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Research article

A novel greedy adaptive ant colony algorithm for shortest path of irrigation groups

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Abstract: With the full-scale implementation of facility agriculture, the laying of a water distribution network (WDN) on farmland plays an important role in irrigating crops. Especially in large areas of farmland, with the parameters of moisture sensors, the staff can divide the WDN into several irrigation groups according to the soil moisture conditions in each area and irrigate them in turn, so that irrigation can be carried out quickly and efficiently while meeting the demand for irrigation. However, the efficiency of irrigation is directly related to the pipe length of each irrigation group of the WDN. Obtaining the shortest total length of irrigation groups is a path optimization problem. In this paper, a grouped irrigation path model is designed, and a new greedy adaptive ant colony algorithm (GAACO) is proposed to shorten the total length of irrigation groups. To verify the effectiveness of GAACO, we compare it with simple modified particle swarm optimization (SMPSO), chaos-directed genetic algorithms (CDGA) and self-adaptive ant colony optimization (SACO), which are currently applied to the path problem. The simulation results show that GAACO can effectively shorten the total path of the irrigation group for all cases from 30 to 100 water-demanding nodes and has the fastest convergence speed compared to SMPSO, CDGA and SACO. As a result, GAACO can be applied to the shortest pipeline path problem for irrigation of farmland groups.

Keywords: irrigation pipe network; shortest path; path model; greedy adaptive ant colony algorithm

1. Introduction

The development of IoT has accelerated intellectual advancement of agricultural irrigation [1–3], which is reflected in the fact that smart farm irrigation equipment has been established in many countries, and this series of equipment is usually cooperated with a water distribution network (WDN) [4,5] to achieve efficient irrigation in China. Its accurate and efficient irrigation of farmland is achieved by setting a series of sensors [6,7], such as soil moisture wireless sensors, solenoid control sensors and flow sensors, in the field, pipe outlets, and water pipes. In the actual farm irrigation process, the water supply power of the pump house is constant, and as the path of the water pipeline grows, the useful power decreases with it, which leads to a lower irrigation efficiency [8,9]. However, it has been worthwhile to think about how to improve irrigation efficiency when farmers irrigate their farmland, especially when they face large farmland with multiple water supply pipe paths forming a WDN. In addition, grouping irrigation and on-demand water supply are considered to be effective methods to achieve the goal of water conservation and precision irrigation on large fields.

On-demand irrigation means that different areas of a large farmland are irrigated at different rates [10,11], as determined by the parameters collected by soil moisture sensors at different locations. Usually, the whole farmland is divided into several small irrigation plots of irregular size, with little difference in soil moisture conditions inside each plot, which ensures that the soil water demand points in each plot are roughly similar. As a result, the farmer can control the irrigation amount or time at different water-demanding nodes. Grouping irrigation [12], also known as rotational irrigation, allows farmers to divide all water demand points into irrigation groups according to the specific situation, because the water supply is limited at a fixed time, i.e., the fields are grouped according to the moisture contents of different areas, and then the water supply is rotated to solve the problem.

Compared with the power grid and drainage network, the actual design process of a farmland WDN has obvious differences [13,14], which should fully consider the irrigation rules and different subdivisions of soil environments and crops in the farmland. With the increase of farmland area, the pressure of irrigation operations on water supply is increasing. the pressure brought by Because the optimal design of a WDN is an NP-hard problem, it is difficult to find the optimal method by traditional irrigation mathematical processing [15]. The traditional method can cope with small amount of data, but if the amount of data is too large, it is almost impossible to use the traditional mathematical method to solve it in a short time.

The shortest path of WDN irrigation groups is a path optimization problem. To design the WDN in a rational way, researchers have used a series of heuristic methods, such as PSO [16], GA [17] and other swarm intelligence algorithms, to solve complex WDN route planning problems [18]. Other path optimization problems, such as logistics and distribution route optimization [19] and wireless sensor network path optimization [20,21], also use methods such as the fast randomized exploration tree (RRT) algorithm. However, there are areas where these algorithms can be further improved. For example, the paths found by the RRT algorithm are often not optimal. Compared with the RRT algorithm, GA and PSO incorporate heuristic ideas, and the performance is somewhat improved, but they are prone to fall into local optimality. In recent years, many researchers have improved the original algorithm and proposed methods such as simple modified particle swarm optimization (SMPSO) [22], chaos-directed genetic algorithms (CDGA) [23] and self-adaptive ant colony optimization (SACO) [24] to improve the performance of heuristic algorithms in solving WDN optimization design problems.

Compared to the above solutions, this paper proposes a new algorithm, greedy adaptive ant colony (GAACO), which has the advantage of not easily falling into a local optimum and is more suitable for solving complex continuous problems. To accelerate the convergence speed while enhancing the search capability of the algorithm, the adaptive mechanism adaptation and greedy strategy are designed in this paper. Moreover, GAACO is applied to optimize the irrigation partition path planning model, which can quickly make a reasonable plan for it and find the shortest path.

The main contributions of this paper are as follows.

1) An irrigation grouping path planning model was designed. The intelligent algorithm ensures a sufficient number of irrigation groups, i.e., setting a reasonable number of water demand points that can be served by each irrigation round, which can optimize the irrigation network structure and minimize the water delivery path.

2) A new algorithm, GAACO, is proposed to solve the shortest path problem of irrigation groups of a WDN from the whole WDN.

3) In this paper, a new adaptive mechanism and greedy strategy are designed for ACO, which improves the convergence speed of the algorithm and effectively prevents the algorithm from falling into a local optimum, and the path of the irrigation group of a WDN obtained by this algorithm is better than those of SMPSO, CDGA and SACO.

The structure of this paper can be formulated as follows. Section 2 gives related papers of the path optimization problem. Subsequently, Section 3 presents the irrigation grouping path planning model. In Section 4, a new GAACO is introduced to obtain the shortest irrigation grouping path of a WDN. The performance of the proposed model and algorithm is analyzed and discussed in Section 5 through simulation experiments based on real coordinates. Finally, the conclusion is given in Section 6.

2. Related works

The shortest path problem (SPP) exists in many disciplines and engineering fields [25,26], and irrigation grouping path optimization for farmland WDNs is just one of them. We can draw on other research results of path optimization, such as sensor node deployment path optimization in wireless sensor networks, and vehicle path optimization, for aiding the research.

2.1. Related work for WDNs

The paper [27] discussed the cost of WDNs, which concluded that the cost mainly comes from the plumbing pipes and other components, and that the cost of pipes was the highest percentage of the total cost. In addition to this, the authors synthesized two optimization objectives, the minimum cost of the WDN and toughness of the WDN, into one objective function, and then they used a mathematical approach, which is a normalized objective function, to perform a weighted arithmetic process to arrive at the optimal design of the WDN. The effectiveness of the approach was experimentally demonstrated. However, this approach is too inefficient for dealing with complex WDNs.

The paper [28] proposed an improved ACO for path optimization design of WDNs. It successfully solves the problem of handling the penalty factor of ACO in many nonlinear constrained problems such as WDNs by invoking an adaptive mechanism. Compared with traditional methods, this method has better optimization efficiency in designing WDNs, and more importantly, the algorithm exhibits better global adaptability, but it also faces the problem of slow convergence.

