Desalination and Water Treatment
www.deswater.com

doi: 10.5004/dwt.2023.30032

314 (2023) 304–313
December

Application of simulated annealing algorithm in multi-objective allocation optimization of urban water resources

Fu Wang[a,b], Weide Chun[a,*], Wenbin Wu[b]

[a]*College of Management Science, Chengdu University of Technology, Sichuan 610059, China, email: chunweide2023@163.com (W. Chun)*
[b]*Key Laboratory of IOT Security at Mianyang Teachers' College of Sichuan Province, Mianyang Teachers' College, Mianyang 621000, China*

Received 20 August 2023; Accepted 22 October 2023

ABSTRACT

A reasonable allocation can improve the allocation rate of water resources, and ensure ecological coordination and promote economic development. However, with cities developing quickly, urban water resources allocation is becoming more and more prominent. This study designs a multi-objective optimal allocation model of urban water resources based on simulated annealing algorithm, introduces the sudden jump of probability, adopts the multi-objective Pareto effective solution, and further improves the simulated annealing algorithm. The actual total water demand in 2022 is 6,606.53 million·m^3 larger than the actual water supply 6,556.53 million·m^3. The small probability errors of water demand and water supply forecasts are 0.8532 and 0.9586, the average relative errors are 0.0231 and 0.0212, and the variance ratios are 0.2125 and 0.2109, indicating that the forecasts are valid and the prediction accuracy is good. The model convergence is the fastest when using the multi-objective simulated annealing algorithm to close compared with other algorithms. By using an improved simulated annealing method to solve this multi-objective optimal allocation model effectively avoids the iterative process from falling into local optimum and improves the accuracy of prediction evaluation. The experimental results show that the algorithm has high accuracy and stability for water resources optimal allocation, which has certain practical significance and economic value in water resources.

Keywords: Multi-objective allocation; Simulated annealing algorithm; Water resources; Water supply; Water demand

1. Introduction

Water is an important natural resource indispensable for human development and an essential element for human survival. Overall, China is one of the countries with serious shortage of water resources (WR). China's total water resources (WR) account for 6% of the world, ranking fourth, but the per capita WR are less than 1/4 of the world average, and the per capita possession is extremely low [1,2]. Locally, China's WR are unevenly distributed, and there are regional problems, such as the problem of WR differences between the north and the south [3]. WR allocation refers to the scientific use of relevant measures to plan the allocation of WR within a certain area. Rational allocation of WR not only improves the distribution rate of WR, but also ensures ecological harmony and promotes economic development [4]. However, with the accelerated growth of cities, the issue of urban water allocation is becoming increasingly important [5]. The expansion of cities has led to a significant increase in water demand and pressure on regional water supplies, while the increase in factories and the discharge of effluent from unscrupulous enterprises has resulted in

* Corresponding author.

polluted WR and a reduction in available resources [6]. To make the urban water supply demand alleviated effectively, an optimal allocation analysis of WR is needed according to city developing level. Based on this background, this study proposes a multi-objective simulated annealing (SA) algorithm-based optimization method for urban WR allocation, aiming to provide ideas for solving water conflicts in urban WR and alleviating water supply conflicts.

This study has four parts. The second part provides a review of the current status of research on urban WR optimal allocation and SA algorithm. The third section proposes the design of multi-objective optimal allocation model (MBOAM) based on SA algorithm setup. The first section constructs the urban WR MBOAM, and the second section combines the SA algorithm to solve and improve the model. In the fourth section, the MBOAM of WR is experimentally validated and the experimental results are analyzed.

2. Literature review

The optimal urban WR allocating is generally studied from several perspectives. Lv et al. [7] explored the effective WR allocating in urban metabolic systems from a climate perspective. Management pathways to cope with climate change are deployed with full consideration of climate change and regional differences. The study proves that climate exacerbates the vulnerability of WR and makes WR management more complex. Wu and Liu [8] designed a regional WR optimal allocation scheme based on industrial structure upgrading using a two-tier optimization and master-slave recursive model. A three-step management approach and upgrading of industrial structure are used to promote the optimal WR allocating in the Beijing–Tianjin–Hebei region. In addition, the researchers introduced a water market benefit compensation function to adjust the water resource allocation scheme. This model can promote industrial structure upgrading, improve water use efficiency and achieve comprehensive and optimal WR allocating. Kang et al. [9] proposed a WR allocating model based on water quality, which was established under water quality and WR allocation. The model analyzes the influence of water quality on WR allocation and studies water pollutant treatment technology. This water resource allocation model can better conserve and protect WR and improve the water environment and assist managers' decision making. Tian et al. [10] proposed a comprehensive WR evaluation and management framework based on the optimal WR allocating. The framework first analyzed water demand, followed by the evaluation of vulnerability indicators using a non-dominated sorting genetic algorithm. As water demand increases and water transfer projects expand, water supplying risk increases and the water supplying system's reliability and resilience decrease. This study proposes a comprehensive WR evaluation and management framework that facilitates WR management.

Multi-water resource system is complex. Different algorithms and models have been proposed by domestic and foreign researchers to study the optimal WR allocating. Liu et al. [11] proposed a fuzzy coalition game model for multi-country water resource allocation, which is based on the spatial and temporal characteristics of the geographic location of each country on the impact of water use, that is, water demand. It is better to increase the overall efficient WR allocating than the allocating strategy based on agricultural water demand. Wang et al. [12] used an improved backpropagation neural network (BPNN) model instead of a numerical groundwater simulation model, aiming at coupling the simulation model with the optimization model. This improved BPNN and optimization technique can fully utilize the WR of the whole region, and the traditional scheme's water shortage rate is about 10% reduced at 75% guarantee rate. The output of the improved model is more consistent with the results of the simulation model, improving computational resources and running time. Li et al. [13] improved a multi-population method to deal with two-dimensional constrained model. The algorithm extends genetic optimization to two dimensions to fit the region-specific model to optimize WR allocating. The improved multi-population genetic algorithm uses individuals as the horizontal dimension and population as the vertical dimension, and replicates genetic operators to replace the cross-genetic operators. The results show that the improved algorithm has a strong optimization capability and that the algorithm can be practically applicated for optimal water resource allocation. Cunha and Marques [14] proposed a SA algorithm that combines an annealing procedure with a finite budget for function evaluation. This algorithm has a better performance and produces better frontiers compared to other algorithms. Mousavi et al. [15] proposed an optimizing model for optimal WR allocating for Salman Farsi irrigation network. The model was optimized using the whale algorithm and the decision variables of the model were the irrigation water depth of the crop and the planted area. The total cropped area of the network increased by 981 ha, but the total water use did not decrease.

