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Optimal allocation of multi-objective water treatment based on hybrid particle swarm optimization algorithm

Zhanping Wang[a,b,*], Juncang Tian[a,c,d], Kepeng Feng[a,c,d]

[a]*College of Civil and Hydraulic Engineering, Ningxia University, Yinchuan 750021, China, email: wzp_0416@163.com (Z. Wang)*
[b]*School of Mathematics and Statistics, Ningxia University, Yinchuan 750021, China*
[c]*Ningxia Research Center of Technology on Water-Saving Irrigation and Water Resources Regulation, Yinchuan 750021, China*
[d]*Engineering Research Center for the Efficient Utilization of Water Resources in Modern Agricultural in Arid Regions, Yinchuan 750021, China*

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ABSTRACT

It is complicated to plan well and manage water resources. Therefore, a better regional development plan requires effective modeling tools for water management. The work aims to put forward a method for optimizing water system, that is, to optimize water supply and distribution facing water shortage. In term of water system, users' total demand for water is over the water supply. On that account, it is necessary to consider the priority among the conflicting demands. To put it more specific, a mathematical method is developed in the study for optimally allocating water resources of different sources exhibiting different supply and use cost to different users. A feasible framework is put forward for evaluating how the proposed measures can impact the best water resource allocation. We adopted the hybrid particle swarm optimization (HPSO) algorithm for the purpose of obtaining a set of optimal solutions. We put the abovementioned model and framework in a case study. In general, according to study result, the framework, which is used to evaluate the impact of measures laid out on the allocation of water resource is proved to be beneficial for the management of water resources, which, in addition to the study area, can be seen in different places which see different condition of water use resulted from the climate variation and human behavior.

Keywords: Water resources allocation; Mathematical modeling; Multi-objective; Particle swarm optimization (PSO) algorithm

1. Introduction

The increase in population, consumption patterns and anthropogenic activities as well as the climate change make fresh water shortage a key issue in various areas all over the world [1,2]. Water scarcity remains a big issue in nearly all continent and over 40% of population in the world suffer from water scarcity. It is predicted that about 1.8 billion people will live in water-scarce places and 2/3 of global population will suffer water stress by 2025 [3].

The world is suffering an imbalance between water supply and demand and water quality is lowering, leading to more treatment alternatives. As a result, there are more and more complicated management decisions of water resources. Considering the quality and source, water can achieve its intended use after experiencing desalination, filtration, disinfection and other treatment process. It requires decision makers to confirm the most proper amount of water resources transported from supply source to treatment plants. These waters should be treated with proper technologies so as to meet users' demand and at the meantime meet water quality requirement at the lowest environmental and economic costs.

* Corresponding author.

The allocation of limited water resource should be considered from the perspective of procedural and distributive justice. Water resources should be utilized in a reasonable way, which is beneficial for poverty elimination and economic development [4]. According to WWAP [5], equity appears as a tough issue and in order to define equity components, it is needed to make a better allocation between water resources used for environment and residents. People pay more attention to the efficiency rather than equity as the judgment standards of equity remain individualized [6]. Dwaf held the view that during the process of water management, there is a difficulty in measuring sustainability of aquifers and rivers [7]. Local authorities conduct administrative management and control such as water regulations and infrastructure, with the goal to satisfy demand from social economy for water on the premise that the ecological sustainability will not be impacted [8]. Although there may be some practical problems, people seldom take into account how to ensure the use sustainability of water in subareas with multiple objectives. The water resource system involves a variety of activities and goals which are accompanied by complicated conflicts between demand and supply [9].

