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Optimal Allocation of Water Resources Using Agro-Economic Development and Colony Optimization Algorithm

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Abstract: Water is an irreplaceable commodity with a high economic value. Today, water scarcity is the biggest challenge in the world, and the crises arising from lack of freshwater resources are serious threats to sustainable environmental development and human health and welfare. As the problems grow in complexity and dimensions, it becomes less possible to solve them with conventional optimization methods or explicit computational methods in a proper amount of time and with the currently limited computation memory, making it very difficult to achieve an optimal absolute solution. In this regard, metaheuristic algorithms that are generally inspired by nature are used in complex optimization problems. The Pishin Dam is an important dam in the eastern basin of Iran in the south of Sistan and Baluchestan province. This region faces severe water stress due to very low precipitation and very high evaporation on the one hand and the growing increase in urban, agricultural, and industrial demand on the other hand. The water development plans executed by the Ministry of Energy in the studied region influence water supply and demand profoundly. This research investigated the optimal allocation of water resources of this dam under management scenarios using the metaheuristic technique of the ant colony optimization algorithm (ACO). The results showed that the best value of the objective function was 82.3658 million m^3. When applying the scenario of developing the cultivation area, the best value was obtained at 67.1258, which was significantly different from the base state. The results show that the ACO algorithm is suitable for the water resources of the Pishin Dam and can be used in planning and policymaking.

Keywords: management scenarios; ant colony optimization algorithm; optimization; Pishin Dam

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1. Introduction

Water is necessary for life, so socioeconomic development has always been interwoven with water. On the one hand, it is the primary factor for prosperity. It is impossible to imagine prosperity without water. Water is an irreplaceable and economically valuable commodity. Currently, water shortage is a global problem, and the crises arising from the lack of freshwater resources pose severe threats to sustainable environmental development, as well as human health and welfare. As a result, governments have been compelled to change their approach in dealing with these resources and to adopt cooperative management methods to involve users in all steps and levels of water and environment management [1]. Water serves a multitude of economic, social, and cultural purposes in communities beyond its essential role in human sustenance. Water has a closed cycle in the world, so there is a specific quantity.

Any imbalance between access to water resources and food demand in a region can affect the supply and demand of water in the downstream regions in terms of topography and create a competitive arena in which each region and catchment area plays a role [2]. Indeed, access or lack of access to water resources can have many effects, such as an imbalance in population growth in different regions, unbalanced distribution of surface and groundwater resources, severe pollution of water resources, changing consumption patterns, and lack of water resources. Therefore, international water consumption patterns and laws that can reduce regional challenges and tensions and create optimal allocation among different sectors are very important. Freshwater is naturally stored in the form of ice sheets on the earth's surface and mainly in mountain and polar glaciers in the north and south. Freshwater lakes, rivers and streams, and groundwater flow are other sources of freshwater. Freshwater resources account for only 3% of the planet's total water resources. In addition, much of the water is locked up in glaciers and inaccessible, with the rest stored deep underground. Meeting the water demands of different regions is becoming increasingly difficult due to population growth, increased water-related activities, and competition among different sectors that consume water. This challenge is further compounded by the increasingly limited availability of water resources. Thus, there has been a growing emphasis on planning for fair water distribution in line with sustainable development. Ideally, water allocation must be economically efficient, technically feasible, and socially fair. Economically efficient allocation aims to maximize profit, while socially fair distribution prioritizes resource preservation and water supply to economically poor groups. Therefore, we need a well-designed water distribution system in which water is treated as a socioeconomic commodity [3].

Iran is one of the countries in Asia that has many water problems and limited water resources. Iran is climatically located in the world's arid and semiarid zone. Its mean annual precipitation is only 250 mm, which is significantly lower than the average precipitation of both Asia (732 mm) and the world (831 mm). It is evident that meeting the water needs of this country solely from its renewable water resources is not feasible. This has turned water scarcity and the degradation of water quality into a significant challenge for national development programs in the future [4].