The paper [29] uses GA to effectively solve the problem of determining the optimal position of valves in WDN optimization to improve the efficiency of the WDN and achieve the shortest pipeline path, and it proposes a new optimization model combining the knowledge of the WDN system to effectively reduce the search space. While it shows good robustness in dealing with complex WDN design, the algorithm does not perform well in the design of WDNs with multiple objectives, such as water supply and water demand.

The paper [30] presents an improved PSO to compute complex WDN cost problems by considering factors such as the length of the pipeline path. The improved algorithm is able to balance the global and local minima of the WDN cost obtained by solving the problem by introducing a correction factor to continuously adjust the inertia weights with the algorithm running time. Although this method improves the performance of PSO, the slow convergence rate is its fatal drawback.

The paper [31] proposes an improved crow search algorithm for WDN least-cost optimization. It introduces operation symbol parameters based on the crow algorithm, which effectively improves the performance of the original algorithm. When faced with the same problem, the paper [32] proposes a whale optimization algorithm and considers optimization indexes such as pipe diameter, overall length of pipe, etc. In the simulation experiments, the method achieves the best results. However, both optimization algorithms have the disadvantage of slow convergence speed.

2.2. Related work for other shortest path problems

The paper [33] uses reinforcement learning to compute the shortest path problem for the edge length of a random directed graph of sensor nodes in a wireless sensor network. Two reinforcement learning algorithms, the QSSP algorithm and the SARSASSP algorithm, were proposed. To improve the convergence speed and accuracy of these two algorithms, the authors pair them with a special reward and averaging mechanism that enables the online computation of shortest paths. However, these two algorithms cannot be used uniformly, and the algorithms are prone to local optimum deadlock.

The authors in the paper [34] applied a base minimization approach to solve the shortest path problem for vehicle path planning. Before processing the data, the authors obtained the ephemeral samples of vehicles on each road of from GPS and then turned them into the minimum base problem, and finally the base minimization approach was carried out to solve the problem. This method can estimate the unknown road vehicle travel time with higher accuracy than the traditional way. Nevertheless, the approach requires a large number of data samples, and the base minimization approach is less suitable for path optimization.

The paper [35] did a study on self-driving path planning for cars. The authors combined the neural network and round-trip time (RTT) algorithm and proposed a hybrid neural RTT-NRTT algorithm. The algorithm can quickly find the optimal path with the vehicle fuel and power as the main constraints, and it has good accuracy and scalability. However, the algorithm has the disadvantage of slow convergence.

The paper [36] used an improved ant colony algorithm to plan the transport paths of automated guided vehicles (AGVs) on a factory floor. In addition, a mathematical model was constructed with the goal of shortest transportation time. Regarding the algorithm, they employed a new coding method to improve on the original ant colony algorithm. Algorithmic simulation proves that the algorithm does easily to fall into a local optimum when solving the mathematical model. However, the proposed algorithm and model are only suitable for solving the path planning of a single AGV and lack practicality.

To address the shortcomings of the above work, our research solves the farmland grouping irrigation pipeline path planning problem from the whole WDN and shortens the path of the WDN grouping irrigation. Meanwhile, this paper establishes a new shortest path model for grouped irrigation according to reality and designs a GAACO algorithm, which can effectively improve the convergence performance and also avoid falling into a local optimum.

3. The model of grouping irrigation shortest paths

3.1. Problem description

The complete WDN of the farmland in Northwest China is shown in Figure 1, and it consists of four parts: a water supply center, water demand points, pipes and valves. The main task of the water supply center is to provide water service to the water demand points through water pipes, and the planner connects it with different water demand points with water pipes to form a complex irrigation water pipe network. The pipes usually consist of mains, branches and capillary pipes. In this study, the field is divided into zones by soil moisture, each zone represents a water demand point, and the different demand points are formed into irrigation groups. Then, the water is supplied in rotation according to the group number. In addition, this study also takes into account the problem of limited water supply power per unit time in the water center when group irrigation path planning, that is, the maximum water supply is limited per unit time.

In Figure 1, 0 represents the water supply center, 1–10 represent the demand points, and 4 connecting lines from 0 represent 4 irrigation groupings. Assuming that all demand points are met, the total path of the irrigation groups can be calculated as the sum of the pipe path lengths of the four irrigation groups, 0-1-2-3, 0-4-5, 0-6-7, 0-8-9-10. In this way, we can find the shortest total path for all irrigation groups according to the principle that the water demand of each irrigation group is satisfied and build the corresponding mathematical model.

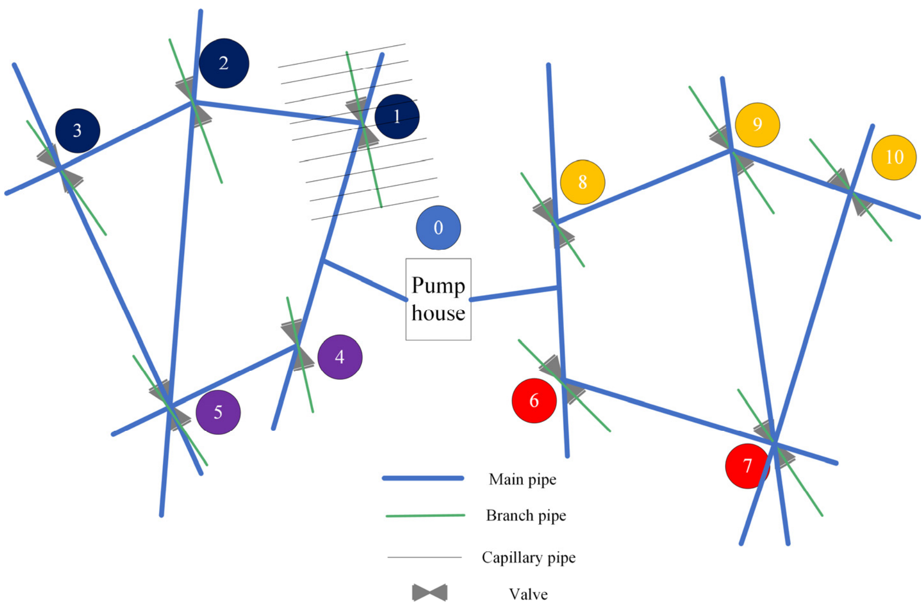

Figure 1. Description of farmland WDN.

3.2. Path planning model

To minimize the distance between the water supply point and the water discharge point, this paper designs a model with plane coordinates, which can realize the irrigation pipe length calculation when grouping irrigation in farmland WDN rotation. The model can be simplified as $S(V,D)$, where V represents the set of coordinates consisting of N water outlet points, $V = (0,1,2 \dots, n-2, n-1, n)$, where 0 represents the water supply point, and $1 \rightarrow n$ represents the water demand points. We assume that the location of each irrigation group outlet is fixed in the farmland, then the two-dimensional coordinates of the n water demand points in the farmland will along with being determined.

$$d_{ij} = \sqrt{(i_x - i_y)^2 + \left(j_x - j_y\right)^2} \tag{1}$$

where d_{ij} is to be the distance between nodes i and j, i_x, i_y are the horizontal and vertical coordinates of i, and j_x, j_y are the horizontal and vertical coordinates of j. $D = \left\{d_{ij},\ 1 \leq i \neq j \leq n\right\}$ represents the set of distances between any two points. The ultimate goal of this paper is to find the shortest length of irrigation group water pipes to help farmers irrigate their farmland quickly.