Against this background, the intelligent optimization algorithm enjoys a wide application in model solution. Kennedy and Eberhart [10] first proposed the particle swarm optimization (PSO) under the inspiration of the paradigm of bird lock, which is a heuristic search technology based on population. PSO exhibits robustness, quick convergence as well as simplicity and enjoys a successful application to dealing with problems of single-objective optimization design. Also, relying on these characteristics, PSO has been used for multi-objective problems under the motivation of researchers. Specifically, some algorithms based on PSO [11,12] have been applied to solve the multi-objective problems about redundancy allocation. Cai [13] applied a distributed PSO algorithm with multiple objectives to a constraint-handling technique, finding the non-dominated solution for a problem about constraint multi-objective optimization. Although PSO boosts the special advantage of the quick convergence rate, the feature can also make it stuck in the local optimal solutions. A new PSO, that is, PSOMS (PSO with mutation similarity), is developed by Tu et al. [14] for overcoming the defect. It is proved that PSOMS has the function to maintain particle diversity and facilitate PSO to get a global optimal. PSO is applied by Sharma et al. [15] to the water distribution and wastewater system in urban areas in three case studies, suggesting a better performance of PSO over the dynamic programing (DP) and genetic algorithm (GA). Specific to the APP problem with multiple products, steps and periods in the cement field, a multi-objective programming model is introduced by Kennedy and Eberhart [10]. The problem is successfully solved in virtue of an extended objective function together with a variant of proposed PSO with inertia weight defined as a function. According to the comparison in simulation results between PSO and GA, the PSO exhibits a better performance than GA.

The rest of the paper is structured as follows. Section 2 shows a mathematical model for regional water resources allocation, followed by describing methods adopted here including PSO, HPSO. Section 3 involves a case study application. The last section is the conclusion.

2. Methodology

2.1. Optimal water resources allocation model

The optimal water resource allocation model consists of the objective function, the system constraint as well as the optimization technique. Water resource system is affected by many factors and its objectives can exhibit diverse proportion scales and dimensions based on these influencing factors. Also, a mutual restriction can be observed among them. On that account, optimal water resource allocation can be defined as multi-objective.

2.1.1. Objective functions

$F_1(x)$, $F_2(x)$, and $F_3(x)$ below are objective functions:

2.1.1.1. Water shortage minimization ($F_1(x)$)

The objective means water resource's equal sharing in different operating zone which represents the water shortage amount/person/operating zone and can be expressed as,

$$\text{Minimize } F_1(x) = \sum_{t=1}^{12}\left\{\frac{1}{n}\sum_{i=1}^{n}\left[\frac{\sum_{j=1}^{l}\left(\mathrm{DW}_{ij}^{t} - x_{ij}^{t}\right)}{\mathrm{NPO}_i}\right]\right\} \quad (1)$$

where t stands for the month number (ranging from 1 to 12). n means the number of operating zones. l represents the number of water user or sector/operating zone, such as farming, domesticity, industry as well as ecology; x_{ij}^t denotes decision variable, that is, water resource allocated to the section j in i^{th} operating zone in t^{th} month. NPO_i represents population in i^{th} operating zone based on the Statistical Yearbook or the predictions of social and economic development. DW_{ij}^t denotes the water demand in the section j in i^{th} operating zone in t^{th} month, which is confirmed in virtue of quota method.

2.1.1.2. Economic interest maximization ($F_2(x)$)

$F_2(x)$ stands for the second objective function which, by definition, refers to the overall economic value throughout the year in the whole zone. The purpose is to optimize the economic benefit in the zone.

$$\text{Maximize } F_2(x) = \sum_{t=1}^{12}\sum_{i=1}^{n}\sum_{j=1}^{l}\left(x_{ij}^{t} \times \mathrm{NER}_{ij}\right) \quad (2)$$

Among them, NER_{ij} stands for the net return/water quantity unit in sector j in the i^{th} operating zone (RMB/m^3). In farming sector and industrial sector, NER_s, by calculation, refers to the gap between total production benefit and total production cost. It is impossible to quantify the water use benefit in the sector of domesticity. As the most significant sector, domesticity sector presents the largest NER compared with other sectors.

