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Comprehensive dispatch model of agricultural water resources based on multi-objective quantum genetic algorithm

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ABSTRACT

In order to solve the problems of slow convergence speed, poor optimization effect, the large deviation between irrigation area and yield, and low water resource utilization rate, the integrated scheduling model of agricultural water resources based on a multi-objective quantum genetic algorithm is proposed. Taking the largest fully irrigated area and the largest crop yield as the optimization goals, construct a comprehensive scheduling model of agricultural water resources. On the basis of quantum genetic algorithm and multi-objective optimization algorithm, multi-objective quantum genetic algorithm is adopted, combined with real number coding of qubits, and quantum state interference characteristics are used to carry out probability crossover. According to the non-dominant sorting group classification mechanism and the non-inferior solution level sorting population classification, multi-objective optimization strategies such as elite retention and hierarchical clustering are used to solve the comprehensive scheduling model of agricultural water resources and realize the comprehensive scheduling of agricultural water resources. The experimental results show that the deviation of irrigation area proportion and irrigation yield of the proposed algorithm is small, and the optimization effect is good, which can effectively improve the utilization rate of water resources and accelerate the convergence speed.

Keywords: Multi-objective quantum genetic algorithm; Quantum genetic algorithm; Multi-objective optimization algorithm; Quantum bit coding

1. Introduction

The water resource is an indispensable basic resource for human daily life and social and economic development, and also an irreplaceable important natural resource. The essential difference between water resources and other solid resources is that it has mobility. It is a dynamic resource formed in the water cycle and is cyclical [1]. However, in fact, the global storage of freshwater resources is very limited. The global freshwater resources only account for 2.5% of the total global water resources, and most of the freshwater resources are stored in polar ice caps and glaciers, and the freshwater resources that can be directly used by people only account for 0.796% of the global total water amount [2]. In recent years, with the continuous growth of population and the rapid development of the social economy, people are developing and using extremely limited water resources at an unprecedented speed and scale. From the use of surface water and natural precipitation to the exploitation of groundwater resources, people's demand for water resources has increased dramatically, and the water resources problem has evolved from some water shortage countries and regions to a global problem [3]. At present, the global water resources not only have a small per capita share and serious pollution, but also present the characteristics of unreasonable space-time distribution, the prominent contradiction between supply and demand, high utilization rate, low utilization efficiency and serious waste. Therefore, it is necessary to optimize and dispatch the limited water resources, realize the sustainable utilization of water resources, promote the virtuous cycle of the ecological environment, and ensure the sustainable development of the social economy.

Water is the key factor to control the evolution of the ecological system and limit the sustainable development of the social economy. The comprehensive regulation of water resources is one of the effective ways to solve the shortage of water resources and the deterioration of the ecological environment. Wang et al. [4] uses dynamic parameter strategies to avoid manual adjustment of step factors and builds linear, exponential and mixed estimation models based on historical water consumption and local economic structure. The normalization method is used to eliminate the influence of different data units, and the water demand scheduling estimation algorithm based on the dynamic firefly algorithm is realized. The evaluation accuracy of this method is high. You-Chiun and Kai-Chung [5] proposed a framework for energy-saving pricing and water resources scheduling. Considering the HetNet scenario, select the coordinator to divide the services into groups. In order to save energy and reduce water consumption as optimization objectives, a two-layer scheduling strategy is adopted to build energy-saving pricing and water resource scheduling model according to user flow, channel quality and packet delay. Through the use of peak and off-peak rates, user fees can be adjusted adaptively to achieve energy-saving pricing and water resource scheduling. This method has high throughput and can effectively save resources. However, the above algorithm does not consider the situation that the algorithm itself is easy to fall into the local optimal solution, resulting in slow convergence speed and poor optimization effect, resulting in a large deviation between irrigation area and yield, and low water resource utilization rate.

In order to solve the above problems, a comprehensive scheduling model of agricultural water resources based on a multi-objective quantum genetic algorithm is proposed. The water supply source is set as the decision variable, the maximum fully irrigated area and the maximum crop yield are taken as the objective function, and the constraints of irrigation water quantity, water balance equation and reservoir capacity are taken as constraints to construct the comprehensive operation model of agricultural water resources. The multi-objective quantum genetic algorithm (MQGA) is adopted, and the quantum state interference characteristics are used to carry out probability crossover. The population classification mechanism based on nondominated sorting is adopted to classify the population according to the level of non-inferior solution. The multi-objective optimization strategies such as elite retention and hierarchical clustering are used to solve the comprehensive scheduling model of agricultural water resources to realize the comprehensive scheduling of agricultural water resources. Using the multi-objective quantum genetic algorithm to solve the comprehensive scheduling model of agricultural water resources has a high convergence speed and optimization effect, and the deviation between the irrigation area ratio and the irrigation output is small, which can effectively improve the utilization rate of water resources.