According to the actual need, the water is supplied to the water demand point in k_m times. In order to ensure that each water demand point is distributed, a variable φ_{ijk} is defined to perform an iterative judgment on each demand point, which can be described by Eq (2).

$$\varphi_{ijk} = \begin{cases} 1, The\ kth\ round\ of\ water\ supply \\ \quad passes\ through\ the\ edge\ (i,j) \\ \quad 0, \qquad\qquad else \end{cases} \left(0 \leq i \neq j \leq n,\ 1 \leq k \leq k_m\right) \tag{2}$$

where i, j, k represent node i, node j and the irrigation group k. As long as the access object of irrigation group k includes the path composed of nodes i, j, φ_{ijk} is set to 1 (and 0 in other cases), so that the information of the access demand points of each irrigation group can be discriminated. Accordingly, the pipe path length of each irrigation group can be calculated by Eqs (1) and (2), and then the paths after the completion of all rounds of water supply are summed to obtain the total path length S of the irrigation group's water pipes, which is the objective function of this study, and can be described by Eq (3).

$$S = min \sum_{i=0}^{n} \sum_{j=1}^{n} \sum_{k=1}^{k_m} d_{ij}\, \varphi_{ijk} \tag{3}$$

3.3. Constraints

3.3.1. The principle of one visit to the demand point

In accordance with the actual situation of farm irrigation, each demand point will be supplied with water only once. For achieving this goal, we need to set a variable y_{ik} to determine the demand point visits for each irrigation group, which can be specifically described by Eq (4).

$$y_{ik} = \begin{cases} 1, The\ kth\ round\ of\ water\ supply \\ \quad passes\ through\ point\ i \\ \quad 0, \qquad else \end{cases} \left(0 \leq i \leq n,\ 0 \ll k \leq k_m\right) \tag{4}$$

where i and k represent the demand node and irrigation group serial number, respectively. When the

kth irrigation group passes the demand point i, ϕ_{ik} is set to 1, and otherwise it is 0, so that each irrigation group's water demand point visit information can be recorded very easily. However, Eq (4) is only the completion of the definition of the access judgment variables only to achieve a single visit to a group of demand points limited, but not to limit other irrigation groups to continue to provide water service to the group's demand points for secondary water supply, so we also need to set a constraint as in Eq (5) to ensure that each demand point will only be in a certain irrigation group water supply once.

$$\sum_{k=1}^{m}\sum_{i=1}^{n}\phi_{ik} = 1 \tag{5}$$

Here, the formula starts from the whole irrigation level, considering all irrigation groups, and limits each demand point to one visit in all irrigation groups. Once the demand point is visited by the previous irrigation group, all subsequent ϕ_{ik} values will be set to 0, so that the demand point is limited to one visit.

3.3.2. Irrigation group single group water allocation limit

In addition to limiting the access to each demand point at this time, the amount of water allocated to a single group of irrigation teams is also limited in the actual group irrigation process. Currently, when farmers irrigate large fields in groups, each irrigation group is usually set to irrigate for approximately the same amount of time. In this case, assuming the same water supply efficiency at the water point, the amount of water supplied to each irrigation group is the same and fixed. Consequently, it is necessary to constrain the single group water allocation so that the water supply can be achieved faster while meeting the water supply demand of that group of demand points, which has been achieved for efficient irrigation. Combining to (4), the single group water allocation constraint is obtained, which is expressed by Eq (6).

$$\sum_{i=1}^{n} q_i\,\phi_{ik} \leq Q, 1 \leq k \leq n \tag{6}$$

where $q_i (i = 1,2, \ldots n-1, n)$ represents the water demand of each demand node i, the value of which is much smaller than the actual water allocation Q of a single group. ϕ_{ik} is the access judgment variable of the water demand node i, which realizes a single access to each demand point of the group. The sum of $q_i y_{ik}$ of each group represents the single group water allocation of the irrigation group, and the setting of its data should not be greater than the actual single group water allocation Q. In this way, the single group water allocation of the irrigation group is limited.

4. Greedy adaptive ant colony algorithm for solving the shortest path of Farmland WDN

To get the minimum length of pipe needed during the irrigation group arrangement for the whole farmland WDN, a GAACO algorithm is designed in this paper. In GAACO, this study designs an adaptive mechanism and greedy strategy based on the traditional ant colony algorithm, which makes the hybrid algorithm have better global optimality. GAACO is to a bionomic algorithm, and its core essence originates from the behavior of ants seeking paths in nature. Individual ants always leave pheromones under the path they walk when looking for food. The main idea of GAACO's greedy strategy is to use the local optimal problem to approximate the global optimal solution when solving the shortest path of a farmland WDN. Furthermore, the algorithm uses a hierarchical approach to obtain the local optimal solution, and only the current level state is considered for a certain level without considering the overall optimal solution. Ultimately, GAACO can find an approximate solution to the global optimum in a short time by comparing the local optima at each level.

For improving the early search capability of GAACO, avoiding premature algorithm convergence and speeding up the convergence speed in the middle and late stages, this study designs a hybrid algorithm GAACO with adaptive mechanism and greedy strategy. The adaptive mechanism is mainly reflected in the pheromone volatility factor being dynamically adjusted with the number of iterations of the algorithm, and the greedy strategy is added in the ant selection next node, which makes GAACO have better global optimality. The execution steps of GAACO are shown in Figure 2, and the following detailed steps will be used in this study to illustrate the algorithm flowchart shown in Figure 2.