2.1.1.3. Minimization of wastewater amount ($F_3(x)$)

There is the third objective function aiming at minimizing the total wastewater amount around the whole region.

$$\text{Minimize } F_3(x) = \sum_{t=1}^{12}\sum_{i=1}^{n}\sum_{j=1}^{l}\left(x_{ij}^t \times \text{PP}_{ij}\right) \quad (3)$$

Here PP_{ij} denotes the amount of wastewater discharge for each unit of supplied water (SW_{ij}) in sector j in the i^{th} operating zone. It is largely dependent on the $\text{PW}_{ij}/\text{SW}_{ij}$, thereinto, PW_{ij} stands for the wastewater amount which is available in the bulletins of water resource.

2.1.2. System constraint

2.1.2.1. Water balance equation

$$Q_i^t = Q_i^{t-1} + \sum_{k=1}^{m}\text{RR}_{k,i} \times O_k^t + R_i^t + \sum_{j=1}^{l}\left(x_{i,j}^t \times \text{ret}_{i,j}^t\right) - U_i^t - \sum_{j=1}^{l}\left(x_{i,j}^t\right) - \text{TW}_i^t \quad (4)$$

where Q_i^t denotes the water discharge in the i^{th} operating zone at the t time. Q_i^{t-1} denotes the water discharge at the $(t-1)$ time. m stands for the number of large and medium reservoirs. O_k^t stands for the discharge from the k^{th} reservoir. $\text{RR}_{k,i}$ stands for the water connection proportion of the i^{th} operating zone to the k^{th} reservoir, which depends on the river water diversion ratio of k^{th} reservoir to the i^{th} operating zone. R_i stands for the water yield amount in watersheds located in the i^{th} zone. x_{ij} and l represents the variables as in Eq. (1). $\text{ret}_{i,j}^t$ denotes the coefficient of return flow (dimensionless) and $1 \geq \text{ret}_{i,j}^t \geq 0$. U_i^t stands for the water loss amount which includes the seepage, evaporation and loss of conveyances. TW_i^t represents the quantity of water which was transferred out of the zone.

2.1.2.2. Reservoir constraint

- Below is the continuity equation of the k^{th} reservoir:

$$S_k^t = S_k^{t-1} + I_k^t - O_k^t - \text{EV}_k^t \quad (5)$$

Here S_k^t denotes the storage at t time, thus S_k^{t-1} denotes the storage at $t-1$ time. I_k^t stands for the net inflow of reservoir (seepage excluded) during time t. O_k^t denotes the outflow of reservoir during time t. EV_k^t represents the water loss as a result of evaporation during time t.

- The storage for the k^{th} reservoir is proved to be a constraint according to physical limits:

$$S_{\min,k}^t \leq S_k^t \leq S_{\max,k}^t \quad (6)$$

Here $S_{\min,k}^t$ represents the lowest storage at time t and $S_{\max,k}^t$ represents the largest storage at time t.

2.1.2.3. Water demand constraint

$$x_{i,j}^t \leq \text{DW}_{i,j}^t \quad (7)$$

2.1.2.4. Constraint from water availability and non-negativity

$$0 \leq \sum_{j=1}^{l} x_{i,j}^t \leq \text{AW } R_i^t \quad (8)$$

AW R_i^t stands for water amount available in the i^{th} operating zone in t^{th} month.

Khalili-Damghani et al. [16] and Firdaus et al. [17] proposed the methods to determine the parameters in Eqs. (1)–(8).

2.1.3. Optimization technique

It is hard to use the model to get a better solution considering its complicity. Thus our study adopted the HPSO algorithm with the purpose to get the best solution. The weighted sum method is used to combine the three functions into a single-objective optimization issue. To maximize $F_2(x)$ means to minimize $-F_2(x)$, thus the single-objective optimization is presented in Eq. (9) below:

$$\text{Minimize } F(x) = \sum_{i=1}^{3}\left(\omega_i \times \tilde{F}_i\left(x_{i,j}^t\right)\right) \quad (9)$$

where $\tilde{F}_i(x)$ stands for the standard form of the i^{th} objective from the non-dimensionalization. ω_i stands for weight of the i^{th} objective, where $\Sigma_{i=1}^{3}\omega_i$ is 1. To normalize the function $F_s(x)$, the first step is to optimize each objective separately ($F_1(x)$, $F_2(x)$ and $F_3(x)$) and then segment them based on optimized values obtained.