The province of Sistan and Baluchestan, which is exposed to severe limitations in terms of water resources and has been excluded from the development cycle of water resource management, is facing more complex conditions compared to other parts of Iran and experiencing peculiar hydrological conditions due to its climate and water resource management. The watershed of the South Baluchestan rivers is located in the most eastern part of Iran and covers an area of 48,662 km^2. Approximately 40,811.5 km^2 of this area is situated in mountainous regions, while the remaining 7850.5 km^2 is in plains. The Pishin Dam, located 150 km away from Chabahar County, is one of the most crucial water reserves in the region. The mean annual precipitation in the dam's watershed basin ranged from 44 mm to 499.5 mm over the past 15 years. The mean annual temperature has also fluctuated between 17.7 °C and 35.7 °C, with an average evaporation rate of 3590 mm per year. The Pishin Dam is the region's primary water source, supplying agricultural, drinking, and environmental sectors as well as all economic activities. However, the dam is reportedly in critical condition due to precipitation deficiency, dispersion, uncertainty, and a high evaporation rate. While the water reserve of the dam cannot meet the stakeholders' needs, the imbalance in water resources and consumption in the dam has created conflicts over water allocation to downstream consumers.

In the study area, the main beneficiaries of water are three sectors. The first sector is agriculture (as the main beneficiary), the second sector is domestic demand for drinking water, and the third sector is the environment. According to the water resource engineering system of the region, there are several dams and water sources in this watershed that feed these three sectors. For example, for the environment sector, diverting dams and earthen dams are used around the area, and the required water is supplied by floods. For water supply in the drinking sector, due to the serious water stress in the studied area, this sector needs to be supplied from two sources of water desalination from the Oman Sea and an earthen dam. The dam studied in this research is the first and foremost priority of the agricultural sector, which also deals with the management of its water resources in this study.

Understanding the factors that affect water supply and demand and establishing their relationships based on economic theories for various applications can assist policymakers in developing appropriate policies to tackle problems and crises caused by water scarcity, considering the availability of water reserves and using the analysis of the sensitivity of supply and demand to influential variables such as population, capital, technology, income, and others [5]. With this knowledge, they can predict the outcomes of their policies and scenarios and subject them to economic analysis and evaluation. The Ministry of Energy has developed and put into action various water management scenarios for the Pishin Dam basin based on the current water conditions of the dam. Each scenario has specific impacts on water resources and consumption. The overall focus of the research is to find the most optimal way to allocate water resources under these managerial scenarios in the south of Baluchestan using the ant colony optimization (ACO) metaheuristic algorithm. Several research studies have been conducted on metaheuristic algorithms. Below is a brief review of these studies. Borhanidarian and Mortazavi Naeini [5] utilized the ACO algorithm with a discrete reservoir volume structure to optimize the operation of the single-reservoir system of Dez. They claimed that solving continuous problems with a discrete decision variable structure using the ACO algorithm did not yield better results than the genetic method. Afshar et al. [6] tested two types of the ACO algorithm—the rank-based ant system and the max–min ant system (MMAS)—regarding the problem of operating the reservoir of hydroelectric dams. Afshar et al. [7] proposed a stochastic adaptive refinement process to promote the performance of the ACO algorithm in finding solutions close to the continuous optimal solutions. In this method, the discretization is performed first uniformly and then by the Gaussian distribution. Hosseinzadeh and Sharifi [8] explored the potential of the ant multi-population algorithm in solving multi-objective optimization problems of pollution charge. Borhanidarian and Moradi [9] used the algorithm of ant colony optimization for continuous domains (ACOR) in operating the multi-reservoir systems of the Karkheh basin and compared the results with the genetic algorithm. Banibashar et al. [10] used an ant behavior-based algorithm for optimal operation of the Alevis reservoir dam in the Sufichai basin of Marageh. The results proved the suitability of the ant society algorithm for optimal utilization of the dam reservoirs. Hasheminasab et al. [11] utilized the ant society algorithm to develop an optimal policy for the operation of the Kalanmalayer Dam Reservoir. The objective was to supply drinking and agricultural water. The optimized result was to achieve optimal coefficients of abstraction from the reservoir in each period and the optimal reservoir operation policy. Gasemi and Ghasemi [12] first introduced fuzzy logic, the genetic algorithm, and the extended elite ant colony algorithm as a sort of ACO algorithm. Afshar et al. [13] investigated the capabilities of four algorithms in solving two single-objective problems of the operation of the Dez Dam reservoir to supply the water requirement and generate hydroelectricity. The four algorithms, which were all subsets of ACO, included the basic ant colony optimization, the elitist ant system, the rank-based ant system, and the max–min ant system. Najafi and Afshar [14] focused on the management of the aftermath of chemical invasions for urban water distribution networks, considering two main objectives of minimizing the number of polluted nodes and a new objective called minimizing the network's return time to its normal operation, along with minimizing the number of reactive operations, using the ACO algorithm. Solving the model by the ACO algorithm revealed the efficiency of these metaheuristic algorithms in solving similar problems. Jalali et al. [15] developed an ACO algorithm for reservoir operation. They optimized Dez's single-reservoir system in the short term by considering the release as a decision variable. Afshar et al. [16] introduced a continuous ant colony optimization (CACO) algorithm to optimize reservoir operation. They introduced a method for setting the problem parameters and an elitist strategy for the proposed algorithm. Jalali et al. [17] developed an ACO algorithm to optimize the reservoir of the Dez Dam. They employed mechanisms like pheromone propagation, searching ants, and local search to prevent the rapid movement of ants to the same section of the search space. Kumar and Reddy [18] studied the efficiency of the ACO algorithm in multi-objectively optimizing the multi-reservoir system of Hirakud in India. They formulated the ACO model considering a finite horizon of inflow time-series and reservoir volume classification. Jalali et al. [19] proposed an ant algorithm for solving the continuous reservoir operation problem. In this method, the continuous search space of the decision variables is discretized randomly and heterogeneously within the allowed range. As a result, the probability of losing the optimal solution range is minimized. Moeini and Afshar [20] conducted a study on applying the ACO algorithm for the optimal operation of resources. They investigated three proposed designs for water resources and the problems of the operation function of hydraulic resources in the Dez Dam. López-Ibáñez et al. [21] optimized pump operation using the ACO algorithm, considering the number of ons/offs as a constraint. The results proved the superior performance of the ACO algorithm. Socha and Dorigo [22] proposed a new version of the ACO algorithm that can lead to optimization in a continuous environment, unlike previous versions. Darian and Moradi [23] used the ACO algorithm to determine the path of optimal operation of a single-reservoir system. Hashemi et al. [24] used the ACO algorithm to optimize the pumping program in a water distribution network by using variable-speed pumps under the fluctuations of daily water demand. In their research, Dorigo and Di Caro [25] used the ant colony efficiency algorithm. They use this method for optimality. In another study, Dorigo et al.'s [26] ant algorithm was introduced for optimization.