2. Construction of a comprehensive dispatch model for agricultural water resources

Agricultural water resources can be used for agricultural production, including surface water, groundwater and soil water. Among them, soil water is the only form of water resource that can be directly absorbed and utilized by dryland crops. Surface water and groundwater can only be used by crops after being transformed into soil water. Based on the principle of efficient and sustainable utilization of water resources, the multi-objective water resources optimal scheduling is adopted to comprehensively dispatch agricultural water resources, to seek the optimal allocation of agricultural water consumption, and to realize the sustainable utilization of water resources and the maximization of comprehensive benefits.

2.1. Decision variables

According to the situation of agricultural water resources and agricultural water supply, the water supply sources are divided into surface water, groundwater and soil water, and the water demand is divided into four categories: irrigation, livestock, living and ecological environment. The decision variables determined by different water sources and water demand are shown in Table 1.

2.2. Objective function

In the current process of agricultural water resources regulation, the maximum irrigation area or the maximum crop yield is generally selected as the scheduling objective. However, in actual production, it is often necessary to comprehensively consider the two and select the scheduling method. Therefore, this paper chooses to calculate irrigation area and crop yield respectively, and on this basis, determines the comprehensive function of the two objectives.

- Largest fully irrigated area:

$$\max F_1(Z) = \sum_{l=1}^{p} \min\left(\frac{(A_c)_k^l}{(A_n)_k^l}\right) \times U_l \tag{1}$$

Table 1
Decision variables

Water source	Irrigation water consumption	Livestock water consumption	Domestic water consumption	Ecological water consumption
Surface water	y_{11}	y_{12}	y_{13}	y_{14}
Ground water	y_{21}	y_{22}	y_{23}	y_{24}
Soil water	y_{31}	y_{32}	y_{33}	y_{34}

In Eq.3 (1) $(A_c)_k^l$ represents the actual water supply of crop l at stage k, $(A_n)_k^l$ represents the water demand of crop l at stage k, and U_l represents the planting area of crop l.

- Largest crop yield:

$$\max F_2(Z) = \sum_{l=1}^{P}\prod_{k=1}^{P}\left(\frac{(A_c)_k^l}{(A_n)_k^l}\right)^{\tau} \times U_l \times O_l \tag{2}$$

In Eq. (2), τ represents the sensitivity index of crop l at stage k, and O_l represents the unit yield of crop l.

By processing the above two sub-objectives, the synthetic objective function is proposed as follows:

$$\max F(Z) = \left(F_1(Z), F_2(Z)\right) \tag{3}$$

The comprehensive regulation of agricultural water resources can indirectly control the scale and speed of social and economic development, protect the ecological environment, and the ultimate goal is the sustainable utilization of water resources and the sustainable development of social economy, and give full play to the maximum utility of water resources under the condition of limited water resources.

2.3. Constraints

- *Irrigation water volume constraint*: The irrigation water volume of each crop in each time period should not exceed the water demand of the corresponding time period, namely:

$$0 \le (A_c)_k^l \le (A_n)_k^l \tag{4}$$

- *Water balance equation*: The storage capacity V of each period of the reservoir should be equal to the storage capacity V_l of the previous period plus the incoming water L_i of this period minus the water q_i, namely:

$$V = V_l + L_i - q_i \tag{5}$$

- *Reservoir capacity constraint*: The reservoir should satisfy that the storage capacity is less than the storage capacity V_r at any time during the dry season, namely:

$$0 \le V \le V_r \tag{6}$$

3. Solution of agricultural water resources comprehensive scheduling model based on multi-objective quantum genetic algorithm

A quantum genetic algorithm (QGA) is a probability optimization genetic algorithm based on the principle of quantum computing. Based on the expression of the quantum state vector, the probability amplitude representation of quantum bits is applied to chromosome coding, so that a chromosome can express the superposition of multiple states, making it more parallel and diverse. Using quantum rotation gate and quantum non-gate to complete chromosome updating operation can maintain population diversity and avoid selection pressure problem, which has higher search efficiency and better convergence characteristics [6]. The multi-objective ant colony algorithm is adopted. On the one hand, the pheromone in the ant algorithm guides the genetic selection by QGA; On the other hand, the result of QGA causes the update of the pheromone and is used to guide the next genetic selection. It makes full use of the parallelism, positive feedback mechanism and high efficiency of the ant algorithm to complement each other, so as to improve the accuracy and efficiency of the solution and realize the optimization of the solution.

3.1. Quantum genetic algorithm

3.1.1. Quantum bit coding

In quantum computing, the physical medium acting as the information storage unit is a two-state quantum system, called qubit or qubit [7]. A qubit can not only represent two states of 0 and 1, but also any superposition state between these two states at the same time. That is, a qubit may be in $|0\rangle$ or $|1\rangle$, or in an intermediate state between the two, that is, different superposition states of $|0\rangle$ or $|1\rangle$. The state of a qubit can be expressed as:

$$|\psi\rangle = \chi|0\rangle + \delta|1\rangle |\psi\rangle = \chi|0\rangle + \delta|1\rangle \tag{7}$$

In Eq. (7), $\chi|0\rangle$ and $\delta|1\rangle$ represent the spin-down state and the spin-up state, respectively, and χ and δ represent the probability amplitudes of $|0\rangle$ and $|1\rangle$ respectively and satisfy the normalization conditions:

$$|\chi|^2 + |\delta|^2 = 1 \tag{8}$$

In Eq. (8), $|\chi^2|$ represents the probability that the observed value of the quantum state is 0, and $|\delta^2|$ represents the probability that the observed value of the quantum state is 1.

