Acta Technica 62 (2017), No. 4A, 845–852

Combination of pareto PSO algorithm with GIS for urban water resources optimization

TING CHENG CHANG[2], SHILIANG ZHANG[2]

Abstract. The paper integrates the Pareto Neighborhood Crossover into the Particle Swarm Optimization algorithm (PSO), and through the combination with the GIS technology, a new multi-target optimism algorithm is proposed (referred to as PPSO). The new algorithm combined the Pareto PSO and GIS technology and successfully applied to the urban water management issues in Ningde City, China. The optimization objective is to establish the configuration to achieve the minimization of costs and utilization to maximize water supply, while minimizing harm to the environment. PPSO towards high density of pheromones achieve the boundary movement for the best measures, enhance global search capability and improve the convergence rate. Via solving the multi-objective model, the use of PPSO found the optimal allocation of water resources in the program with the help of a grid map. The results show that: compared with genetic algorithm (GA) and BP neural network algorithm, PPSO's convergence performance can effectively solve the problem of large-scale optimal allocation of water. Therefore, the multi-objective optimization model not only possesses a stronger global search capability and has high convergence speed and accuracy in this paper.

Key words. Urban water resources, PSO, multi-objective optimization, Pareto frontier.

1. Introduction

Limited water resources is an increasingly growing conflict, including the relative lack of new, cheaper resources being a common challenge for the urban water supply system[1]. Therefore, it is an efficient complex decision problem, because most of these problems need to be simulated under multiple objectives with uncertainty and

[1]Acknowledgement - This work was supported by the Science and Technology Project of Education Department of Fujian Province of China (No.JA15561), the Vital Construction Project for Ningde Science and Technology Department (No.20160065) and the Project of Ningde Normal University (No.2016Z02). The authors would like to appreciate the valuable comments and suggestions from the editors and reviewers.

[2]Workshop 1 - Department of Computer and Information Engineering, Ningde Normal University

a variety of constraints. In 1999, Moore and Chapman proposed a multi-objective particle swarm algorithm mainly based on Pareto dominance relation [2-3], but they did not adopt any measures to maintain the distribution of the algorithm. In 2002, Parsopoulos and Vrahatis proposed a multi-objective particle swarm algorithm target aggregation [4], this algorithm possesses similar shortcomings to that of the traditional multi-objective algorithm: one round only produces one Pareto optimal solution. Hu and Eberhart proposed a dynamic neighbor method[5] to solve the multi-objective optimization problem by applying the dynamic neighborhood strategy to select the optimal experience for the particle, but targeting one at a time for optimization, which by its very nature is a one-dimensional approach to handling multiple targets. In order to improve the algorithm's performance on nonlinear optimization of complex objects, a method is proposed based on Pareto neighborhood crossover, together with the PSO algorithm to generate new populations and adjust the weights of the two online weights. Then, combine the improved algorithm and the GIS technology integration and optimal allocation of water used in urban to achieve good results.

2. Methodologies Review

2.1. Particle Swarm Optimization Algorithms

In the PSO algorithm[6], each particle represents a candidate solution in the solution space. The particles travel through the search space at a certain speed according to the degree of adaptation to the environment. During the flight, the particles rely on their own experiences and peer dynamics to adjust their flight speed and position, eventually finding the global optimum. Flying experience means the optimum location found by the particle itself, called the individual extreme; peer flying experience means the optimal location the particles around the particle found, called groups extremes. When the entire population consists of peers, it is called the global particle swarm optimization algorithm; when only a part of the population is taken for peers, it is called the localized particle swarm optimization. All particles in PSO have a fitness value, determined by the function being optimized, while each particle has a speed that determines the direction and distance of their flight, and then particle swarm follows the optimum particle in the solution space. Let the optimized objective function be$f(X)$, the dimension of X is D, the population size of the particle swarm algorithm is M. Use$X_i^t = (x_{i1}^t, x_{i2}^t, x_{i3}^t, ..., x_D^t)$ to represent a particle in a group, t represents the current evolution of the population, $V_i^t = (v_{i1}^t, v_{i2}^t, v_{i3}^t, ..., v_D^t)$represents the current speed of the particle i. The preferred position experienced by particle i is called the individual extreme, denoted as$P_i = (p_{i1}, p_{i2}, p_{i3}, ..., p_D)$. The preferred position for the entire population is called the population extreme, denoted by$P_g = (p_{g1}, p_{g2}, p_{g3}, ..., p_{gD})$. In the process of iterative algorithm, particles track individual and population extremes and adjust their speed and position accordingly to achieve evolutionary groups. Particle velocity and position updated equation:

$$V_{id}^{t+1} = wv_{id}^{t} + c_1 r_1 (p_{id} - x_{id}^{t}) + c_2 r_2 (p_{gd} - x_{id}^{t}) \tag{1}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1}, (1 \leq i \leq M, 1 \leq d \leq D) \tag{2}$$

In which w is called inertia weight, usually taken from 0.9 to 0.4 linearly decreasing value; c1, c2 are called acceleration factors, usually c1 = c2 = 2; r1, r2 are random numbers taken between (0,1).

The improved PSO model differs from the basic PSO model through inertia weights to coordinate global and local Particle Swarm Optimization [7]. A large inertia weight is beneficial for expansion of global optimization, and a small inertia weight for local searching. Therefore, during the iterative computation process, if the inertia weight is gradually decreased, then the Particle Swarm Optimization algorithm has good global search capability in the beginning and ability to quickly locate the area approximate to the global optimum, while having good local search capability and ability to accurately obtain the global optimal solution later.

2.2. Pareto Neighborhood Crossover

In a multi-objective optimization problem we seek to simultaneously extremis D objectives: $y_i = f_i(x)$, where i = 1, . . . ,D and where each objective depends upon a vector $\boldsymbol{x}$ of K parameters or decision variables. The parameters may also be subject to the J constraints: $e_j(x) \geq 0$ for j = 1,. . . ,J. Without loss of generality it is assumed that these objectives are to be minimized, as such the problem can be stated as:

$$\min imize \quad y = f(x) \equiv (f_1(x),\ f_2(x), ..., f_D(x)) \tag{3}$$

Subject to $e(x) \equiv (e_1(x), e_2(x), ..., e_J(x) \geq 0$.

A decision vector $\boldsymbol{u}$ is said to strictly dominate another $\boldsymbol{v}$ (denoted **u**<**v**) if $f_i(\mathrm{u}) \leq f_i(v), \forall i = 1, ..., D$and $f_i(\mathrm{u}) < f_i(v)$for some i; less stringently $\boldsymbol{u}$ weakly dominates $\boldsymbol{v}$ (denoted$u \leq v$) if $f_i(\mathrm{u}) < f_i(v)$ for all i. A set of decision vectors is said to be a non-dominated set if no member of the set is dominated by any other member. The true Pareto front is the non-dominated set of solutions which are not dominated by any feasible solution.

Particle swarm optimization is a global optimization algorithm and has great global search capability, but poor local search algorithm causing premature convergence. To avoid premature convergence, we introduce Pareto Neighborhood Crossover, described as follows:

Let the current evolution of the population as Pop, Pareto optimal solution set as Opti. Set$(x_1, x_2, ..., x_n) \in Pop$, randomly select a $(r_1, r_2, ..., r_n)$ from the Opti body, according to formula (3) to generate a new entity$(z_1, z_2, ..., z_n)$,

$$z_i = r_i + U(-1, 1) \times (r_i - x_i); i = 1, 2, 3, ..., n \tag{4}$$

U (-1,1) indicates uniformly distributed random numbers between -1 and 1. There may be a better solution in the vicinity of Pop Pareto optimal solutions; the role of formula (4) is equivalent to the Pareto optimal solution for local evolution operator, giving full potential to the local search capability. Taking into account the strong global search capability of the PSO algorithm and the local search ability of the Pareto neighborhood crossover in which their advantages complements each other, the scale factor w is introduced, randomly generating a random number r between 0 and 1. When r <w, the use of particle swarm optimization algorithm is used to generate new individuals, when r w, the use of Pareto neighborhood crossover operator generates new individuals. In the early evolution, in order to ensure that the solution space can be effectively searched, take advantage of the PSO global search capability, guided by the PSO Pareto neighborhood crossover search to close up to the Pareto front. With the evolution developing, the algorithm should gradually shift from a broad to a more in depth search. Gradually reduce w gives full power to the role of Pareto cross to ensure that the solution converges to the exact Pareto front. The scale factor is determined by formula (5), where$w_{\max}, w_{\min}$: the maximum and minimum values of the scale factor w; t represents the current iterations; $T_{\max}$indicates the maximum number of iterations.