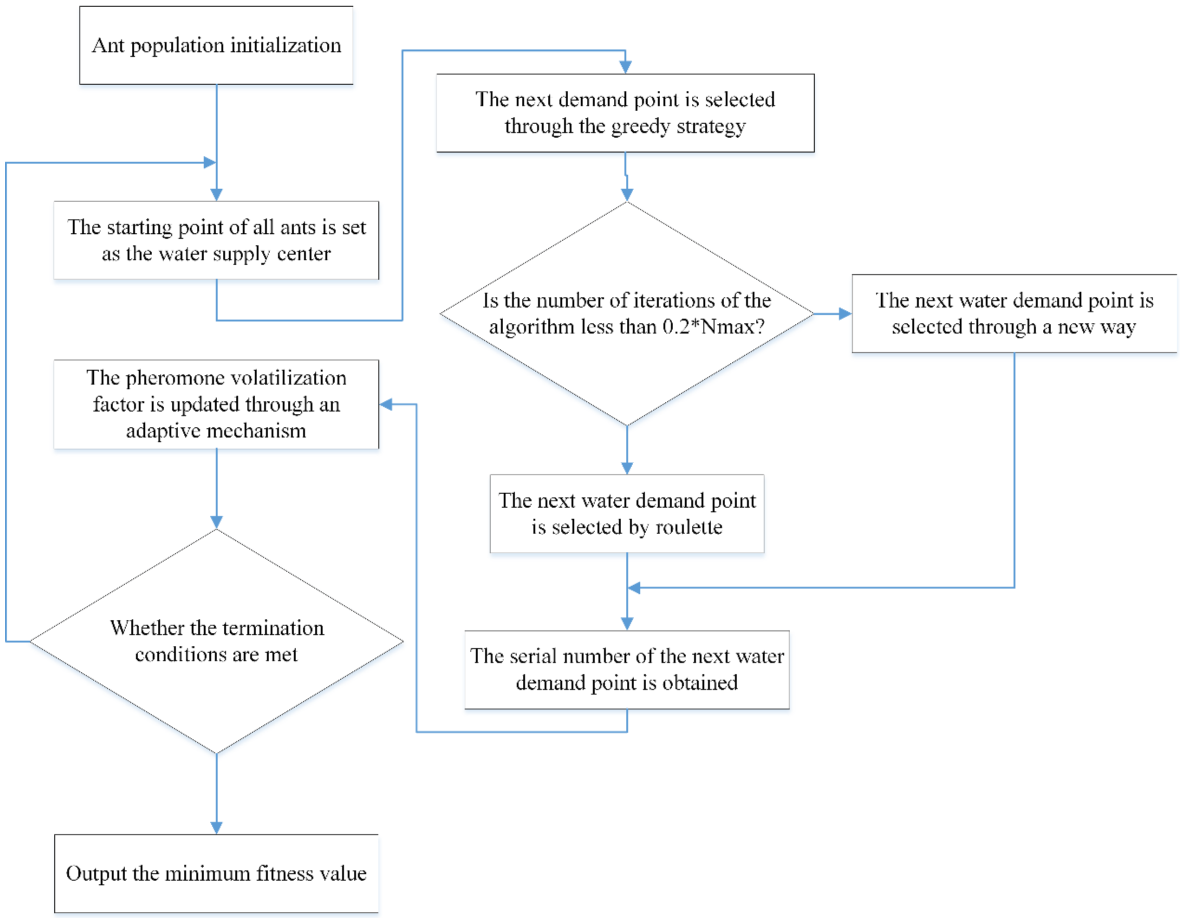

Figure 2. Steps of GAACO.

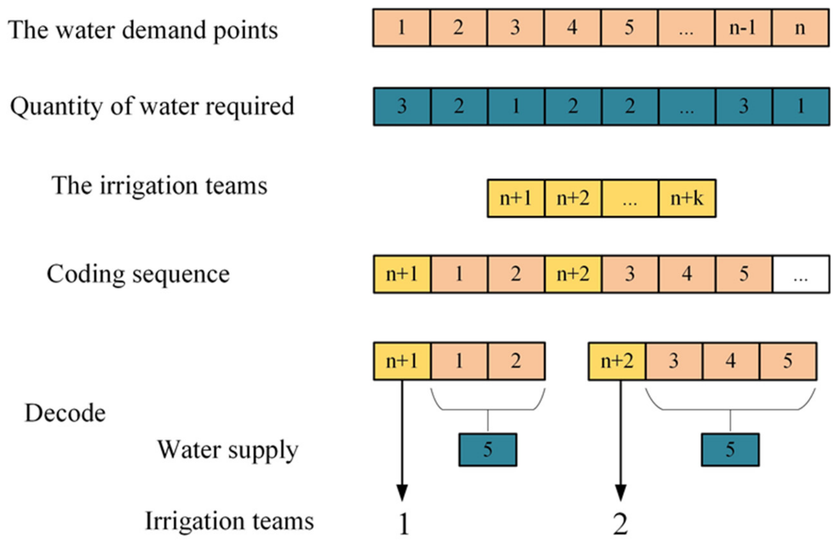

Figure 3. Coding scheme of GAACO.

4.1. Coding scheme

Coding is the primary problem to be solved when applying GAACO and a key step when designing a group intelligence algorithm. The farmland WDN shortest irrigation path optimization problem is to connect known points through different orders to ensure the shortest length of laid pipes, which is essentially an integer combinatorial optimization problem. According to the algorithm characteristics, this study proposes an encoding strategy based on irrigation groups. This strategy is different from the traditional random coding method, but it adopts the irrigation group as the basic service unit to encode the water demand points in a multi-segment way. The coding approach numbers all pipes uniformly, and when the algorithm selects an irrigation group and arranges water supply tasks for it according to the constraints, the remaining unselected demand points are served by the remaining other irrigation groups, which is obviously more flexible. In this case, the representation of the solution for the shortest path of the WDN is also more detailed compared with the traditional coding method. This is not only beneficial for the algorithm in performing global breadth search in the solution space and producing more diverse solutions but is also beneficial in achieving local depth search, and it is convenient for the user to arrange the pipes in a reasonable way.

The specific coding scheme is shown in Figure 3. Assuming that there are n demand points, the water supply center can complete up to k irrigation groups, and the single water supply quantity of irrigation groups is set to 5. Then, the N demand points are coded as $(1,2 \ldots, n-2, n-1, n)$, and the corresponding water demand Q is (3,2,1,2,2, ...,3,1). For the k irrigation groups correspondingly numbered as $(n+1, n+2, n+3, \ldots, n+k)$, therefore, the number of genes an individual has is $n+k$, where the genes numbered less than or equal to n represent demand points, and genes numbered than n represent irrigation groups, then these genes can be disordered to obtain different individuals.

The coding sequence in Figure 3 is decoded according to the irrigation group number, which shows that the customers served by irrigation group 1 are 1, 2, and the customers served by irrigation group 2 are 3, 4, 5. Obviously, after decoding, we can get the information of water supply object, order, path and water supply quantity of each pipeline, which is needed for digital management of agricultural irrigation or water distribution.

4.2. Ant colony initialization

The aim of encoding the algorithm according to the farmland WDN path planning model is to establish a connection between the farmland WDN and GAACO, so the primary step in the execution of the algorithm is to initialize the ant colony. In accordance with the input demand points, reasonable values are set for parameters such as the number of ants, pheromone factor, and information volatility factor, and n ants are randomly generated as the initial colony, assuming that the first search of the ant colony is not influenced by other factors such as pheromones to ensure the initial global search capability of the ants. Subsequently, considering the specificity of the farmland WDN, where each ant's starting point is set as water supply point 0, with the traversal points of ants can be described as $(0, x_1, x_2, x_3, \dots, x_n)$, and corresponding paths can be described as $(d_{01}, d_{12}, d_{23}, \dots, d_{n-1\,n})$. Finally, according to the adaptation Eq (3), the WDN path length is derived, and the quality of the test route plan is evaluated.

4.3. Fitness evaluation

When solving the problem of shortest path of irrigation grouping for a farmland WDN, each ant has its own path selection rules and fitness values, so it is important to set the fitness function that meets the purpose of this study. The purpose of this paper is to find the shortest length of the WDN arrangement pipeline in general, which is the shortest path between pipeline nodes, so the evaluation of ants in this study is based on the overall length of the check path, and the evaluation value of the check path can be calculated by Eq (3). As the check path length decreases, the probability that the path will be chosen again by the ants behind increases.

4.4. Greedy strategy path search

In common cases, the roulette wheel is used to calculate the next node transfer probability of an ant individual in the traditional ant colony algorithm. The probability of ant c transferring from node i to node j at moment n, $p_{ij}^{c^1}$, can be derived from Eq (7). τ_{ij} is the pheromone on edge (i, j), α is the pheromone factor, $\eta_{ij} = 1/d_{ij}$ is the expectation heuristic, β is the expectation heuristic factor, and a_c is the set of nodes that ant c can transfer to next.

$$p_{ij}^{c^1}(n) = \begin{cases} \dfrac{[\tau_{ij}(n)]^{\alpha}[\eta_{ij}(n)]^{\beta}}{\sum_{s \in a_k}[\tau_{is}(n)]^{\alpha}[\eta_{is}(n)]^{\beta}} & , j \in a_c \\ 0 & , others \end{cases} \tag{7}$$

This traditional node selection makes $p_{ij}^{c^1}$ more dependent on the pheromone concentration of the paths. In this way, if the pheromone concentration above a path is high, the effect of η_{ij} will be ignored, and the algorithm will converge quickly, thereby obtaining the result as only a local optimum instead of a global optimum.