In a typical quantum genetic algorithm, the structure of the chromosome encoded by the quantum bit amplitude is expressed as:

$$\boldsymbol{Q}_j^t = \begin{bmatrix} \chi_{11}^t\chi_{12}^t\cdots\chi_{1\varpi}^t \left|\chi_{21}^t\chi_{22}^t\cdots\chi_{2\varpi}^t\right|\cdots\left|\chi_{m1}^t\chi_{m2}^t\cdots\chi_{m\varpi}^t\right| \\ \delta_{11}^t\delta_{12}^t\cdots\delta_{1\varpi}^t \left|\delta_{21}^t\delta_{22}^t\cdots\delta_{2\varpi}^t\right|\cdots\left|\delta_{m1}^t\delta_{m2}^t\cdots\delta_{m\varpi}^t\right| \end{bmatrix} \tag{9}$$

In Eq. (9), $\boldsymbol{Q}_j^t$ represents the chromosome of the j individual in the t generation, m represents the number of chromosomal genes, the number of variables corresponding to the function, ϖ represents the number of qubits of each gene encoded, $\chi_{m\varpi}^t$ and $\delta_{m\varpi}^t$ represent two complex constants and $\left|\chi_{m\varpi}^t\right|^2 + \left|\delta_{m\varpi}^t\right|^2 = 1$.

3.1.2. Quantum gate selection

Quantum revolving gate is the executive mechanism of evolutionary operation [8], and its adjustment operation is as follows:

$$\begin{pmatrix} \chi_i^t \\ \delta_i^t \end{pmatrix} = \begin{pmatrix} \cos(\sigma_i) & -\sin(\sigma_i) \\ \sin(\sigma_i) & \cos(\sigma_i) \end{pmatrix} \begin{pmatrix} \chi_i \\ \delta_i \end{pmatrix} \tag{10}$$

In Eq. (10), (χ_i,δ_i) represents the i qubit in the chromosome, and σ_i represents the rotation angle, the size and direction of which are determined according to the designed adjustment strategy. The selection method of rotation angle is shown in Table 2.

Rotation angles $\sigma_i = S(\chi_i\delta_i)\Delta\sigma_i$, $S(\chi_i\delta_i)$ and $\Delta\sigma_i$ represent the direction and angle of rotation, and their values are determined by the selection method in the table. The adjustment process is: the first measure the individual chromosome $\boldsymbol{Q}_j^t$ and calculates its fitness $f(x)$, then compare it with the current target value of fitness $f(b)$, and adjust the corresponding qubit in $\boldsymbol{Q}_j^t$ according to the comparison result. When $f(x) < f(b)$, it means that the fitness of individual chromosomes is small, and the probability amplitude pair (χ_i,δ_i) should evolve in a direction favorable to the emergence of $f(b)$, otherwise, it should evolve in a direction favorable to the emergence of $f(x)$.

3.1.3. Quantum position variation

In the quantum ant colony algorithm, the quantum mutation operation is designed through the quantum not gate. The specific steps are as follows:

- Select several individuals from the quantum ant population with a certain probability Q_m;
- Determine one or more mutation positions for the selected individual quantum ant according to a certain probability;
- The quantum non-gate operation is performed on the probability of the selected qubit, that is, the mutation operation of the qubit is completed.

3.1.4. Pheromone production and diffusion

The update of the pheromone strength is to integrate the fitness function value reflecting the pros and cons of the current position of the ant into the pheromone, so that the better the position, the higher the pheromone strength; The gradient information of the fitness function is integrated into the visibility, so that the greater the gradient, the greater the visibility [9]. After each and completes a one-step search, the current position is mapped from the unit space to the solution space of the optimization problem, and the fitness function value and gradient value are calculated.

The formula of pheromone generation is as follows:

$$P_t\left(\boldsymbol{Q}_j^t\right) = \left[f\left(\boldsymbol{Q}_j^t\right) - f_t^{\min}\right] \times w \tag{11}$$

In Eq. (11), $f_t^{\min}$ represents the smallest fitness among individuals of the t generation, $f(\boldsymbol{Q}_j^t)$ represents the fitness of the individual $\boldsymbol{Q}_j^t$, $P_t(\boldsymbol{Q}_j^t)$ represents the pheromone produced by the individual $\boldsymbol{Q}_j^t$ at the source center of the t generation, and w represents a constant, which is specifically determined by the fitness function.

The pheromone diffusion formula is as follows:
When $e < r$,

$$P_{tt}(x_0) = P x_0^{\min} + P_t\left(\boldsymbol{Q}_j^t\right)\left(\frac{(r-e)}{r}\right) \tag{12}$$

When $e \geq r$,

$$P_t(x_0) = P_t x_0^{\min} \tag{13}$$

In Eqs. (12) and (13), $P_t(x_0)$ represents the pheromone that the source center point x_0 diffuses at the chromosome $\boldsymbol{Q}_j^t$, r represents the diffusion radius of the source, $P_t x_0^{\min}$ represents the smallest pheromone in the t generation chromosome, and e represents the distance between the source center point x_0 and $\boldsymbol{Q}_j^t$.