$$w = w_{\max} - t \times (w_{\max} - w_{\min})/T_{\max} \tag{5}$$

3. Mathematical model of optimal allocation of water resources

3.1. The objective function

The objective function of the optimal allocation of water resources, including social, economic and environmental benefits. First, register and interpret the TM remote sensing image in the study area to gain access to the types of land used in the study area. Then calculate the water requirement for various types of lands through relevant information; finally establishing the pixel-based objective function. After interpretation, assuming the image pixel rows have I rows and J series, a total of L pixels, a mathematical model of K water industries, and the multi-objective optimal allocation of water is:

$$f_1(x) = \max \sum_{k=1}^{K} \{[(e_k^m - v_k^m)x_k^m \alpha_k^m + (e_k^n - v_k^n)x_k^n \alpha_k^n + (e_k^p - v_k^p)x_k^p \alpha_k^p]\, \beta_k \sigma_k\} \tag{6}$$

$$f_2(x) = \min \sum_{k=1}^{K} [D_k - (x_k^m + x_k^n + x_k^p)] \tag{7}$$

$$f_3(x) = \min \sum_{k=1}^{K} \left[0.01 \times (x_k^m + x_k^n + x_k^p) \sum_{\varepsilon=1}^{\varepsilon} C_k^\varepsilon O_k^\varepsilon \right] \tag{8}$$

Since the economy of the sub-objective function $f_1(x)$is seeking the greatest value, and the social sub-objective function$f_2(x)$ and ecological benefits of sub-objective function$f_3(x)$ seek the minimum requirements, therefore, in order to determine the maximum overall efficiency of the objective function$f_z(x)$, for $f_2(x)$and$f_3(x)$, negative results are taken respectively. Thereby, maximizing a problem is from a minor problem.

3.2. Constraints

$$\sum_{k=1}^{K}[(x_k^m + x_k^n + x_k^p)] \le W; \sum_{k=1}^{K} x_k^n \le W_{\max}^n; \sum_{k=1}^{K} D^k \ge \sum_{k=1}^{K} P_k S_k; \sum_{k=1}^{K}\sum_{\varepsilon=1}^{\varepsilon} \frac{\psi_k^\varepsilon D_k^\varepsilon}{D_{\max}^\varepsilon} \ge E_{\min} \tag{9}$$

Where: (9) as the available water constraints, pixel (i; j)'s amount of water available for water projects cannot exceed the average of the pixel to the maximum supply capacity W (Unit: m3); the groundwater exploitation constraints, pixel (i; j)'s the total amount of groundwater extraction does not exceed the pixel as exploitable groundwater (unit: m3), $W_{\max}^n > 0$. If the groundwater has been overdrawn, that is $W_{\max}^n \le 0$, then$x_n^k = 0$. the water demand constraints, according to pixel (i; j) k type of industry (domestic, industrial, agricultural and ecological environment), P_k can denote the total projected population of the planning year, industrial output, arable land and the environment forecast area. S_k presents the standards for domestic water per capita, thousands of yuan output value for water consumption, water for farmland irrigation quota and ecological standards for the environment. the water environment comprehensive evaluation index constraint, $E_{\min}$is the lowest value for the water environment index requirements; $D_k^\varepsilon, D_{\max}^\varepsilon$were planning k industry emissions of pollutants and the maximum allowable emissions; levels in cell (j i) (unit: tons / year); rights for the pollution factor weights.