In summary, the urban WR optimal allocating requires higher algorithms and models as the objects under consideration change. Some studies have designed WR allocating models from the perspectives of metabolic system, water quality, and agricultural water use, but there is still room for improvement in the optimization effect. In order to design a better model for water allocation optimization, this study will first construct a multi-objective optimization model for urban WR, and then improve and solve the model with SA algorithm. The optimization model will be used to optimize urban WR allocation and improve WR utilization.

3. Design of multi-objective optimal configuration model based on SA algorithm

This section includes two parts: model construction and model solving. Firstly, the objective benefit function of urban WR optimal allocating, the constraints that the variables should satisfy, and the quantitative analysis of relevant parameters are established to construct the objective function (OF) model of WR allocating. Then, on the foundation of the model's characteristics, the traditional SA method can be optimized by combining Pareto effective solution to form the solution scheme of the urban WR optimal allocation model on the foundation of SA multi-objective algorithm.

3.1. Urban WR MBOAM construction

Multi-objective planning theory is a mathematical planning method for solving the optimal solution of two or more OFs in a given region. The problem of urban WR allocation is mainly an imbalance between social, economic and ecological benefits, which can be mitigated by multi-objective optimal allocation [16]. The multi-objective planning theory is used to transform the urban WR allocation problem into a multi-objective solution problem. According to the urban WR allocation problem, the OF of urban WR MBOAM is established by combining the social, economic and ecological benefits. Eq. (1) is the OF.

$$F = \mathrm{opt}\left\{f_1(y), f_2(y), f_3(y)\right\} \tag{1}$$

where y is the decision variable of the OF, which represents the water supply of the actual area. $f_1(y)$ represents the optimization of social benefits, $f_2(y)$ represents the optimization of economic benefits, and $f_1(y)$ represents the optimization of ecological benefits. The urban WR MBOAM is composed of several decision variables. The urban sub-region is set as the decision object according to the geographical characteristics and administrative features of the region, and the expression of the decision object is shown in Eq. (2).

$$A = \left\{A_1, A_2, \ldots, A_M\right\} \tag{2}$$

where A denotes the decision object, M denotes a total of M sub-regions, and m denotes the m sub-region. The water use sectors in the region are classified as K, and there are five water use sectors in the $K = 1, 2, \ldots, 5$ subzone, namely agricultural, industrial, urban public, domestic and ecological water. Fig. 1 is the urban water allocation.

In Fig. 1 the first layer is the allocation of total water between sub-regions, and the second layer is the allocation of sub-region water between sectors. The social benefit objective is a more abstract objective in water allocation, and is more difficult to measure than the economic and ecological benefit objectives. In order to better measure the social benefit target, the Eq. (1) of $f_1(y)$ is improved by converting the water deficit into the water deficit rate, which is expressed in Eq. (3).

$$v_j^m = \frac{\left(x_j^m - y_j^m\right)}{y_j^m} \tag{3}$$

where v_j^m represents the water shortage rate, and j represents the first water user. j y_j^m m j x_j^m represents j water users' water demand in m. The OF of social benefits based on Gini coefficient combined with Eq. (3) is shown in Eq. (4).

$$\min f_1(y) = \frac{1}{M \times J \times (M \times J - 1)/2} \sum_{m=1}^{M-1} \sum_{m=m+1}^{M} \left| \sum_{J=1}^{J-1} \sum_{J=j+1}^{J} \frac{v_j^m}{v} - \frac{v_{j'}^{m'}}{v} \right| \tag{4}$$

where v represents the total water shortage rate of allocation area, M represents the total sub-areas in this area, and J represents the total water users in this area. In the economics OF, unit revenue is equal to the unit revenue minus the unit cost. The unit revenue multiplied by the total amount is the economic revenue of each water user, and the efficiency OF is expressed in the form of Eq. (5).

$$\max f_2(y) = \sum_{m=1}^{M} t_m \sum_{j=1}^{J} \gamma_j^m \left\{\left(\vartheta_j^m - c_j^m\right) y_j^m\right\} \tag{5}$$

where the objective of optimal water allocation is to obtain greater economic benefits, so the economic benefit function takes the maximum value. ϑ_j^m represents the economic income of j water users in the m subzone, and c_j^m represents the water supply cost of j water users in the m subzone. t_m γ_j^m represents the water order coefficient of water users in m subzone. The smaller the eco-efficiency OF is, the more optimal it is, and its functional expression is shown in Eq. (6).

$$\min f_3(y) = \sum_{m=1}^{M} \sum_{j=2}^{4} q_j^m d_j^m y_j^m \tag{6}$$

where d_j^m represents the pollutant discharge coefficient of j water users in the m subzone, and q_j^m represents the pollutant content of the discharge of j water users in the m subzone. The variables of the OF are valid only if the actual situation of the WR is satisfied, for which constraints need to be set. The total water supply of the regional WR cannot exceed the upper limit of the total WR available in the region.