When calculating the pheromone of the source diffusion of an individual at a certain point, we first find the individual of the source center point nearest to the point, then the pheromone of the individual at a certain point is obtained by the individual diffusion of the source center point [10]. Information is diffused in a cone model. The closer an individual is to the center of the source, the stronger the pheromone is, and vice versa. However, each individual has a minimum pheromone, which makes each individual have a chance to be selected into the next generation population.

Table 2
Rotation angle selection method

		$S(\chi_i\delta_i)$			
$f(x) \geq f(b)$	$\Delta\sigma_i$	$\chi_i\delta_i > 0$	$\chi_i\delta_i < 0$	$\chi_i = 0$	$\delta_i = 0$
False	0	0	0	0	0
True	0	0	0	0	0
False	0	0	0	0	0
True	0.05π	–1	+1	+1	0
False	0.01π	–1	+1	+1	0
True	0.025π	+1	–1	0	+1
False	0.005	+1	–1	0	+1

3.2. Multi-objective optimization algorithm

Taking the minimization of a multi-objective problem under a set of constraints as an example, the multi-objective optimization problem can be described as:

$$\begin{cases} \min S(X) = \left[S_1(X), S_2(X), \cdots, S_n(X)\right] \\ s.t. \qquad g_q(X) \leq 0 \end{cases} \tag{14}$$

In Eq. (14), $\boldsymbol{X} = [x_1, x_2, \ldots, x_D] \in R^D$ represents a vector with D decision variables to form a decision space, $\boldsymbol{S}(\boldsymbol{X}) \in R^T$ represents a vector with T objective functions to form a target space, and $g_q(X)$ represents q inequality constraint functions, which form a feasible solution area.

Several basic definitions commonly used in multi-objective optimization are given below:

- *Pareto domination*: Solution X_1 Pareto dominates $X_2(X_1 < X_2)$, if and only if both satisfy:

$$S_\beta(X_1) \le S_\beta(X_2), \forall\beta = 1,2,\cdots,n$$
$$S_\beta(X_1) < S_\beta(X_2), \exists\beta \in \{1,2,\cdots,n\} \tag{15}$$

- *Pareto optimal*: If S is Pareto optimal, if and only if $\neg\exists S_\beta : S_\beta < S$.
- *Pareto optimal set*: The set $W_s = \{S|\neg\exists S_\beta < S\}$ of all Pareto optimal solutions.
- *Pareto optimal frontier or equilibrium surface*: The region formed by the objective function values corresponding to all Pareto optimal solutions.

3.3. Multi-objective quantum genetic algorithm

A multi-objective quantum genetic algorithm (MOQGA) is proposed on the basis of a quantum genetic algorithm and multi-objective optimization algorithm. It uses qubit real number coding to improve calculation accuracy and uses quantum state interference characteristics for probability crossover. Improve optimization efficiency and convergence speed, while maintaining population diversity based on multi-objective optimization strategies such as non-branch sorting, elite retention, and hierarchical clustering, ensure that evolution is progressing toward the Pareto global optimal solution set.

3.3.1. Qubit chromosome real number encoding

The multi-objective quantum genetic algorithm uses one real qubit instead of multiple binary qubits to represent the variable [11]. The chromosome structure encoded by the real number of qubits is expressed as follows:

$$\boldsymbol{P}_g^v = \begin{bmatrix} \lambda_l^v & \lambda_2^v & \cdots & \lambda_y^v \\ \varepsilon_1^v & \varepsilon_2^v & \cdots & \varepsilon_y^v \end{bmatrix} \tag{16}$$

In Eq. (16), $1 \le g \le N_p$, N_p represent the population size, $\lambda_y^v \in \left[\lambda_{y\min}^v, \lambda_{y\max}^v\right]$ represents the real variable, ε_y^v represents the phase angle corresponding to the variable, and there are:

$$\varepsilon_y^v = \arcsin\left[\frac{\lambda_y^v - \lambda_{y\min}^v}{\lambda_{y\max}^v - \lambda_{y\min}^v}\right] \tag{17}$$

In this way, the information of each chromosome can be expressed simultaneously in real space and phase space.

3.3.2. Group classification mechanism

The population classification mechanism based on non-dominated ranking is adopted to classify the population according to the level of noninferior solution. The algorithm needs to calculate the parameters N_c and S_c of each individual c of the population, where N_c represents the number of individuals dominating individual c in the population, and S_c represents the collection of individuals dominated by individual c in the population [12]. The specific steps of fast non dominated sorting are as follows:

- Find all N_c = 0 individuals in the population and save them in the current set K_1.
- For each individual c in the current set K_1, the set of individuals dominated by it is S_c. Traverse each individual ω in S_c and execute $S_\omega = S_\omega - 1$. If $S_\omega = 0$, save ω in the set H_1.
- Record the individual obtained in K_1 as the first non-dominated individual, and use H_1 as the current set, and repeat the above operations until the entire population is stratified.
- According to the sequence number of the ranking, a virtual fitness value is assigned to each level of the individual. The higher the ranking, the stronger the degree of non-domination of the corresponding individual.