2.2. HPSO algorithm

2.2.1. PSO review

As an evolutionary calculation technology, the PSO algorithm is developed on the basis of the theory of swarm intelligence. Kennedy and Eberhart put forward the algorithm for the first time in 1995, and the discrete binary PSO was then developed in 1997, which was called the binary particle swarm optimization (BPSO). BPSO is usually applied to get the solution of certain combined optimization problems practically.

The PSO algorithm, under the inspiration of some organism's behavior such as bird flocking, fish schooling and so on, follows the principle that group members' social sharing about information boosts a progressive advantage [18]. To be specific, a flock of birds are searching for food randomly. In the case that there is only one piece of food in the area, if the bird wants to find the food, the simplest and the most effective, it should search the peripheral region of the nearest bird. Inspired by the behavior, PSO algorithm is applied to solving optimization problems. Recently, it is reported that the BPSO has been successfully applied in many fields, like the adjustment of the parameters and structure of neural network [19], the selection and classification of gene [20], characteristic selection [21], engineering electromagnetics [22] and the scheduling of job shop [23].

The PSO can be performed as follows: an optimization function $f(X)$ is set with n real-valued decision variables, thereinto, $X = (x_1, x_2, \ldots, x_n)$. PSO evolves a large group of candidate solutions, that is, particles iteratively so as to look for optimal solution $X = (x_1^*, x_2^*, \ldots, x_n^*)$). The initial swarm can be formed randomly. Each particle can be expressed as $P_i = (p_{i1}, p_{i2}, \ldots, p_{in})$, $i = 1, 2,\ldots, S$, thereinto, S stands for the size of swarm, P_i stands for the particle quality, which can be tested based on the calculation $f(P_i)$. The PSO can sort the best solutions which are observed so far by each particle, so as to fatten swarm intelligence [24–29]. Especially, the particle could remember the most proper site it had visited before, that is, pbest$_i$, as well as the best position which is observed by its neighbors. Two versions can be used to define the best position of its neighbors, namely the Ibest version and the gbest version. In term of the Ibest version, the best position of neighbors can be reached by particles which are in a topological neighborhood. On contrast, in the gbest version, the best position of neighbors depends on particles within the entire swarm. On that account, gbest version can be treated as the special case of the Ibest version. According to literature review, Ibest version exhibits a better performance, especially that applying the random topology neighborhood in which every particle can product the L links randomly post to the iteration provided that no improvement is observed, that is, provided that the best solution from swarm remains the same. During the implementation process, L is set as 10. Particles move under the guidance of distributed awareness (i.e., pbest$_i$) together with the collective awareness (i.e., lbest$_i$) [30–34]. As for each iteration, the particle i regulates v_{ij} the velocity and p_{ij} the position in virtue of each dimension j, which is shown below:

$$v_{ij} = K\left[v_{ij} + c_1 r_1\left(\text{pbest}_{ij} - p_{ij}\right) + c_2 r_2\left(\text{lbest}_{ij} - p_{ij}\right)\right] \tag{10}$$

and

$$p_{ij} = p_{ij} + v_{ij} \tag{11}$$

where c_1 and c_2 stand for acceleration constants, r_1 and r_2 stand for the real numbers which are randomly drawn from $U(0,1)$. K represents constriction factor. Based on Clerc and Kennedy [35], in order to make sure the PSO convergence, it is necessary to use the constriction factor, which can largely depend on [35]:

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \tag{12}$$

where $\varphi = c_1 + c_2$, $\varphi > 4$. In specific, we set φ as 4.1 and thus K is 0.729.