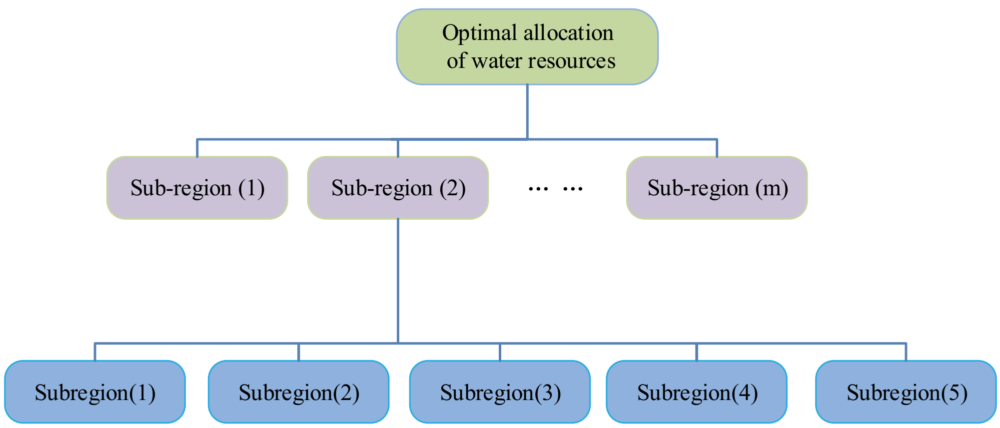

Fig. 1. Schematic diagram of optimal allocation and division of urban water resources.

Based on the total WR available in the standard year, the total water supply available in the planning year is predicted, and the constraint for WR supply is shown in Eq (7).

$$\begin{cases} \sum_{m=1}^{M}\sum_{j=1}^{j} y_j^m \le Y_k \\ y_{j\min}^m \le y_j^m \le y_{j\max}^m \quad i=1,2,\ldots,5 \quad m=1,2,\ldots,M \end{cases} \tag{7}$$

where Y_k represents the total amount of water available for the planning year. After the water supply quantity constraint, it needs constrain each user's water consumption and set a reasonable minimum value for the water consumption of the user. Setting a minimum value also reduces iterations number and optimizes this algorithm. According to the actual meaning of the variables, the water supply cannot be negative, so the decision variables should also satisfy the non-negative constraint, which is shown in Eq. (8).

$$y_j^m \ge 0 \tag{8}$$

where y_j^m represents the decision variables and satisfies the non-negative constraint. The water demand prediction value using the optimal water allocation conditions of each city needs to meet the red line target set by each province and city to satisfy the global constraints, and the constraints are shown in Eq. (9).

$$\sum_{m=1}^{M}\sum_{j=1}^{j} y_j^m \le X_{\mathrm{hx}} \tag{9}$$

where X_{hx} represents the water consumption red line control target set by the province and city. In 2011, the country put forward the No. 1 document on the three red lines of WR, which refer to total water consumption, using efficiency and pollutant discharge [17]. Fig. 2 shows the relationship between the three red lines and the optimal allocating of urban WR.

From Fig. 2, the red line of water consumption is the binding indicator, and the red line of water consumption is the minimum target for urban WR allocation, followed by water demand and supply indicators. In other words, the total amount of urban WR allocation cannot exceed the red line constraint index of water consumption.

3.2. SA algorithm based urban WR MBOAM solving

The common methods for solving multi-objective optimal configuration models include the integrated efficiency optimization method, penalty function method, objective programming method and intelligent optimization algorithm. Comparing these methods, the intelligent optimization algorithm is more adaptable to the optimization problem and is also applicable to both linear and nonlinear problems [18,19]. In this study, SA algorithm, which is one of the intelligent optimization algorithms, is used for solving this model. SA algorithm simulates a solid material's annealing process from a high temperature liquid state to a low temperature solid state in physics. In the solid matter's annealing process, the overall energy gradually decreases from high, and the energy change corresponds to the optimization of the function. In order to avoid the iterative process from falling into local optimum, the SA algorithm introduces the sudden jump of probability to receive the optimal solution with a certain probability. Fig. 3 shows a schematic representation of SA algorithm.

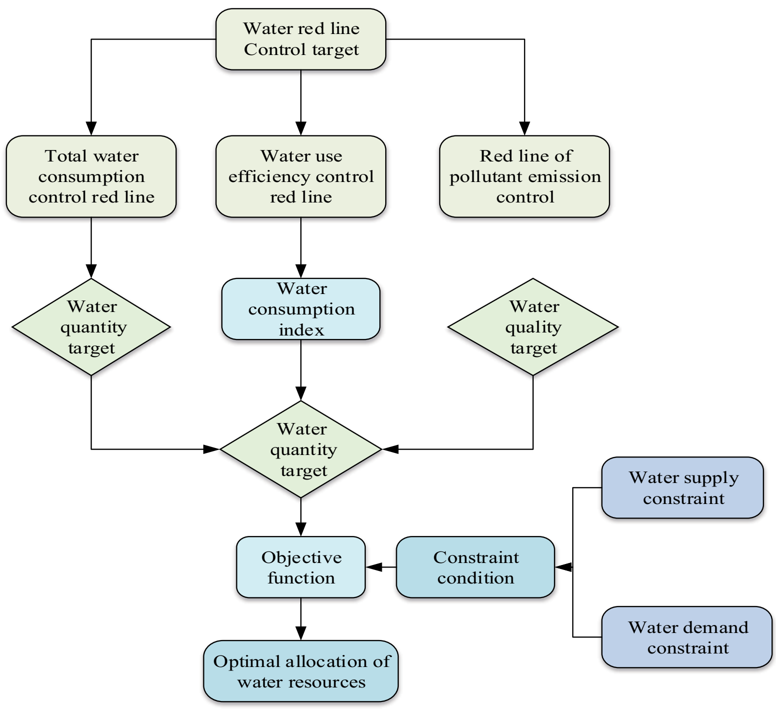

Fig. 2. Relationship between red line of water consumption and water resources.