Based on the above considerations, this paper designs a greedy strategy to increase the upfront search capability of the ant colony algorithm. Specifically, we define an indirect expectation heuristic z_{ij} and introduce it into the transfer probability calculation. When ant c selects the next node j at node i, the distance factor d_{ij} between two nodes and the distances of other nodes connected to j are considered comprehensively. In addition, avr_{ij} is defined by Eq (8) as the average of the distances from node j to the other $(n-1)$ nodes except node i, and z_{ij} is the inverse of avr_{ij}.

$$\begin{cases} avr_{ij} = \dfrac{1}{n-1}\left(\displaystyle\sum_{c=x}^{xn} d_{cj} - d_{ij}\right), c \neq j \\ z_{ij} = \dfrac{1}{avr_{ij}} \end{cases} \tag{8}$$

In this paper, the formula for calculating $p_{ij}^{c^1}(n)$ is modified, and a new ant transfer probability, Eq (9), is proposed to improve the diversity of algorithmic paths, where γ is the indirect expectation heuristic factor.

$$p_{ij}^{c^2}(n) = \begin{cases} \dfrac{[\tau_{ij}(n)]^{\alpha}[\eta_{ij}(n)]^{\beta}[z_{ij}(n)]^{\gamma}}{\sum_{s\in a_k}[\tau_{is}(n)]^{\alpha}[\eta_{is}(n)]^{\beta}\,[z_{ij}(n)]^{\gamma}}, j \in a_k \\ 0 \qquad\qquad\qquad\qquad , others \end{cases} \tag{9}$$

When the number of algorithm iterations $N \in (0, 0.2N_{max})$, $p_{ij}^{c^2}$ is chosen to calculate the next node chosen by ants, which increases the diversity of ant path search ability in the early stage of the algorithm and improves the algorithmic merit-seeking ability. In such a context, the ant chooses the traditional way to compute $p_{ij}^{c^1}$ when $N \in (0.2N_{max}, N_{max})$, enhancing the diversity of the algorithmic paths through the greedy strategy.

4.5. Adaptive mechanism

The existence of pheromones makes GAACO an algorithm combining heuristic ideas and positive feedback principles. In this paper, the maximum-minimum ant system idea is utilized to update the pheromone only on the optimal path, which can effectively overcome the possible stagnation phenomenon in the basic ant colony. The pheromone updating approach of the basic algorithm can be expressed by Eq (10), where τ is the pheromone concentration, and ρ is the pheromone volatility factor. $\Delta\tau^{best}$ is defined as the pheromone update on the optimal path, expressed by Eq (11), where Q is the pheromone capacity, and D^{best} is the optimal path length.

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}^{best}(t) \tag{10}$$

$$\Delta\tau_{ij}^{best} = \begin{cases} \dfrac{Q}{D^{best}}, & (i,j) \in D^{best} \\ 0, & others \end{cases} \tag{11}$$

Due to the positive feedback mechanism of pheromone accumulation in GAACO, the path with relatively high pheromone concentration tends to have a higher probability of being selected again by the next ant, so that the concentration of the path becomes higher and higher, resulting in the “premature” stagnation of the algorithm. As a consequence, the GAACO uses an adaptive factor to adjust the pheromone volatility coefficient to prevent the algorithm from converging prematurely. By adaptively adjusting the pheromone volatility coefficient and setting the volatility rate of the previous generation pheromone reasonably, the above situation can be improved. The addition of the adaptive operator dynamically adjusts the next generation pheromone retention in real time, allowing more paths to have greater chances of being selected, and the ant search process becomes more flexible. In view of the above, this paper proposes a new adaptive pheromone volatility factor mechanism to improve the global search capability of the hybrid algorithm. The mechanism can be expressed by Eq (12), where ρ^* is the adaptive pheromone volatility factor, ρ_{max} is the maximum volatility factor set, and δ is a constant.

$$\rho^*(t+1) = \begin{cases} 1 - \delta\rho^*(t), & \delta p(t) \leq \rho_{max} \\ \rho_{max}, & others \end{cases} \tag{12}$$

Consequently, the GGACO pheromone update can be expressed by Eq (13).

$$\tau_{ij}(t+1) = \rho^* \cdot \tau_{ij}(t) + \Delta\tau_{ij}^{best}(t) \tag{13}$$

With the introduction of the adaptive volatility factor, the pheromone accumulation volatility factor in the early stage of the hybrid algorithm will become larger, weakening the amount of pheromone accumulation and obviously enhancing the early search capability of the hybrid algorithm. At the same time, the pheromone volatility factor in the late stage of the algorithm will become small, which can accelerate the convergence rate of the late stage of the algorithm.

4.6. The steps of GAACO to solve the shortest path of farmland WDN

The specific steps of GAACO to solve the shortest path for irrigation grouping on farmland are as follows:

Step 1. Perform problem coding, coding the water supply center, water demand point, demand and irrigation group serial number separately.

Step 2. Initialize the ant colony, and each type of reference is set to pass the demand point.

Step 3. The ants search for the next demand point by greedy strategy. When the number of algorithm iterations $N < 0.2N_{max}$, the ant determines the next water demand point by $p_{ij}^{c^2}$ derived from Eq (9), followed by $p_{ij}^{c^1}$ obtained from Eq (7) as the transfer probability.

Step 4. Cycle each ant, compute its fitness S by Eq (1), and record the best ant colony solution.

Step 5. Adjust the pheromone fluctuation coefficient; the algorithm uses the adaptive mechanism in Eq (12) to adjust the pheromone fluctuation coefficient $\rho^*(t+1)$.

Step 6. Update the pheromone. Update the pheromone on the ant path according to Eq (13).

Step 7. Repeat Steps 3–6. Stop when the upper limit of iterations is satisfied.

Step 8. Output the shortest check path.