In this way, these particles can evolve to obtain the better solution positions under the navigation of pbest$_i$ as well as lbest$_i$, yet, they keep exploring novel potential solutions in virtue of passing over local optimality with random multipliers. The number of iterations shall be maximized so as to terminate the PSO algorithm, otherwise, a large number of iterations will lead to the failure to improve the best position of particle of the entire swarm.

2.2.2. Hybrid PSO

The HPSO algorithm is conducted by the following steps:

Step 1: Initialize parameters for PSO, create an empty solution set.

Step 2: Generate S particles, $P_1, P_2, \ldots, P_s$ according to the particle formulation

$$P_i = \left(p_{i1}, p_{i2}, \ldots, p_{iT}\right) \tag{13}$$

$$\text{Subject to } a'_j \le p_{ij} \le b'_j \quad \forall j = 1,2,\ldots,T-1, \tag{14}$$

$$p_{iT} = Q - \sum_{j=1}^{T-1} p_{ij}. \tag{15}$$

and the adaptive resource bounds.

Step 3: Get the velocities v_{ij}, $1 \le i \le S$ and $1 \le j \le T$, thereinto, v_{ij} has a random range of [–1.0–1.0].

Step 4: Determine the pbest$_i$ and lbest$_i$.

Step 5: Update velocities v_{ij} using Eqs. (10) and (12).

Step 6: Update particle's positions using Eq. (11).

Step 7: Apply the hill-climbing heuristic to improve each particle.

Step 8: Add the non-dominated particles from current swarm to solution set.

Step 9: Check solution set and remove dominated solutions.

Step 10: Output the final solution set.

As the solution room has not been searched in an exhaustive manner, members of solution set are unlikely to be pareto-optimal. Conversely, the metaheuristic paradigm is adopted to expand and explore areas with high-quality solutions efficiently.

3. A case study In Yinchuan

Yinchuan City is located at east longitude 105°49′~106°53′, northern latitude 37°29′~38°53′, the study area include Yinchuan City, Lingwu City, Helan Country and Yongning Country. The total area of Yinchuan City is 9,555.38 km^2 of which Yinchuan area is 2,310.53 km^2, Lingwu area is 4,538.97 km^2, Helan country is 1,527.20 km^2 and Yongning Country is 1,178.68 km^2. Yinchuan City is located in the temperate continental climate zone. Which the climate characteristic is four distinct seasons, mild, abundant sunshine, short frost period and long growth period of crops. The annual average precipitation is 200 mm, annual mean temperature is 8.5°C. The maximum and minimum temperature in the area are 36°C and –9.3°C. The annual average evaporation is 1,332 mm, maximum annual evaporation is 1,489 mm, and minimum evaporation is 1,105 mm. The annual average wind speed 2.3 m/s. Every season the wind direction change is not obvious, the most common wind is northeast direction.

This model can be used for the optimization of water allocation in Yinchuan City, which aims at reducing wastewater amount, fitting increasing demand for water due to the increase in population and economic growth. As stated in the Yinchuan City Planning about the optimal allocation of water resources, the first principle is to meet people's demand for domestic water and ecologic water, then to meet people's demand for industrial water, agricultural-use water, and others. The paper takes water demand in the year of 2015 (Table 1) as the research basis and takes water demands in the year of 2020 for expectation. A linear weighting method

Table 1
Water demand of Yinchuan in 2015 (unit: 10,000 m^3)

Zone	Agriculture	Industry	Domesticity	Ecology	Total
Yinchuan	39,839	6,012	5,552	2,705	54,108
Yongning	43,023	688	402	396	44,508
Helan	51,050	633	332	941	52,956
Lingwu	26,848	2,954	484	19	30,306
Total	160,760	10,287	6,770	4,060	181,877

Table 2
Results of optimizing allocation of Yinchuan in 2020 (50%) (unit: 10,000 m^3)