3.3.3. Elite retention strategy

The elite strategy is to keep the good individuals in the parent directly into the offspring. According to the concept of hierarchical clustering, the crowding distance of α_1 is calculated and sorted. The basic method is:

- Combine the parent population F_t and the offspring population Z_t into a population Q_t, $Q_t = F_t \cup Z_t$, Q_t pair to perform non-dominated sorting, and the determined Q_t non-dominated solution front surface $\zeta = (\zeta_1, \zeta_2, \ldots)$ is all.
- Calculate the crowded distance of α_1 and execute $F_{t+1} = F_{t+1} \cup \alpha_1$ until $|F_{t+1}| + |\alpha_1| \le N_p$.
- According to the concept of niche, the crowding distance $Y(\phi)$ is introduced to sort all non-inferior front ends α_1 according to crowding comparison operations. The higher the level and the smaller the crowding distance, the lower the ranking in the population. Choose the best ranked (N_p – $|F_{t+1}|$) solution in α_1, namely $F_{t+1} = F_{t+1} \cup \alpha_1\left[1:\left(N_p - |F_{t+1}|\right)\right]$.
- According to the non-inferior stratification and the crowding distance, assign a virtual fitness value to each level of the individual. The higher the ranking of the target value, the stronger the degree of non-domination of the corresponding individual [13].

This strategy can automatically adjust niche (niche) to protect good individuals, and at the same time, make the calculation results more evenly distributed in the target space, and has good robustness. The calculation method of congestion distance is as follows:

$$\begin{cases} Y(\phi) = \sum_{o=1}^{n} Y(\phi, o) \\ Y(\phi, o) = \dfrac{g_{\phi\text{next},o} - g_{\phi\text{from},o}}{g_{o\max} - g_{o\min}} \end{cases} \tag{18}$$

In Eq. (18), $Y(\phi)$ represents the crowding distance of the ϕ individual in the population, $Y(\phi,o)$ represents the crowding distance of the ϕ individual on the o target component. The values of the o target component corresponding to all individuals with the same level of merits and demerits of the ϕ individual are sorted from small to large, and $g_{\phi\text{next},o}$ represents $g_{\phi,o}$ (the value of the ϕ individual on the o target component) $g_{\phi\text{from},o}$ represents the previous adjacent value of $g_{\phi,o}$, $g_{o\max}$ and $g_{o\min}$ represent the maximum and minimum values, respectively.

3.3.4. Quantum bit probability crossover

In this paper, a vector modulus fitness function is used as the evaluation standard, the objective function value in the target space is regarded as the vector in u dimensional space, and the modulus of the vector (i.e., the Euclidean distance from the origin) is used as the fitness value of the individual to guide the evolution [14]. That is:

$$G\left(P_g^v\right)=\left\|g_\phi\right\|=\sqrt{g_{\phi 1}^2(x)+g_{\phi 2}^2(x)+\cdots+g_{\phi o}^2(x)} \tag{19}$$

In Eq. (19), $g_{\phi o}(x)$ represents the o objective function in the ϕ individual target space. For the minimization problem, the smaller each component of the target vector is, the better, and the smaller the corresponding vector modulus fitness function value is, the better.

According to the crossover probability, the next generation is generated by crossing a generation of individuals in real numbers.

If $\left\|g_\phi\right\| \geq \left\|g_\vartheta\right\|$, then there are:

$$\begin{cases} \Delta\varepsilon_y^v=\varepsilon_y^v-\varepsilon_\vartheta^v \\ P_g^{v+1}=P_g^v\cos\left(\Delta\varepsilon_y^v\right)+P_h^v\sin^2\left(\Delta\varepsilon_y^v\right) \end{cases} \tag{20}$$

Otherwise, there are:

$$\begin{cases} \Delta\varepsilon_y^v=\varepsilon_\vartheta^v-\varepsilon_y^v \\ P_g^{v+1}=P_h^v\cos^2\left(\Delta\varepsilon_y^v\right)+P_g^v\sin^2\left(\Delta\varepsilon_y^v\right) \end{cases} \tag{21}$$

The evolutionary updating of the chromosome is realized by the quantum rotation gate operator, and the conversion between arbitrary superposition states can be realized through the quantum rotation gate, which has high parallelism [15]. Its working principle is as follows:

$$P_h^{v+1}=\begin{bmatrix} \cos\left(\Delta\varepsilon_y^v\right) & -\sin\left(\Delta\varepsilon_y^v\right) \\ \sin\left(\Delta\varepsilon_y^v\right) & \cos\left(\Delta\varepsilon_y^v\right) \end{bmatrix}\cdot P_h^v \tag{22}$$

3.4. Algorithm flow

To sum up, the basic steps of solving the agricultural water resources comprehensive scheduling model based on the multi-objective quantum genetic algorithm are as follows:

Step 1: Set the initial population size N_p, the number of qubits L_s, the number of global iterations $N_{\max,\text{gen}}$, the rotation angle operator $[\rho_{\min},\rho_{\max}]$, and the external archive set size N_{EA};