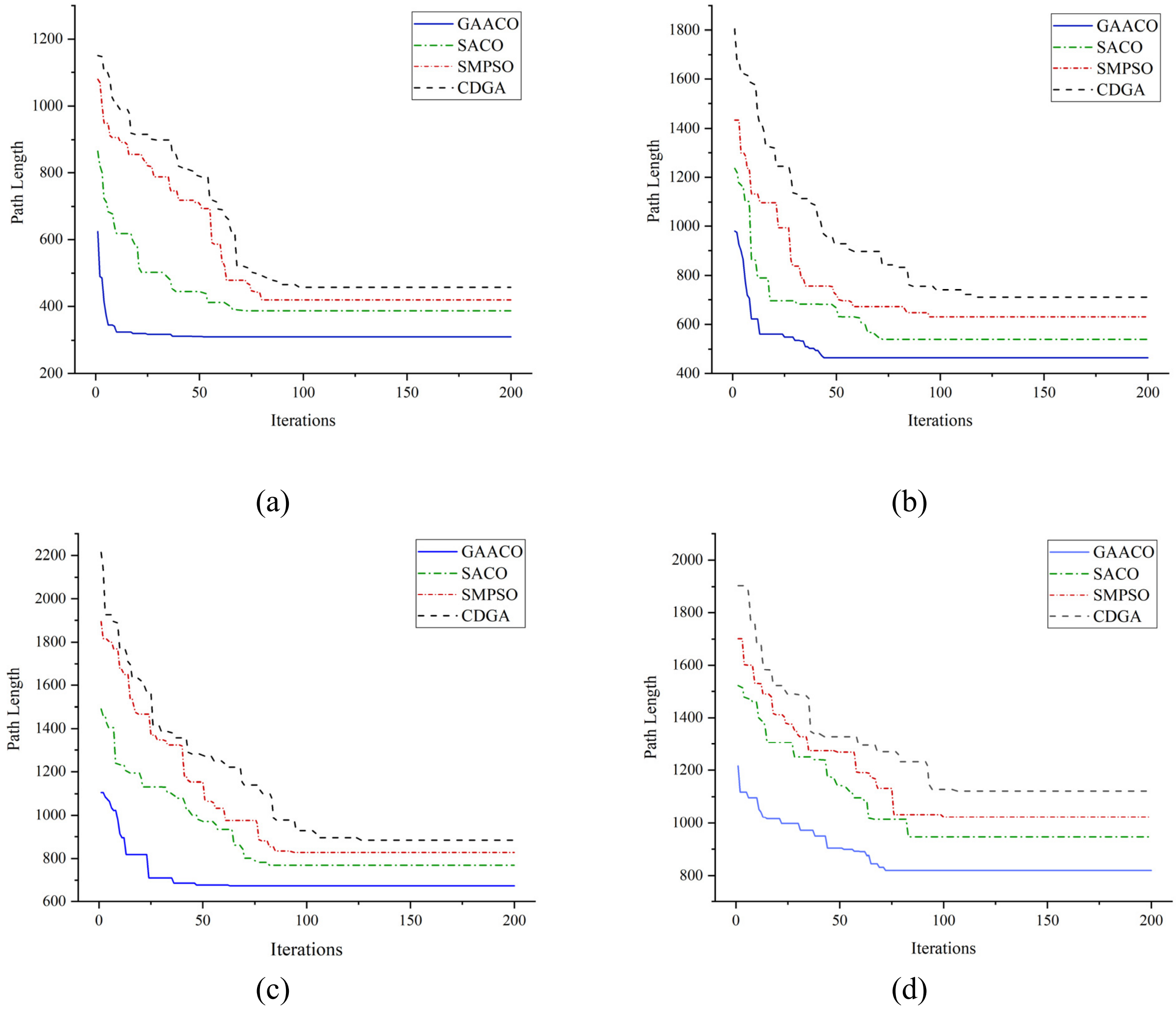

Figure 4. Comparison of the total path lengths of WDN irrigation groups for the four algorithms: (a) 40 water demand points and 4 irrigation groups, (b) 60 water demand points and 60 irrigation groups, (c) 80 water demand points and 8 irrigation groups, (d) 100 water demand points and 100 irrigation groups.

5. Results and discussion

The GAACO method proposed in this paper for solving the shortest path of farmland WDN irrigation group has been carried out in several sets of experiments in which we also compare it with SMPSO, CDGA and SACO for different numbers of water demand points, with different coordinates of water demand points and with different water demand amounts to prove the effectiveness of GAACO. Furthermore, the software and hardware environments are uniformly equipped with AMD R5 4600 H 3.00 GHz CPU computers and the same version of Windows 10, and the programming language is MATLAB. This was done to ensure that the experimental environment is consistent for all three algorithms.

The coordinates of the water demand points for the entire WDN were selected based on the actual situation in a 100*100 m^2 square farmland, with corresponding two-dimensional coordinates, while the water demand of the demand points was determined based on the comprehensive soil moisture condition of the area, and the maximum single water supply for each irrigation group was set to 200 for the water supply center. Moreover, SACO and GAACO have the same settings, with the initial pheromone factor set to 1, the indirect influence factor set to 3–5, the pheromone volatility factor is set to 0.5–0.7 and the adaptive volatility coefficient set to 1.01–1.03. In CDGA, the crossover rate and mutation rate of the population are set to 0.5–0.6 and 0.2–0.3, and crossover method is two-point crossover. In SMPSO, the inertia weights were 0.7–0.9, with learning factors 1 and 3–5, respectively, for learning factor 1 and learning factor 2.