Zone	Item	Agriculture	Industry	Domesticity	Ecology	Total
	Water demand	34,945	7,194	11,724	4,253	58,116
Yinchuan	Water supply	33,290	6,850	11,724	4,253	56,116
	Water shortage	1,656	344	0	0	2,000
	Water demand	36,807	1,240	1,045	622	39,715
Yongning	Water supply	35,040	1,108	1,045	622	37,816
	Water shortage	1,767	132	0	0	1,899
	Water demand	44,185	1,141	865	1,479	47,670
Helan	Water supply	42,653	977	865	1,479	45,975
	Water shortage	1,532	163	0	0	1,695
	Water demand	23,680	2,959	1,261	30	27,930
Lingwu	Water supply	22,750	2,510	1,261	30	26,551
	Water shortage	931	448	0	0	1,379
	Water demand	139,618	12,533	14,895	6,384	173,430
Total	Water supply	133,733	11,445	14,895	6,384	166,457
	Water shortage	5,885	1,088	0	0	6,973

Table 3
Results of optimizing allocation of Yinchuan in 2020 (75%) (unit: 10,000 m^3)

Zone	Item	Agriculture	Industry	Domesticity	Ecology	Total
	Water demand	37,675	7,194	11,724	4,253	60,846
Yinchuan	Water supply	33,772	6,650	11,724	4,089	56,235
	Water shortage	3,903	544	0	164	4,611
	Water demand	39,683	1,240	1,045	622	42,590
Yongning	Water supply	35,548	998	1,045	567	38,159
	Water shortage	4,134	242	0	55	4,432
	Water demand	47,637	1,141	865	1,479	51,122
Helan	Water supply	43,272	960	865	1,289	46,385
	Water shortage	4,366	181	0	190	4,737
	Water demand	25,530	2,959	1,261	30	29,780
Lingwu	Water supply	23,079	2,310	1,261	21	26,671
	Water shortage	2,451	649	0	9	3,109
	Water demand	150,526	12,533	14,895	6,384	184,338
Total	Water supply	135,671	10,918	14,895	5,966	167,450
	Water shortage	14,855	1,615	0	418	16,888

was adopted to achieve the transfer of multi-objective optimization problem into a single-objective optimization problem, where $\omega_1 = 0.33$, $\omega_2 = 0.35$, $\omega_3 = 0.32$. The water allocation scheme optimization had been calculated at different levels, respectively. Tables 2 and 3 illustrate the best water resource allocation results.

Through the optimization and adjustment of water industrial structure and agricultural planning in Yinchuan City, according to the parameter setting of above model and HPSO algorithm, we provide the water resources allocation results for 50% and 75% of 2020. Tables 2 and 3 show that with rainfall decreasing, agricultural water use is increasing, from 13.9618×10^8 m^3 to 15.0526×10^8 m^3, total of water demand and water shortage is increasing, from 17.3430×10^8 m^3 to 18.4338×10^8 m^3 and from 0.6973×10^8 m^3 to 1.6888×10^8 m^3, respectively.

4. Conclusion

The multiple-objective resource allocation problem can be extensively applied in resource allocation and distribution, software testing, project budgeting, allocation of health care resource and so on. There is a variety problem formulations which have been put forward based on different applications. The paper emphasizes on the nonlinear multiple-objective problem related with water resource allocation in virtue of the integer decision variable constraint. An adaptive-resource-bound technology was designed for obtaining practical solutions to the problem, on the premise of meeting all resource constraints. With the application of the PSO paradigm, a mixed implementation plan is put forward, which is able to combine the hill-climbing heuristic into the PSO so as to quicken the convergence. It is necessary to carefully evaluate the experience of PSO in order to deal with the multiple-objective optimization problem. The $pbest_i$ and $lbest_i$ act as the essential experiences of PSO, which can be determined relying on the score function together with the concept of dominance relation. According to study result, HPSO algorithm has the function to solve different intricate nonlinear optimization problems with multiple objectives and suffering multiple constraints in a better way, of which the performance is superior to regular PSO algorithms.

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