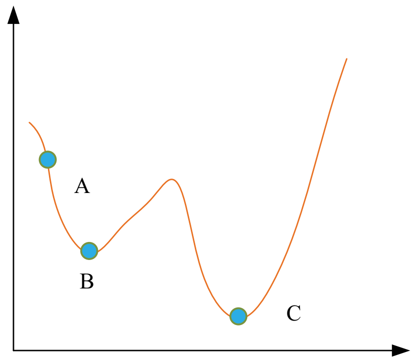

Fig. 3. Schematic diagram of simulated annealing algorithm.

As can be seen from Fig. 3, the function decreases consistently as it iterates from A to B. If solved by the greedy algorithm, the algorithm calculation ends when the value of B is reached. Since the simulated algorithm receives a certain probability of non-optimal solutions, the possibility of then advancing from the value of B to the value of C arises. The goal of SA algorithm is to find the global optimal solution and reduce the probability of missing the global true optimal solution for C value. According to SA algorithm's characteristics and generic parameter analysis, combined with the meaning of Pareto effective solutions in multi-objective programming, the solution step of the model starts with the elimination of the function magnitudes. In order to facilitate the subsequent calculation, the OFs with units $f_1(y)$, $f_2(y)$, $f_1(y)$ are used to eliminate the magnitudes with the function values of the base year, at which time the expressions of the OFs are shown in Eq. (10).

$$\begin{cases} \min f_1\left(y_j^m\right) = \dfrac{f_1\left(y_j^m\right)}{f_1\left(\partial\right)} \\ \min f_2\left(y_j^m\right) = \dfrac{f_2\left(y_j^m\right)}{f_2\left(\partial\right)} \\ \min f_3\left(y_j^m\right) = \dfrac{f_3\left(y_j^m\right)}{f_3\left(\partial\right)} \end{cases} \tag{10}$$

In Eq. (10) after eliminating the magnitudes, the parameters are also initialized. Using the integrated function to calculate these initial values, the smallest corresponding solution is selected as the initial solution of the multi-OF, and the solution process is shown in Eq. (11).

$$\min f_z = w_1 \times f_1\left(y_j^m\right) - w_2 \times f_2\left(y_j^m\right) + w_3 \times f_3\left(y_j^m\right) \tag{11}$$

where w represents the target weight, f_z represents the integrated function. The minimum value's corresponding solution is selected as the multi-OF's initial solution. After obtaining the initial solution, the initial temperature needs to be set, and its formula is shown in Eq. (12).

$$t_0 = \frac{-\Delta f_z}{\text{Pr}} = \frac{-\left(f_Z^{\max} - f_Z^{\min}\right)}{\text{Pr}} \tag{12}$$

where $f_z^{\max}$ represents the integrated function's maximum value, $f_z^{\min}$ represents the minimum value of the integrated function, and Pr represents the ratio of changes number in the initial temperature to the proposed changes number. The temperature reduction strategy is directly related to the global search performance of SA algorithm, and based on the reference [19], the exponential temperature reduction strategy is chosen in this study, and the exponential temperature reduction strategy is shown in Eq. (13).

$$t_{n+1} = \alpha \times t_n \tag{13}$$

where t_{n+1} and t_n denote the temperature of the n+1 and n times, respectively, and α is a constant related to the change of temperature, which usually takes a range of values between (0.95 and 0.99) and [20]. When the external conditions are consistent, the high temperature particles will tend to change to the low temperature particle energy state, the low temperature state of the energy particles more stable. Therefore, the maximum OF is chosen in the calculation of the function value, and its formula is shown in Eq. (14).

$$\bar{f}\left(y\right) = \max\left\{f_1\left(y_i\right), \left|f_2\left(y_i\right)\right|, f_3\left(y_i\right)\right\} \tag{14}$$

where $\bar{f}\left(y\right)$ denotes the maximum sub-OF. As the size of the problem changes, the size of the combinatorial optimization problem solution changes accordingly, and the formula for updating the variables is given in Eq. (15).

$$\tilde{y}_{i+h} = y - \mu + 2 \cdot \mu \cdot \text{Rd} \tag{15}$$

where $\tilde{y}_{i+h}$ represents a randomly selected point around this variable, μ is the step size, which is the ratio of the neighborhood to the number of constant temperature iterations, and Rd represents a random value greater than 1 and less than 0. In summary, the flow of the SA algorithm is shown in Fig. 4.

From Fig. 4 the initial temperature is first set to obtain the initial solution, which is simply transformed to produce the new solution, and then the difference of OF corresponding to the new solution is calculated. The determination of whether new solution is accepted or not is based on the acceptance criterion Δf, and if $\Delta f < 0$ is accepted as the new current solution. When the new solution is accepted, the current solution is replaced by this new solution, and the transformation part corresponding to the new solution's generation is implemented, while OF value is corrected. At this point, the current solution achieves one iterating. The next testing can be started. And when the new solution is discarded, the next trial continues on the foundation of the original current solution.

4. Analysis of urban WR multi-objective optimal allocation application

Taking urban Shenzhen as an example, the constructed MBOAM is applied and the results of its application are analyzed. To verify the effectiveness of this designed optimal allocation model in urban water allocation, the benefit indicators are predicted. To verify the superiority of the