Step 2: Generate the initial solution population based on the quantum two-chain coding scheme, the initial global iteration number $N_{\text{gen}} = 1$, and the external archive set is an empty set;

Step 3: Observe the chromosome encoded by the probability amplitude of the population Q_t, obtain the corresponding definite solution $w(t) = \{x_1^t, x_2^t, \ldots, x_n^t\}$, and modify $w(t)$;

Step 4: Convert the solution space, calculate the individual objective function values, and perform non-dominated sorting on the population individuals, select the strategy and select the global guide to maintaining the non-inferior solution external file set;

Step 5: Calculate the rotation angle σ_i according to the adjustment strategy of the quantum rotation angle, and correct the probability amplitude after the operation of the quantum rotation gate to realize Q_t update;

Step 6: Perform a quantum crossover operation to determine whether a quantum catastrophe is required, if it is satisfied, perform a quantum catastrophe operation; If not, proceed to step 7;

Step 7: Check whether the algorithm termination condition is met, if the termination condition is met, stop the iteration and output the result, otherwise go to step 3.

4. Experimental results and analysis

4.1. Set experimental parameters

In order to verify the feasibility and superiority of the comprehensive scheduling model of agricultural water resources based on the multi-objective quantum genetic algorithm, ZDT test functions (ZDT1, ZDT2, ZDT3, and ZDT6) were used to perform the comprehensive scheduling model of agricultural water resources based on the multi-objective quantum genetic algorithm [16]. Test and compare with the solution results of the Wang et al. [4] algorithm and the You-Chiun and Kai-Chung [5] algorithm. The experimental configuration is Intel Core i5-3470 Processor, 500 g hard disk, 8.00 g memory and 64-bit Windows7 operating system. The algorithm is implemented and tested in the experimental environment of MATLAB 2014a. The experimental parameters are as follows: The population size is 60, the number of iterations is 900, the external file is 50, the number of optimal solutions is 10, the number of quantum bits is 15, the crossover probability is 0.96, and the mutation probability is 0.04 [17–19].

4.2. Comparison results of irrigation area and yield

Analyze the comprehensive dispatch model of agricultural water resources, select and code specific optimized data units, program the objective function and constraint conditions, and determine the experimental parameters [20–22]. The irrigation area and yield of objective 1, target 2 and comprehensive target are calculated by the proposed algorithm, Wang et al. [4] algorithm and You-Chiun and Kai-Chung [5] algorithm respectively, and the optimal scheduling of agricultural water resources is studied. The irrigated area and yield of different algorithms are shown in Table 3.

Table 3
Comparison results of irrigation area and yield of different algorithms

Objective function	Irrigation area			Irrigation yield		
	Proposed algorithm	Wang et al. [4] algorithm	You-Chiun and Kai-Chung [5] algorithm	Proposed algorithm	Wang et al. [4] algorithm	You-Chiun and Kai-Chung [5] algorithm
Objective 1	10.76	8.97	7.35	4.35	3.55	3.32
Objective 2	9.53	6.98	4.36	4.72	3.42	2.92
Integrated objectives	10.49	8.84	7.83	4.68	3.85	3.78

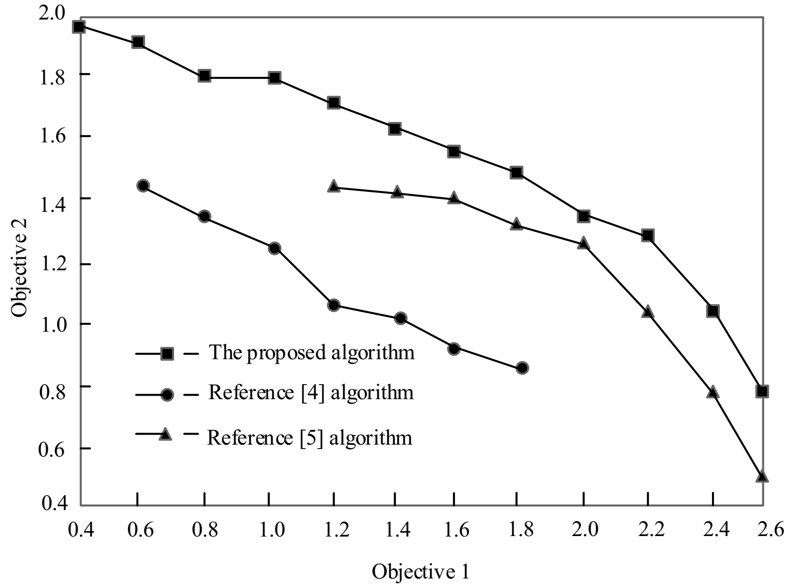

Fig. 1. Spatial distribution of non-dominated solution sets of different algorithms.

It can be seen from the data in Table 1 that after multi-objective optimization, compared with the Wang et al. [4] algorithm and the You-Chiun and Kai-Chung [5] algorithm, the irrigation area proportion and irrigation yield of the proposed algorithm are closer to the optimal value in the case of a single objective, and the deviation between the irrigation area proportion and the irrigation yield is small, which can overcome the situation that the secondary objective is not optimized enough in the single-objective optimization, so as to obtain a relative optimal solution.