The literature review shows that many researchers have been interested in applying the ACO algorithm in water resource management, reflecting the potency of the algorithm in optimal water distribution. Given the significance of water resources and the optimal allocation of these scarce resources among different applications in the south of Baluchestan, it seems necessary to develop a plan to achieve this goal in the studied region. Therefore, this paper studies the optimal allocation of reservoirs by the ACO algorithm under various management scenarios for the first time.

2. Methodology

The ant colony optimization (ACO) algorithm is inspired by the actual behavior of ants that live together in large numbers. In a study on Argentinian ants, Goss et al. [27] found that ants find the shortest path between the nest and the food after some time (Figure 1). The formation of this test is based on the fact that ants leave fixed slight amounts of pheromone per unit length when they are moving. These values are subject to changes.

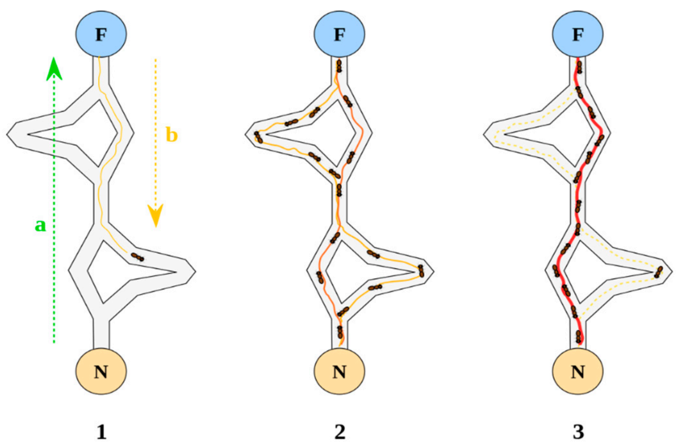

Figure 1. The behavior of Argentinian ants in Goss et al.'s experiment [27,28].