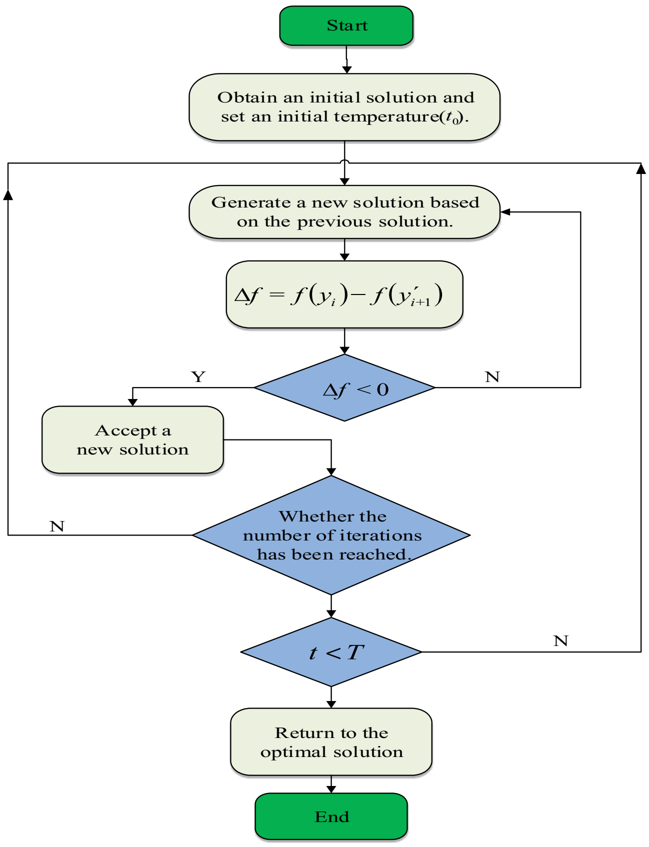

Fig. 4. Flow chart of simulated annealing multi-objective algorithm.

SA algorithm, comparison experiments are conducted with other algorithms.

4.1. SA algorithm performance analysis

With system reforming, city WR across the country is constantly being adjusted in terms of water supply allocation. Places like Hangzhou, Fuzhou and Shenzhen are densely populated and economically developed, but the total water consumption continues to approach the water red line. The contradiction of WR in these cities is becoming more and more prominent, and it is urgent to coordinate the water use structure [21]. Therefore, this study is based on the national three red lines policy and the three red lines scheme for WR in Guangdong Province, and Shenzhen is selected as an example for WR optimization. Table 1 shows the model parameters.

Table 1
Parameter setting

Parameter name	Value
Spatial scale of the initial solution	5000
Initial control acceptance probability Pr	0.9
Cooling index	0.96
End temperature	0.0001
Start temperature t_0	1.3022
Number of external cycles	201
Number of internal cycle terminations	1000

In Table 1, the model parameters are set to a cooling index of 0.96 and an initial control acceptance probability Pr of 0.9. The number of external cycles is 201 according to the formula, and the number of internal cycle terminations is 1,000 through repeated tests. Table 2 shows the water use efficiency parameters, water supply cost coefficients, pollutant emission coefficients and other parameters of the urban WR MBOAM.

From Table 2, the water use benefit coefficient is 0.0663 for domestic water use and 0.0001 for agricultural water use, and water supply's cost coefficient is 3.64 for non-residential water supply and 0.56 for agricultural water supply, while the pollutant discharge coefficient is 0.87 for industrial wastewater and 0.65 for urban public wastewater. The changes of benefit indexes for different annealing stages of the simulation algorithm are shown in Fig. 5.

From Fig. 5 it can be seen that the overall decline rate of the social, economic and ecological OF values is rapid and shows a steep slope change at the initial stage of annealing when the temperature is iterated from 1.4 to 1. In the middle stage of annealing, the decreasing trend of the OF value decreases when the temperature t decreases from 1 to 0.1.

Table 2
Parameter setting of water resources optimal allocating model

Parameter	Specific parameters	Value
Water benefit coefficient	Industrial water benefit	0.0471
	Agricultural water benefit	0.0001
	Domestic water benefit	0.0663
	Ecological water benefit	0.0596
Water supply cost coefficient	Cost coefficient of domestic water supply	2.43
	Non-residential water supply cost coefficient	3.64
	Agricultural water supply cost coefficient	0.56
Pollutant discharge coefficient	Industrial wastewater discharge coefficient	0.87
	Domestic sewage discharge coefficient	0.72
	Urban public sewage discharge coefficient	0.65

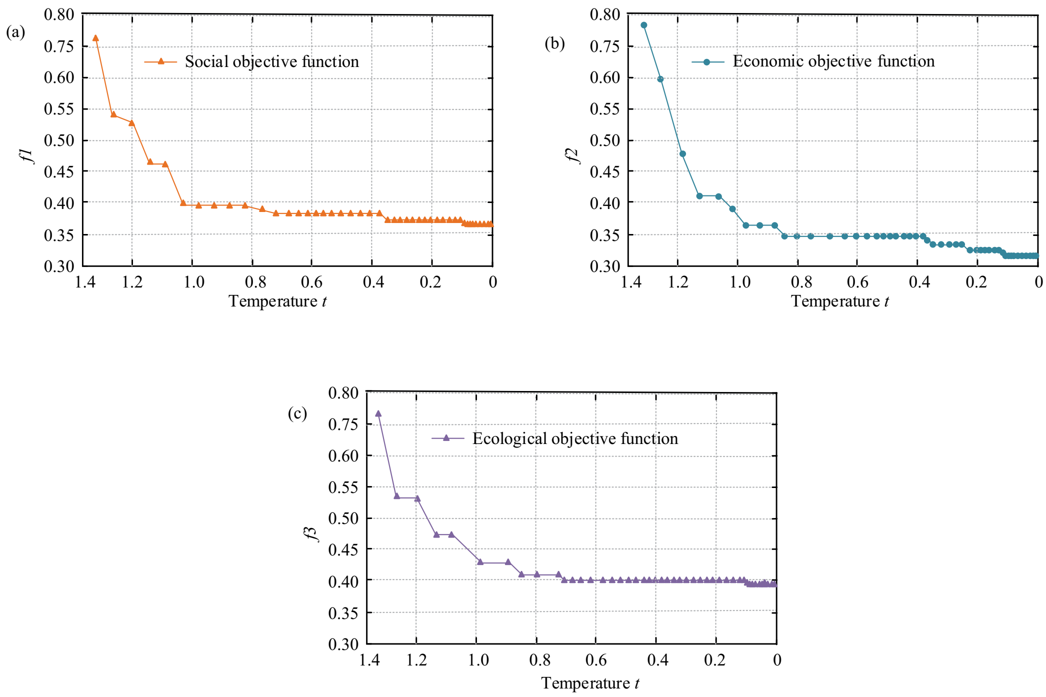

Fig. 5. OF gradually optimizes the process. (a) Trend diagram of social objective function optimization by annealing algorithm, (b) trend diagram of economic objective function optimization by annealing algorithm, and (c) trend diagram of ecological objective function optimization by annealing algorithm test set accuracy comparison results.