4.3. Comparison results of optimization effect

Select the distribution of the solution set in the Pareto optimal front end and the relative coverage of the Pareto optimal solution set to evaluate the proposed algorithm, the Wang et al. [4] algorithm and the You-Chiun and Kai-Chung [5] algorithm, and obtain the spatial distribution of the non-dominated solution sets of different algorithms as Fig. 1.

It can be seen from Fig. 1 that the distribution of non-dominated solutions after 900 generations of different algorithms are run respectively [23]. The proposed algorithm has better solution quality, wider search space and better optimization effect than the Wang et al. [4] algorithm and the You-Chiun and Kai-Chung [5] algorithm. This is because the quantum genetic algorithm is introduced into the proposed algorithm, which uses real number coding of qubits to improve the calculation accuracy, effectively combines local search with global search, and can survey more feasible solutions in the unknown region, so as to maintain the diversity of solutions.

4.4. Convergence speed comparison results

In order to verify the convergence speed of the proposed algorithm, the ZDT test functions (ZDT1, ZDT2, ZDT3 and ZDT6) are used to test the proposed algorithm, the Wang et al. [4] algorithm and the You-Chiun and Kai-Chung [5] algorithm, and the Pareto of the ZDT test function of different algorithms is obtained. The curve is as Fig. 2.

It can be seen from Fig. 2 that for the Pareto curve of the ZDT1, ZDT2, ZDT3 and ZDT6 test functions, the non-inferior solution set of the proposed algorithm can all converge to the optimal frontier, and the solutions obtained are better than those in the Wang et al. [4] algorithm and You-Chiun and Kai-Chung [5] algorithm. This is because the proposed algorithm makes use of quantum state interference

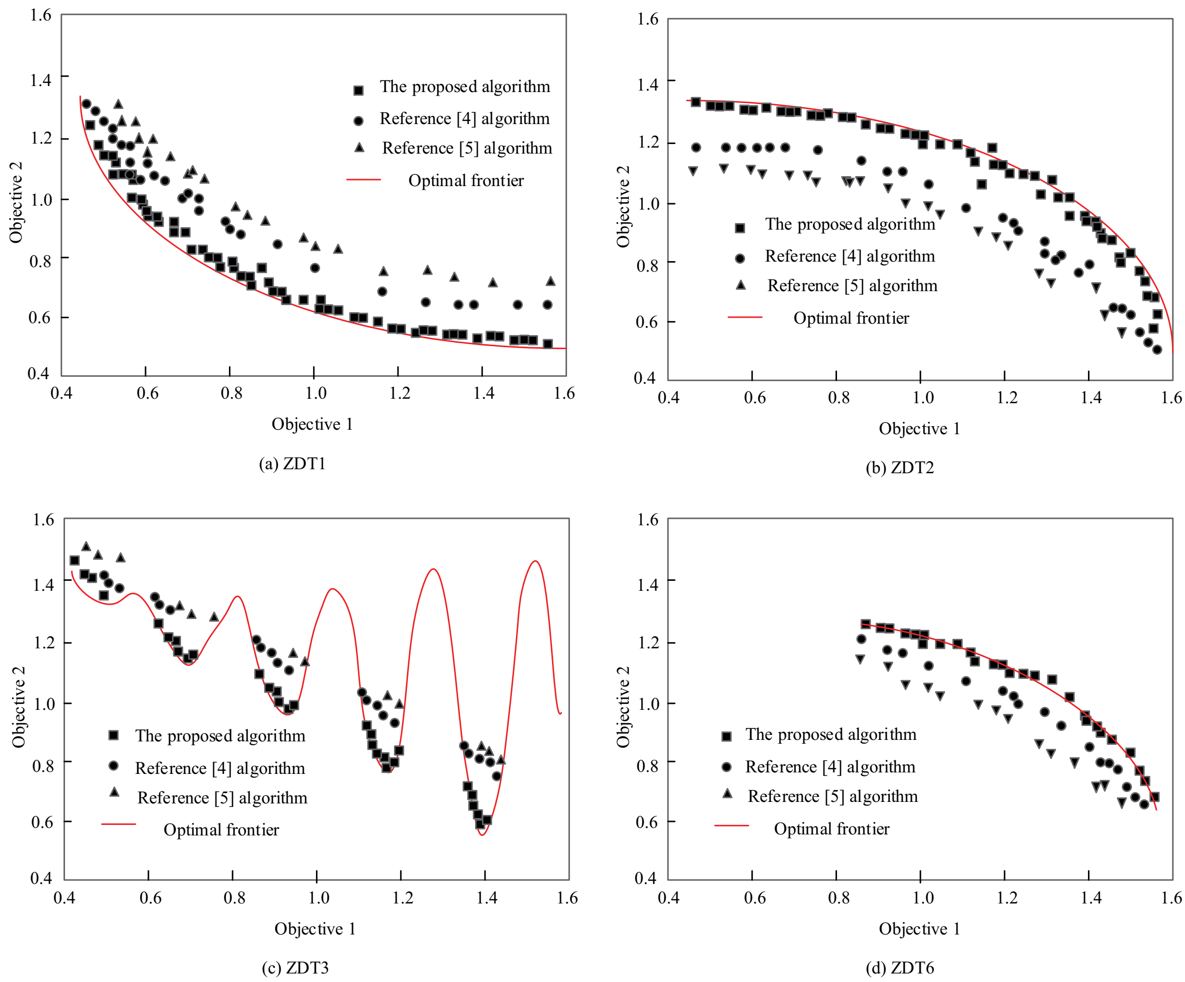

Fig. 2. Pareto curve of ZDT test function of different algorithms.

