influence of the addition of surfactants on the deviation of particles from the object surface, and establishes a relevant mechanical expression. The addition of the surfactant reduces the Van Der Waals force, double electrode layer acting force and hydrated force between the object surface and the particles to separate particles. The parameters with a greater influence include Hamaker constant, Debye length, object's surface potential and ion strength, density, dielectric constant and polarizability of the electrolyte in the solution and so on. The experiment result of the acting force between the object surface and the particles measured through the ultrasonic vibration shows that: Under the influence of no external force, the removal rate of the surfactant solution of the blots is five times as much as that of the distilled water. In other words, the acting force F(h) 1between the particles and the object surface (in the surfactant solution)<F(h) 2 (in the distilled water). The effect and the removal rate of the anionic surfactant and the nonionic surfactant are different, but can all change the physical characteristics of the adherent particles, making blots on the glass surface easier to be removed.
Key words: SURFACTANT, HAMAKER CONTANT, ELECTRIC DOUBLE LAYER, HYDRATION FORCE, PARTICLE