At the end of annealing, when the temperature t decreases from 0.1 to 0.0001, the rate of decrease of the objective value is almost 0, and the overall shows a flat line state, and the algorithm tends to converge. To test the advantage of using the multi-objective SA algorithm for solving in the configuration model, the multi-objective SA algorithm, the population genetic algorithm in the literature [13] and the SA algorithm in the literature [14] with the same parameters are compared in Fig. 6.

From Fig. 6, the function values solved by all three algorithms show a decreasing trend as the temperature decreases. Compared with other algorithms using multi-objective SA algorithm to solve the OF value, the function curve is the steepest decreasing rate and the flatter curve at the end has the best convergence.

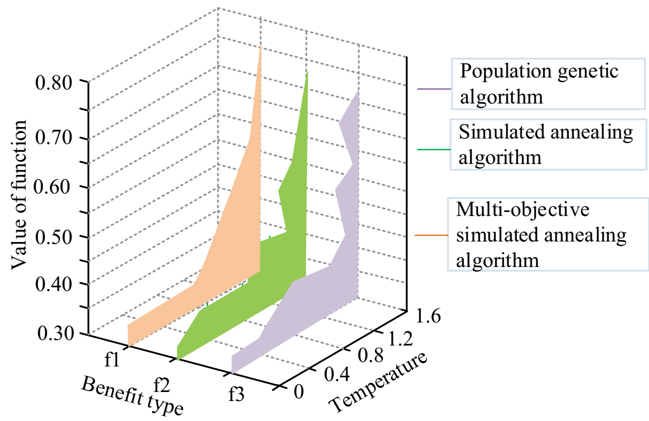

Fig. 6. Algorithm comparison results.

4.2. Analysis of urban WR optimal allocation application

The multi-objective optimal allocating of WR needs to achieve three benefits of three aspects. Table 3 shows the corresponding evaluation indicators' weight values under each objective.

Table 3 shows that the economic benefit objective has a weight value of 0.4702, the ecological benefit objective has a weight value of 0.3734, and the social benefit objective has a weight value of 0.2544. The economic benefit objective has the highest weight value among the three benefit objectives, and the social benefit objective has the lowest weight value. By analyzing water supply and demand in Shenzhen in 2023, a multi-objective SA algorithm was used to optimize WR allocating and coordinate the water supply and demand requirements in Shenzhen. The results of the analysis of the simulation algorithm focusing on the benefit target scenarios are shown in Fig. 7.

In Fig. 7 the Ecological Priority Scenario meets the ecological water target demand but not the industrial water target demand, with an industrial water shortage of 5.69 million·m^3. The Economic Priority Scenario meets the industrial water target demand but not the ecological water target demand, with an ecological water shortage of 5.89 million·m^3. The Economic Priority Scenario meets the ecological and agricultural water target demand but not the industrial and domestic water target demand, with an industrial water shortage of 5.93 and 5.78 million·m^3.

Based on the socio-economic profile, WR profile and sub-region profile of Shenzhen, the water demand and

Table 3
Weight value corresponding to the evaluation index

Performance indicator	Benefit constitutes an indicator	Upper limit	Lower limit	Optimal	Target weights
Social effect results benefit	Household water comfort level	0.0998	0.1085	0.1001	0.2544
	Social development	0.0081	0.0141	0.0106	
	Fairness of water use	0.0985	0.1043	0.0987	
	Water supply pressure	0.0305	0.0363	0.0335	
Ecological benefit	Level of ecological environment construction	0.1203	0.1185	0.1125	0.3734
	Environment is far away from the pollution degree	0.7685	0.1002	0.1001	
	Water resource regeneration capacity	0.0109	0.0156	0.0132	
	Water saving ability	0.1170	0.1121	0.1114	
Economic benefits	Economic development level of the industrial sector	0.0870	0.0952	0.0836	0.4702
	Economic development level of the agricultural sector	0.0301	0.0316	0.0305	
	Agricultural water supply cost coefficient	0.1705	0.1784	0.1695	
	Rationality of the industrial structure	0.1332	0.1352	0.1336	