Let us assume that $G = (G, E)$ is a normal or non-weighted graph with $n = |V|$ nodes, in which V represents the set of nodes and E represents the set of edges connecting the nodes. Using the simplified ACO algorithm, the shortest path between two target nodes can be found on graph G, say, finding the shortest path between an origin node S and a destination node d, in which the path length is defined as the number of edges traveled. An edge connecting the ith node to the jth node is denoted by e_{ij}. For each edge e_{ij}, a quantity is considered as the pheromone trail or quantity, denoted by τ_{ij}. The pheromone amount is read by the ants. The density of the pheromone on an edge is a criterion of its suitability and selection by ants to make better paths.

In the beginning, all edges have an equal amount of pheromones τ_0. Each ant adopts a step-by-step policy to construct a tour path. Local information, maintained in each node or in edges that exit the nodes, is randomly used to select the next destination. When the kth ant is at the ith node, the probability of selecting the jth node as its next destination is calculated by Equation (1) [27,28] as follows:

$$p^k{}_{i\to j} = p_{ij}{}^k = \begin{cases} \frac{\tau_{ij}}{\sum\limits_{m\in N_i} \tau_{im}} & ,j \in N_i \\ 0 & ,j \notin N_i \end{cases}, \tag{1}$$

in which N_i is the set of nodes within one step of the ith node. In other words, N_i is the set of the graph nodes connected to the ith node. When an ant moves on one edge, it leaves pheromones, the amount of which $\Delta\tau$ is fixed in the simiplified algorithm. If an ant moves between the ith and jth edges at time t, the amount of pheromone on that edge is calculated by Equation (2) as follows:

$$\tau_{ij}(t) \leftarrow \tau_{ij}(t) + \Delta\tau, \tag{2}$$

The most common way to reduce pheromones is to use an exponential decreasing function in which the amount of pheromones at each step is multiplied by a positive number smaller than one. This action is generally defined by the following equation:

$$\tau \leftarrow (1-\rho)\tau \quad ,\rho \in \ [0,1], \tag{3}$$

in which ρ is the evaporation rate. In more complicated cases, ρ has a relatively high value at the initial steps of the algorithm and gradually decreases. A simple experiment to find the optimal path between the nest and a hypothetical destination, depicted with a simple graph in Figure 2, demonstrates the good performance of the simplified ACO algorithm.

The ant algorithm and the algorithms derived from it can be used to solve discrete optimization problems. In discrete optimization problems, the set of values that can be assigned to the variables is countable and mostly finite. However, the discrete problems that the ACO algorithms can solve have peculiar properties, including [29].

Assume a finite set with elements $C = C_1, C_2, \ldots, C_{N_c}$.

The finite set has been defined by the possible relations or transfers between the members of set C as $L = l_{C_iC_j}\Big|(c_i, c_j) \in \widetilde{C} \subseteq C \times C$, in which $\widetilde{C}$ is a subset of Cartesian product $C \times C$ (two sets A and B are defined as $A \times B(a,b)|a \in A, b \in B$). On the other hand, the relationship $|L| \leq NC^2$ will always be established. For each relationship $l_{c_ic_j} \in L$, a relationship cost function, which is probably time-dependent, is defined as $J_{c_ic_j} = Jl_{c_ic_j}, t$. The finite set is defined by constraints $\Omega = \Omega C, L, t$. These constraints are defined on the members of sets C and L, and variable t represents the likely dependence of these constraints on time.

The problem states are defined as sequences of the members of C or L. For example, $s = \langle c_i, c_j, \ldots, c_K, \ldots \rangle$ is a sequence defined on the members of C and is called a state. Assume that S is the set of all definable states. The set of states that satisfied the constraints Ω, C, L, and t will be a subset of S as $\widetilde{S}$. The members of the set $\widetilde{S}$ define the feasible states for the problem. The length of the sequence S, which is equal to the number of its members, is represented as $|s|$.