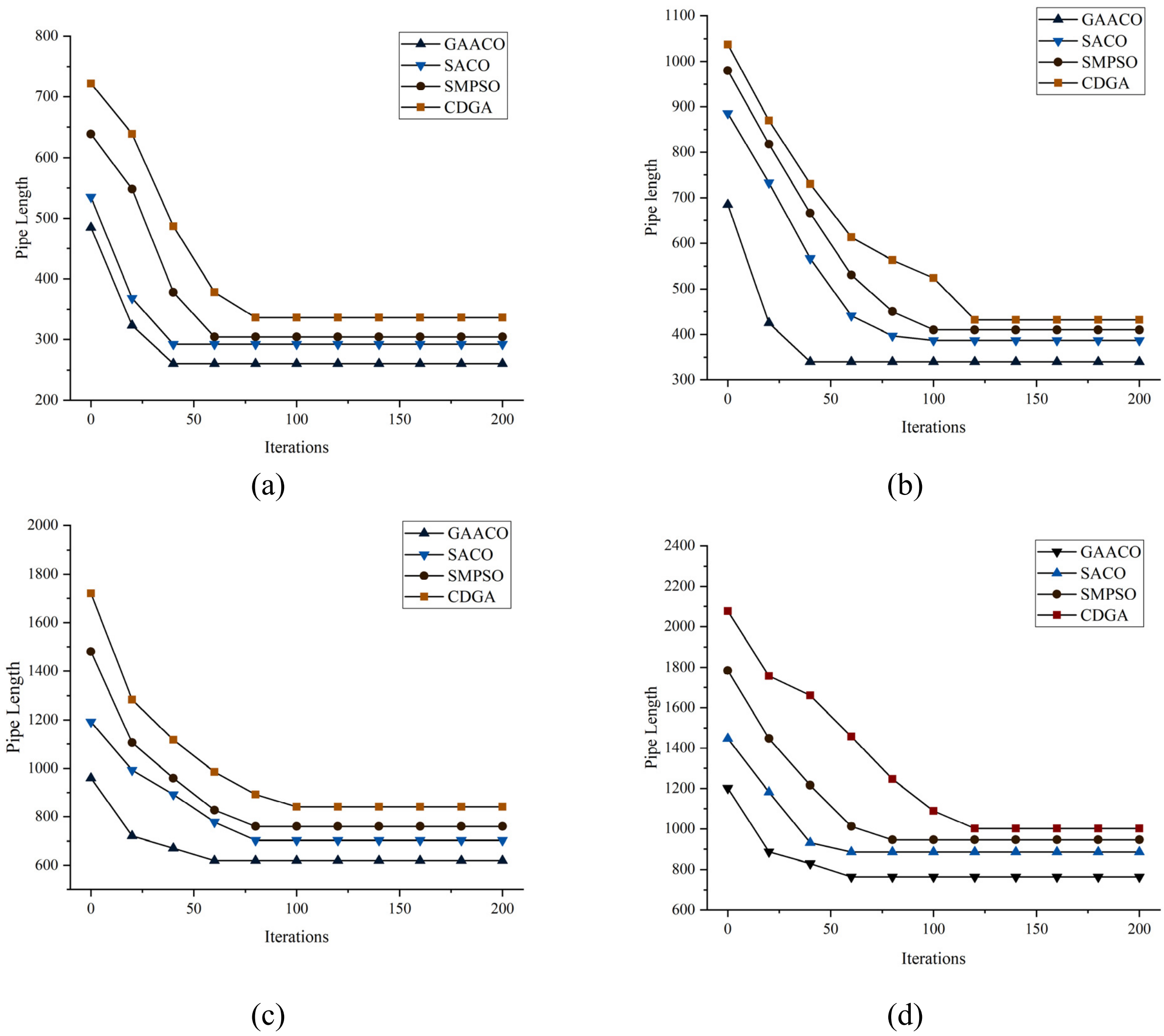

Figure 5. Comparison of the total path lengths of WDN irrigation groups for the four algorithms: (a) 30 water demand points and 4 irrigation groups, (b) 50 water demand points and 6 irrigation groups, (c) 70 water demand points and 7 irrigation groups, (d) 90 water demand points and 9 irrigation groups.

In Figure 4(a)–(d), in general, GAACO maintains fast convergence throughout the solution iterations for the shortest paths of irrigation groups at 40, 60, 80 and 100 water demand points corresponding to 4, 6, 8, 10 irrigation groups for the farmland WDN, respectively. Specifically, Figure 4(a) shows that SACO, CDGA and SMPSO fall into local optima at the 60th, 80th and 110th iterations, respectively, and none finds an optimal solution, while GAACO finds the WDN shortest path for 40 water demand points at the 40th iteration. In addition to this in Figure 4(b)–(d), GAACO also shows the same excellent situation as in Figure 4(a). Therefore, GAACO is able to jump out effectively and use its good global search capability to achieve the search for local optimal solutions, and it convergence faster than CDGA, SMPSO and SACO.

To further prove the fast converges of GAACO, we set 30, 50, 70 and 90 water demand points corresponding to 4, 5, 7 and 9 irrigation groups respectively and performed the corresponding solutions, and the results are shown in Figure 5(a)–(d), GAACO's shows excellent global search ability and fast convergence ability.

Figure 6 and Table 1, respectively, show the path planning diagram and path planning results based on GAACO processing 30 water demand points. Specifically, GAACO divides the 30 water demand points into 4 irrigation groups for irrigation operation, and the path planning is as follows:

0->30->29->28->26->27, 0->24->22->20->19->18->21->23->25, 0->2->1->3->5->4->8->7->6, 0->9->13->11->10->12->14->17->16->15.

Additional water demand point cases are also taken in this way and are not listed in full.

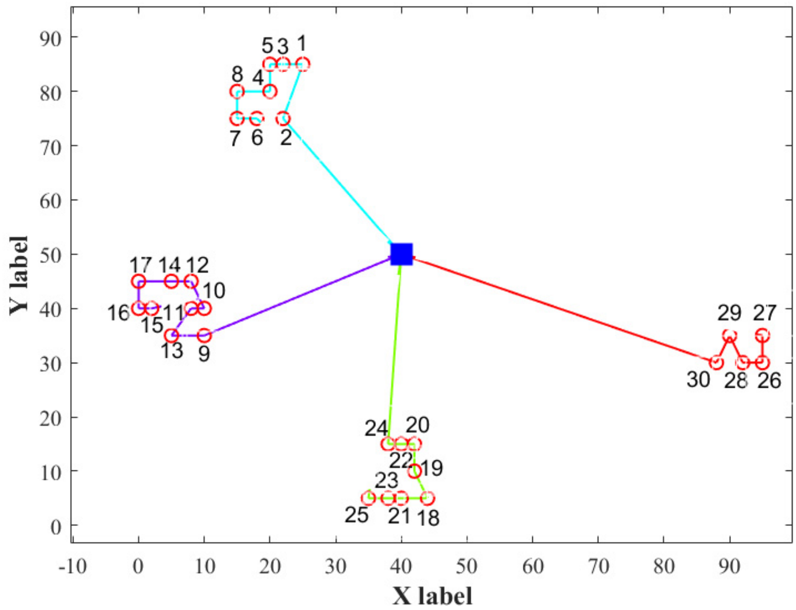

Figure 6. Schematic diagram of GAACO treating 30 water demand points.

Table 1. GAACO handles path planning for 30 water demand points.

Number of Irrigation Group	Distribution of water demand points
1	0->30->29->28->26->27
2	0->24->22->20->19->18->21->23->25
3	0->2->1->3->5->4->8->7->6
4	0->9->13->11->10->12->14->17->16->15

In Figure 7(a)–(d), the shortest path lengths of the four algorithms solving for different numbers of water demand points are shown. In general, for 40, 60, 70 and 90 water demand points, the lengths of the shortest paths of the WDN solved by the GAACO scheme are smaller than those of the CDGA, SMPSO and SACO schemes. Specifically, in Figure 7(a), for a WDN with 40 water demand points, the shortest path lengths were obtained using the four algorithms are CDGA, SMPSO, SACO and

GAACO in descending order of shortest path length, with the GAACO solution obtaining the smallest value. Additionally, in Figure 7(b)–(d), we also get the same results as for Figure 7(a) by comparing the WDN shortest path lengths of the four algorithms. Therefore, the shortest path length value obtained by solving the WDN problem using GAACO is the smallest, and its algorithmic performance is superior to those of CDGA, SMPSO and SACO.