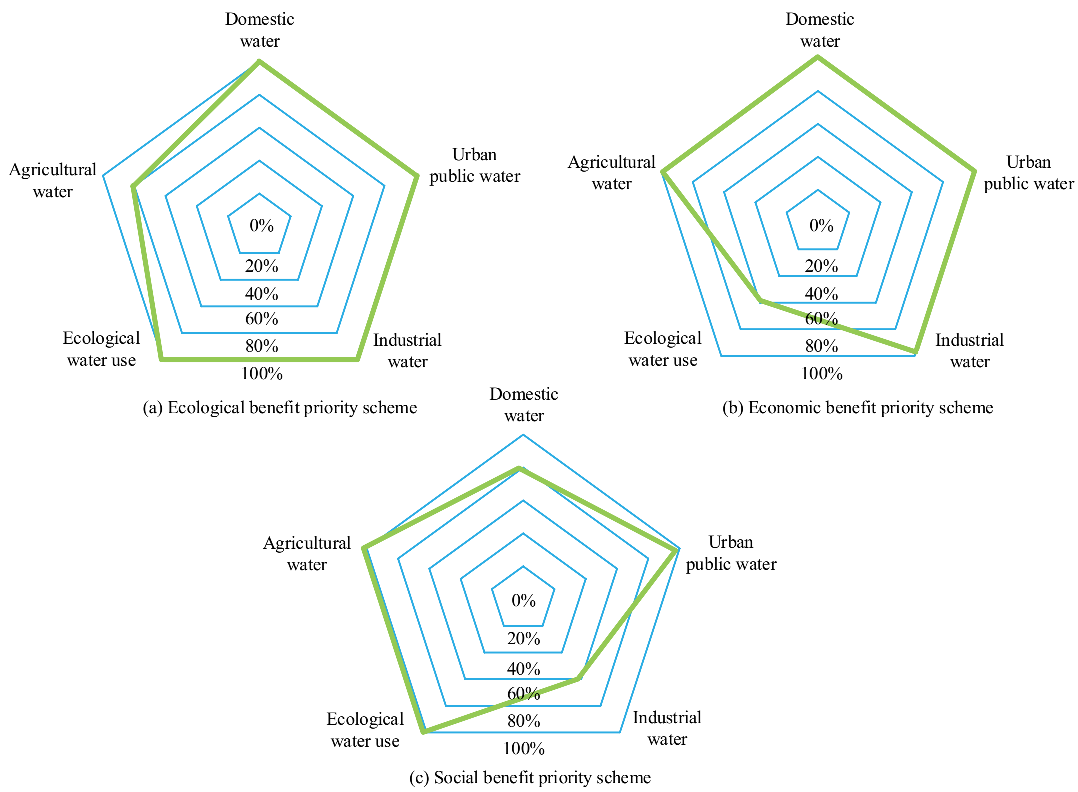

Fig. 7. Achievement degree of each program goal under 50% guarantee rate in 2022. (a) Ecological benefit priority scheme, (b) economic benefit priority scheme and (c) social benefit priority scheme.

supplying in Shenzhen in 2023 were predicted using the water supplying and demand prediction model. The statistical data of Shenzhen from 2011 to 2022 was selected as the original data and calculated cumulatively using the cumsum function series in MATLAB. The water demand forecast results are shown in Fig. 8.

From Fig. 8, the total water consumption forecast for Shenzhen in 2023 is 6,698.29 million·m^3, and the actual water demand is unknown for the time being; the total water consumption forecast for Shenzhen in 2022 is 6,573.27 million·m^3, and the actual total water demand is 6,606.53 million·m^3. The data qualified for this forecast also has good forecast accuracy, with a small probability error of 0.8532, of which the average relative error is. Similarly, the same method was used to forecast water supplying in the region, and these results are shown in Fig. 9.

From Fig. 9 the forecast value of water supply in Shenzhen in 2023 is 6,728.75 million·m^3, the forecast value

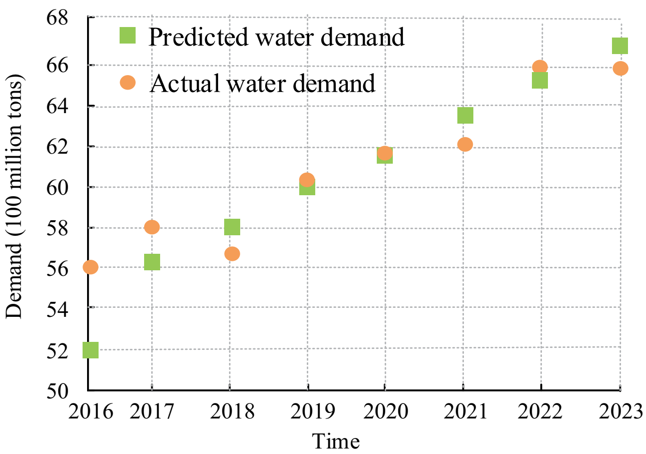

Fig. 8. Forecast map of water demand in Shenzhen.

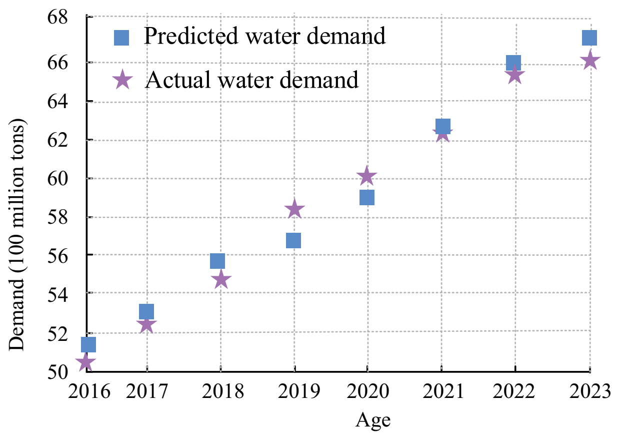

Fig. 9. Total water supply map of Shenzhen City.

of total water supply in Shenzhen in 2022 is 6,603.27 million·m^3, the actual total water demand is 6,556.53 million·m^3. The small probability error is 0.9586, of which the average relative error is 0.0212 and the variance ratio is 0.2109, indicating that the forecast result is valid and the test number is qualified. The actual total water demand in 2022 is 6,606.53 million·m^3 > actual water supply 6,556.53 million·m^3, the water supplying capacity is smaller than the planning year's demanding capacity, and there is a certain pressure of supply and demand.

5. Conclusion

To address the problem of optimal allocating of urban WR, this study designed a MBOAM, which was solved and improved using an algorithmic SA algorithm. The predicted total water consumption in Shenzhen in 2022 is 6,573.27 million·m^3 and the actual total water demand is 6,606.53 million·m^3. The predicted total water supply in Shenzhen in 2022 is 6,603.27 million·m^3 and the actual total water demand is 6,556.53 million·m^3. The small probability error is 0.9586, of which the average relative error is 0.0212 and the variance ratio is 0.2109. 0.2109, indicating that the prediction result is valid and the test number passes. The actual total water demand in 2022 is 6,606.53 million·m^3 greater than the actual water supply capacity of 6,556.53 million·m^3, and the water supplying capacity is less than the planning year's demanding capacity. In the SA algorithm, the temperature iterates from 1.4 to 1, the overall rate of decline of the three OF values is rapid, showing a steep slope change. When the temperature t decreases from 1 to 0.1, the decreasing trend of three OF values decreases, but the target values do not improve significantly with iteration increasing. At the end of annealing, the rate of decline of the objective value is almost 0, and the overall presentation of the flat line state value change is not obvious, and the algorithm tends to converge. Compared with other algorithms using multi-objective SA algorithm to solve OF value, the function curve is the steepest with the fastest rate of decline, and the curve is flat at the end with the best convergence. It shows that the multi-objective SA algorithm designed in this study effectively solves the traditional algorithm for water resource allocation, alleviates water resource conflicts, and is more conducive to the management of decision makers and improves management efficiency. The drawback of this study is that the consideration of factors affecting WR is not comprehensive enough, and more influencing factors will be introduced in the subsequent study.