characteristics for probability crossover, and uses global search to evolve towards the optimal front end of the Pareto direction, which makes the algorithm converge quickly and effectively, thus accelerating the convergence speed [24].

4.5. Comparison results of water resources utilization rate

In order to verify the water resources utilization rate of the proposed algorithm, the proposed algorithm, the Wang et al. [4] algorithm and the You-Chiun and Kai-Chung [5] algorithm are used to comprehensively dispatch agricultural water resources, and the results of comprehensive agricultural water resources scheduling of different algorithms are shown in Table 4.

According to the data in Table 4, the total water consumption of agricultural water resources in the proposed method after comprehensive regulation is reduced under different guarantee rates in each level year. In 2015, 2020 and 2030, the water consumption will be reduced the most when the guaranteed rate is 50%. Irrigation water consumption and livestock water consumption were reduced to varying degrees, among which the surface water and groundwater consumption were more obvious. The water consumption of surface water sources was the largest when the assurance rate was 50% in 2015, and the water consumption of underground water sources was the largest when the assurance rate was 50% in 2030. After comprehensive scheduling, the water consumption is limited, but the proposed algorithm significantly improves the utilization rate of water resources and alleviates the pressure of agricultural water resources to a certain extent.

5. Conclusion

In order to solve the problems of slow convergence speed and poor optimization effect of the current comprehensive water resources scheduling algorithm, which leads to a large deviation between irrigation area and yield and the decrease of water resources utilization rate, a comprehensive agricultural water resources scheduling model based on multi-objective quantum genetic algorithm was proposed. Taking the maximum irrigation area and the maximum yield of crops as the optimization objectives, the comprehensive scheduling model of agricultural water resources is constructed. The multi-objective quantum genetic algorithm is used to solve the comprehensive scheduling model of agricultural water resources to realize the comprehensive scheduling of agricultural water

Table 4
Comprehensive scheduling results of agricultural water resources with different algorithms

Different methods	Horizontal year	Guarantee rate (%)	Irrigation water consumption (10^4 m^3)			Livestock water consumption (10^4 m^3)		
			Surface water	Ground water	Soil water	Surface water	Ground water	Soil water
Wang et al. [4] algorithm	2015	50	16,025	15,412	962	15960	12,032	862
		75	25,614	14,826	1,352	20251	12,695	1,102
		95	25,974	14,258	2,693	20684	12,365	2,484
	2020	50	27,845	12,069	1,230	22651	10,265	1,036
		75	28,610	10,596	1,596	24362	9,851	1,305
		95	27,936	10,697	1,369	25989	9,752	1,254
	2030	50	30,987	9,036	2,615	32651	10,154	2,458
		75	33,458	9,102	2,859	33562	9,651	2,561
		95	35,369	9,220	2,684	34025	9,821	2,513
You-Chiun and Kai-Chung [5] algorithm	2015	50	12,053	13,261	762	13960	10,257	621
		75	22,365	12,054	1,125	18932	10,987	9,127
		95	22,518	12,546	2,423	18232	10,365	2,254
	2020	50	25,615	10,354	1,035	20513	8,264	865
		75	26,154	8,622	1,365	20315	7,512	1,154
		95	25,301	8,612	1,154	22514	7,201	1,089
	2030	50	25,697	8,830	2,462	30697	8,152	2,245
		75	31,526	8,914	2,654	32154	7,152	2,368
		95	33,365	9,025	2,450	32987	7,851	2,347
Proposed algorithm	2015	50	10,254	11,264	513	11654	8,863	425
		75	20,156	10,254	965	16942	8,862	8,962
		95	20,541	10,987	2,261	16978	8,825	2,054
	2020	50	23,641	8,654	865	18654	8,032	694
		75	23,651	8,423	1,154	18972	7,365	954
		95	23,541	8,495	948	20165	7,021	896
	2030	50	23,154	8,674	2,265	28469	7,964	2,056
		75	29,584	8,762	2,469	30154	6,954	2,189
		95	31,654	8,826	2,287	30956	7,654	2,145

resources. The proposed algorithm has a high convergence speed and optimization effect, and the deviation between irrigation area proportion and irrigation yield is small, which can effectively improve the utilization rate of water resources and realize the comprehensive optimal scheduling of agricultural water resources. However, the comprehensive scheduling model of agricultural water resources needs to take into account the optimization objectives of ecological environment, economic growth and social prosperity for the next step of research. Therefore, more optimization objectives will be considered in the next step of research to further improve the scheduling effect.

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