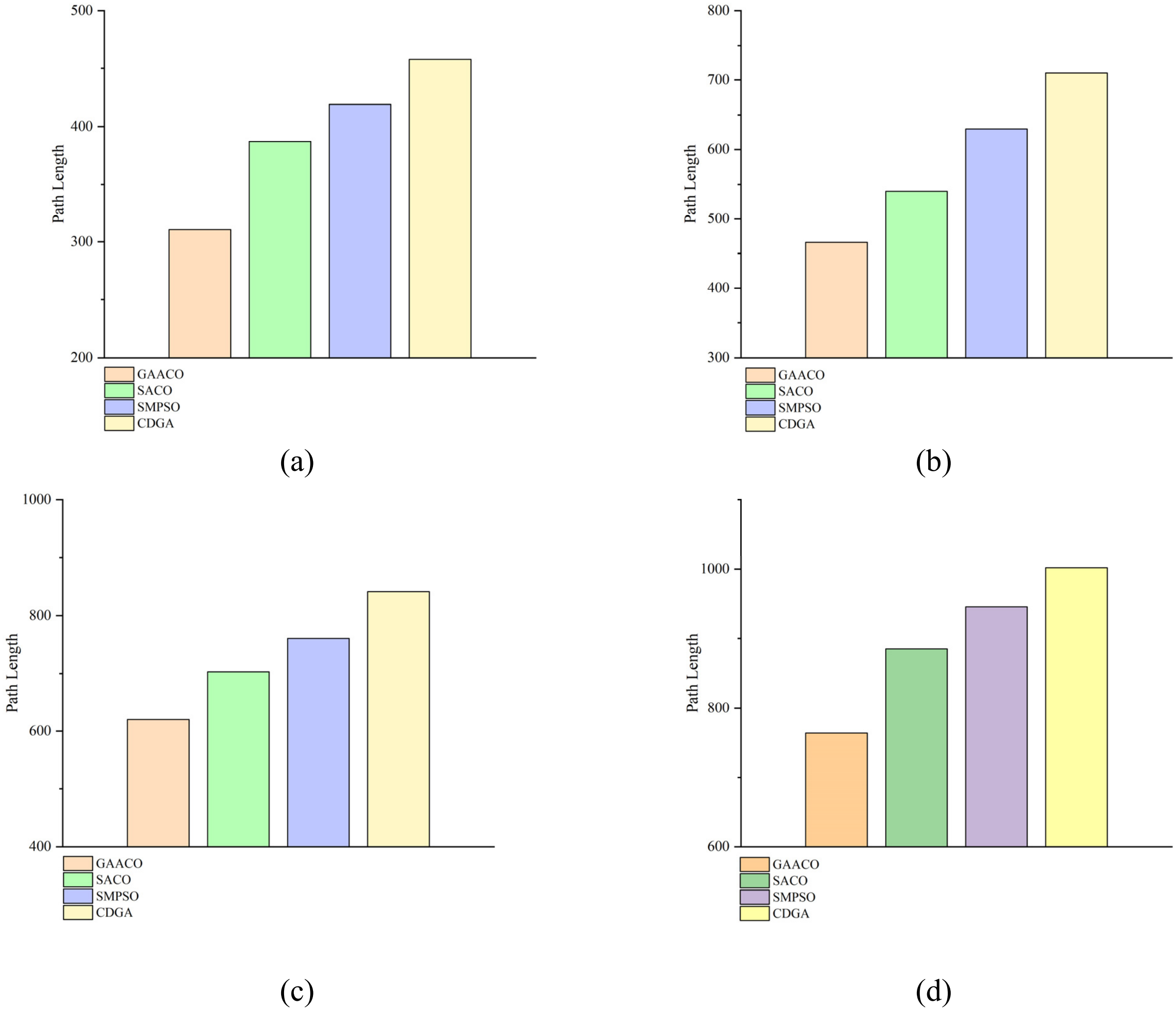

Figure 7 Comparison of the WDN shortest path lengths of the four algorithms in the form of bar graphs: (a) 40 water demand points, (b) 60 water demand points, (c) 70 water demand points, (d) 90 water demand points.

Table 2. Comparison of the shortest paths for different numbers of water demand points obtained by the four algorithms.

Algorithm	30 points	50 points	80 points	100 points
GAACO	260	340	674	820
SACO	292	387	770	947
SMPSO	304	410	827	1023
CDGA	336	432	884	1122

Table 3. Compared with the other three algorithms, the percentage of improvement in the path length of the WDN as optimized by GAACO.

Number of points	SACO	SMPSO	CDGA
40	19.8%	25.9%	32.2%
60	13.7%	26.0%	34.4%
70	11.8%	18.4%	26.3%
90	13.7%	19.2%	23.8%

In Table 2, we give the specific values of the shortest path lengths for the four algorithms used to solve the farmland WDN grouping irrigation., and it can be seen that GAACO always finds the smallest values for 30, 50, 80, and 100 water-demanding nodes. Specifically, for a WDN with 100 water demand points, GAACO computes a value of 820, which is much smaller than the solutions of 947 for SACO, 1023 for SMPSO and 1122 for CDGA. In addition, GAACO also obtains the minimum WDN shortest path length for networks with 30, 50 and 80 water-demanding nodes. In Table 3, we present the optimization percentages of the shortest path lengths of the WDN solved by GAACO compared to CDGA, SMPSO and SACO for the cases of 40, 60, 70 and 90 water demand points. We can see that the shortest path values obtained by GAACO are again always optimal compared to CDGA, SMPSO and SACO for WDNs with 40, 60, 70, 90 water-demanding nodes. In particular, for 60 water demand points, GAACO improves the result by 13.7, 26 and 34.4% compared to SACO, SMPSO and CDGA, respectively. Therefore, the algorithm performance of GAACO in solving the shortest path of the WDN is the best among the four algorithms.

The analysis of the above result data shows that the GAACO algorithm has superior performance in solving the shortest path length problem for farmland WDN grouping irrigation. This is due to our designed adaptive mechanism in the algorithm to control the adaptive volatility of pheromones combined with greedy strategy to help ants find the best node, thus increasing the global search capability of the algorithm and also improving the fast convergence capability of the algorithm.

The simulation results show that the method can effectively reduce the pipe planning path length for farmland WDN grouping irrigation. For a complex farmland WDN water supply network and satisfying constraints such as node water demand points, this paper proposes a method to solve the shortest path model of farmland WDN grouping irrigation under the constraints of limited maximum water supply for a single round of irrigation group in a water supply center and global primary service at water demand points, and it only considers these two cases in two-dimensional fixed coordinates in farmland. We did not consider other factors of more complex cases, such as water main pressure and flow loss during water supply, and differences in water demand point satisfaction for different water demand points of the same irrigation group.

Our research object is closely related to the soil moisture of each small area of the farmland, which is the main basis of our irrigation grouping. We divide a farmland into several small pieces according to the different soil moisture conditions of each small area, which is also treated as a water demand point, and then generate the minimum path for each water demand point to meet the water demand requirement, which is a uniform farmland irrigation problem on a non-uniform field, so our research problem is a non-uniform field problem. In future research, it will be carried out under the combined model to further target other influencing factors, such as soil moisture conditions of farmland and water supply water pipe diameter parameters, and extended to multi-dimensional space to optimize the farmland WDN path. As a result, these issues are what need to be further studied in this paper. Moreover, it is necessary to state that our proposed GAACO method is for the farmer to provide an irrigation grouping strategy before irrigation, which is the pre-planning stage of irrigation, and once the strategy is generated, it is static and invariant at the time of irrigation. Since soil moisture conditions vary at different stages of the crop, each time the crop is irrigated before irrigation grouping is performed using our method, the algorithm runs in less than 5 minutes, which is reasonable since our algorithm works in the irrigation planning stage.

6. Conclusions

To optimize the irrigation group pipeline planning for farmland WDNs, this paper proposed an irrigation grouping path planning model and accordingly designs a greedy adaptive ant colony algorithm (GAACO) to solve the model, which combines the advantages of a traditional ant colony algorithm with the adaptive mechanism and greedy strategy. Through a series of processes such as the encoding of supply and demand points and irrigation groups by GAACO, the initialization of the ant colony, the greedy strategy of path planning for farm irrigation grouping and the update of the ant colony pheromone adaptive mechanism, GAACO has good global search capability and fast convergence in solving the shortest path problem of farmland water network. In the simulation experiments, we compare GAACO with CDGA, SMPSO and SACO, and the results show that the GAACO proposed in this paper has a faster convergence speed. In addition, compared with CDGA, SMPSO and SACO, the planned path length of irrigation pipes of WDN grouping obtained by GAACO is the smallest, so GAACO can effectively shorten the pipe path length of irrigation groups of farmland WDNs.

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Conflict of interest

The authors declare there is no conflict of interest.

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