References

[1] A. Mokhtar, H. He, H. Zhao, S. Keo, C. Bai, C. Zhang, Y. Ma, A. Ibrahim, Y. Li, F. Li, W. He, A.I. Abdogh, J. Zhoui, Risks to water resources and development of a management strategy in the river basins of the Hengduan Mountains, Southwest China, Environ. Sci. Water Res. Technol., 6 (2020) 656–678.

[2] X. Zi-Ying, Z. Jia-Ming, C. Qian, et al., An empirical analysis of China's water resources status and development forecast, J. Huaiyin Teachers Coll. (Nat. Sci. Ed.), 1 (2019) 39–49.

[3] J. Liu, M. Li, M. Wu, X. Luan, W. Wang, Z. Yu, Influences of the south–to-north water diversion project and virtual water flows on regional water resources considering both water quantity and quality, J. Cleaner Prod., 244 (2020) 118920, doi: 10.1016/j.jclepro.2019.118920.

[4] C. Zhang, Y. Liu, H. Qiao, An empirical study on the spatial distribution of the population, economy and water resources in Northeast China, Phys. Chem. Earth Parts A/B/C, 79 (2015) 93–99.

[5] Z. Zhang, X. Wang, S. Cheng, P. Guan, H. Zhang, C. Shan, Y. Fu, Investigation on the difference of $PM_{2.5}$ transport flux between the North China Plain and the Sichuan Basin, Atmos. Environ., 271 (2022) 118922, doi: 10.1016/j.atmosenv.2021.118922.

[6] S.A. Abdulrahman, Water use practice and water law in Kurdistan region: how can sustainability be achieved?, Environ. Policy Law, 51 (2021) 1–11.

[7] H. Lv, L. Yang, J. Zhou, X. Zhang, W. Wu, Y. Li, D. Jiang, Water resource synergy management in response to climate change in China: from the perspective of urban metabolism, Resour. Conserv. Recycl., 163 (2020) 105095, doi: 10.1016/j.resconrec.2020.105095.

[8] D. Wu, M. Liu, Coordinated optimal allocation of water resources and industrial structure in the Beijing–Tianjin–Hebei regions of China, Chin. J. Popul. Resour. Environ., 20 (2022) 392–401.

[9] A. Kang, J. Li, X. Lei, M. Ye, Optimal allocation of water resources considering water quality and the absorbing pollution capacity of water, Water Resour., 47 (2020) 336–347.

[10] J. Tian, D. Liu, S. Guo, Z. Pan, X. Hong, Impacts of inter-basin water transfer projects on optimal water resources allocation in the Hanjiang River Basin, China, Sustainability, 11 (2019) 2044, doi: 10.3390/su11072044.

[11] D. Liu, X. Ji, J. Tang, H. Li, A fuzzy cooperative game theoretic approach for multinational water resource spatiotemporal allocation, Eur. J. Oper. Res., 282 (2020) 1025–1037.
[12] Y. Wang, Y. Cui, J. Shao, Q. Zhang, Study on optimal allocation of water resources based on surrogate model of groundwater numerical simulation, Water, 11 (2019) 831, doi: 10.3390/w11040831.
[13] R. Li, Y. Chang, Z. Wang, Study of optimal allocation of water resources in Dujiangyan irrigation district of China based on an improved genetic algorithm, Water Supply, 21 (2021) 2989–2999.
[14] M. Cunha, J. Marques, A new multi-objective simulated annealing algorithm—MOSA-GR: application to the optimal design of water distribution networks, Water Resour. Res., 56 (2020) e2019WR025852, doi: 10.1029/2019WR025852.
[15] S.Z. Mousavi, A.M. Akhondali, A. Naseri, S. Eslamian, S. Saadati, Evaluation of whale and particle swarm optimisation algorithms in optimal allocation of water resources of irrigation network to maximise net benefit case study: Salman Farsi, Int. J. Hydrol. Sci. Technol., 12 (2021) 333–345.
[16] X.S. Yang, Multi-objective optimization, Nature-Inspired Optimization Algorithms (Second Edition), 29 (2021) 221–237.
[17] H. Guan, L. Chen, S. Huang, C. Yan, Y. Wang, Multi-objective optimal allocation of water resources based on 'three red lines' in Qinzhou, China, Water Policy, 22 (2020) 541–560.
[18] H. Liu, F. Gu, Y.-M. Cheung, An expensive multi-objective optimization algorithm based on decision space compression, Int. J. Pattern Recognit. Artif. Intell., 35 (2021) 2159039 (19 Pages), doi: 10.1142/S0218001421590394.
[19] M. Barma, U.M. Modibbo, Multi-objective mathematical optimization model for municipal solid waste management with economic analysis of reuse/recycling recovered waste materials, J. Comput. Cognit. Eng., 1 (2022) 122–137.
[20] A.M. Alhambra, M. Lostaglio, C. Perry, Heat-bath algorithmic cooling with optimal thermalization strategies, Quantum: Open J. Quantum Sci., 3 (2019) 188, doi: 10.22331/q-2019-09-23-188.
[21] K. Cheng, J. Yao, Y. Ren, Evaluation of the coordinated development of regional water resource systems based on a dynamic coupling coordination model, Water Supply, 19 (2019) 565–573.