4. Results and Analysis

In order to verify the effectiveness of the algorithm, the study area was selected as Ningde City. The total area of the city is 323.57 million in 2013, and a farmland area is.The remote sensing data used are from the 2nd in July 2013 Landsat5 TM data. Using EDARS software to process, interpret and classify remote sensing images. Aided analysis through human-computer interaction, the use of expert classifiers to classify the TM images were generated on construction land, bare land, water, vegetables, arable land, arable crops in 2013; using maps, other supporting information, high, medium and low coverage of woodland and grassland, and statistical calculations to find the area of different types of lands. Finally, combine the total water resources in the city in 2013, various types of land areas and water requirements for plantations to analyze the city's water supply and demand balance. Now all of the optimization methods are applied on the Ningde urban water problem presented by Eqs. (6)-(9). The evolutionary approaches are coded in MATLAB.

In order to verify the effectiveness of the algorithm, obtain the relevant parameters and enter the PPSO algorithm according to the above method (MOPPSO). Run 10 times and the average number of iterations to achieve the optimal value 120 times. Optimal allocation of water resources based on multi-objective genetic algorithms was used referencing the method in Reference [8], the dimension of the input and output of water optimization criteria BP neural network-based configuration takes 3, the number of hidden layer units take 12, the transfer function is the Tangent Sigmoid function, the function of the output layer uses pure line; initial weights is [0;1] and the random number threshold values ??are zero nodes. Random samplings 1000 gray values' images on the remote sensing that had been interpreted are trained for the neural network model, until the training error stabilizes at 0.001. Calculate the trained neural network model for the objective function to determine the optimal allocation of water resources in the results.

To further prove that Pareto particle swarm optimization algorithm performs well, Table 1 lists the comparative results of different years. Table 2 shows the analysis in 2013, 2020 and 2030 with surface water m, groundwater n, and other water p as other water supply quantity. Table 2 lists the optimal allocation of water solutions at different levels in 75% of the guaranteed rate.

Table 1. 2006 - 2015 Water supply of Ningde City (unit: Billion cubic meters)

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014
Surface water	14.94	15.25	15.46	15.73	15.83	16.99	15.21	15.98	15.99
Groundwater	0.14	0.14	0.14	0.17	0.16	0.18	0.11	0.1	0.1
other	0.06	0	0	0	0	0	0	0	0
total	15.08	15.39	15.6	15.9	15.99	17.17	15.32	16.08	16.09

Table 2. The comparison results of water demand forecast with different methods in Ningde on 2013 (Unit: million cubic meters)

method	surface water	groundwater extraction	Other water
GA	19.23	0.38	0.20
BP	18.76	0.21	0.12
MOPPSO	16.03	0.18	0
Actual	15.98	0.10	0

Water demand forecast by the results of "the focus of regional water resources allocation planning in Ningde City, Fujian Province". According to the classification index of the urban master plan, the comprehensive water demand of urban and urban irrigation is estimated by "urban water consumption standard of Fujian Province", 552m3/Mu quota of agricultural irrigation and 40m3/Mu quota of orchard irrigation, rural person is 90 L / (person / day). The results are predicted by the MOPPSO algorithm (table 3).

Table 3. The prediction results of annual water demand with MOPPSO in different guarantee rate (Unit: million cubic meters)

Current year	guarantee rate	city&town comprehensive	rural life	agricultural irrigation	forest& orchard land	livestock	total
Current year (2013)	50	4430	195	5261	24	155	10065
	75	4430	195	6024	24	155	10828
	90	4430	195	6585	24	155	11389
2020	50	12784	204	4410	27	171	17596
	75	12784	204	5050	27	171	18236
	90	12784	204	5520	27	171	18706
2030	50	18180	215	4206	30	188	22819
	75	18180	215	4817	30	188	23430
	90	18180	215	5265	30	188	23878

5. Conclusions

This paper developed and also applied the new PSO algorithm based on Pareto multi-objective and multi-constrained optimization and successfully applied to urban water management issues in Ningde City. The results showed that, PPSO may provide a more appropriate method than other methods of water management issues (PSO and GA), not only because they seem to show higher convergence, it is also a better objective function. PPSO Pareto optimal solution can be achieved through diversity measurement solutions, indicating the spread of Pareto frontier. PPSO can give the correct solution to decision-makers using asymmetric methods to select the best solution to solve multi-objective and nonlinear optimal allocation of urban water problems.

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Received November 16, 2016