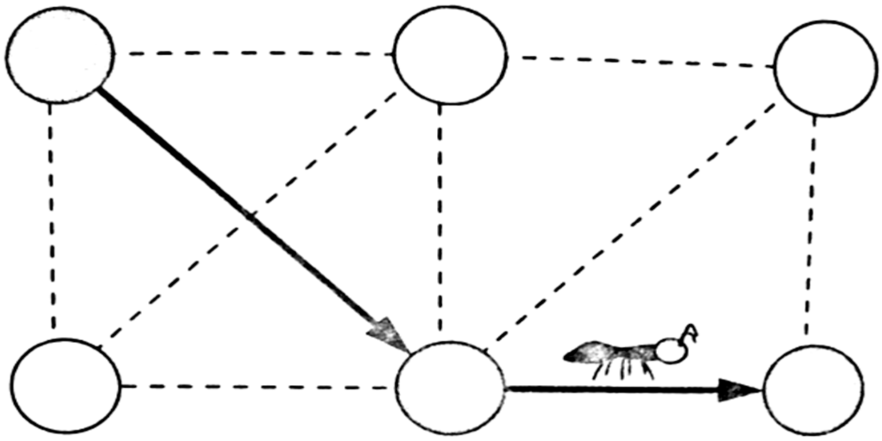

Figure 2. The optimal path of ants in a simple graph [30,31].

2.1. Some Modified ACO Versions

The first version of the ant algorithm, named "ant system" (AS), was proposed by Marco Dorigo in his Ph.D. dissertation in 1992. The AS was composed of three ant algorithms, differing only in how the pheromones changed. They were called ant-density, ant-quantity, and ant-cycle. The latter, i.e., ant-cycle, proved to outperform the other two algorithms by a great margin. So, when speaking about the AS, we mean the ant-cycle algorithm.

2.1.1. Ant Algorithm and Elitism

Dorigo and his colleagues introduced a modified version of the AS in 1996, which included elitist ants. In this version, the ant that finds the best solution, or in other words, the shortest path, and deposits more pheromones on the graph. As a result, the other ants can get closer to the best solutions. How pheromones are deposited, which is defined by Equation (4), creates a sort of elitist-ant algorithm [27,28].

$$\Delta\tau_{ij}^{k} = \begin{cases} \Delta/2\,, & \Psi^{k} = \Psi^{+} \\ \Delta/2\,, & \Psi^{k} = \Psi^{*} \\ 0\,, & otherwise \end{cases}, \tag{4}$$

in which Δ is a constant.

2.1.2. The Ant Algorithm and Reinforcement Learning

The Q-learning or QL method is a method used to solve reinforcement learning problems. In the QL method, the criterion for assessing different actions is the numerical value attributed to an ordered state and action pair. This value, called the state–action value function, is a criterion for selecting an action among several actions available. The state–action values are changed when the algorithm runs so that the agent can achieve the optimal result.

2.1.3. Ant Colony System

The ant colony system (ACS) was developed by Dorigo and Gambardella in 1997 to optimize the performance of the ant algorithm to solve more complicated problems with greater dimensions. This algorithm resulted from changes made in the initial ant algorithm. This changes mainly aimed to achieve a balance between search and operation. The changes made in the ant algorithm to create ACS were as follows [29]:

(a) The principle of destination selection: The ACS and AS differ in how the destination is selected. Assuming that q_0 is a number in the interval of [0, 1], a path is selected for moving with the probability of q_0 that has the highest amount of pheromones and the shortest distance. With the probability of $1 - q_0$, the movement path is selected in the same way as the AS algorithm. Indeed, q_0 strikes a balance between search and operation, too. More searching results in higher diversification of solutions, and operation results in the intensification of the best solution found. The next destination of the kth ant, which is in the ith city, is determined by Equation (5) as follows:

$$j = \begin{cases} \underset{m \in \mathrm{N}_i^k}{\operatorname{argmax}} \left[\tau_{im}^{k\ \ \alpha}\ \eta_{im}^{k\ \ \ \beta} \right] & , \quad q \leq q_0 \\ j_0 & , \quad q \succ q_0 \end{cases}, \tag{5}$$

in which q is a random number within [0, 1] with a uniform distribution and j_0 is a random destination selected by the probability defined by Equation (6) as follows:

$$\rho_{i \to j}^{k} = \rho_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}{}^{\alpha}\ \ \eta_{ij}{}^{\beta}}{\sum\limits_{m \in \mathrm{N}_i^k} \tau_{im}{}^{\alpha}\ \ \eta_{im}{}^{\beta}} & , \quad j \in \mathrm{N}_i^k \\ 0 & , \quad j \notin \mathrm{N}_i^k \end{cases}, \tag{6}$$

in which α and β are constant positive values used to assign weights to pheromone information and mental information. The higher the weight of either type of information, the greater its effect on ants' decisions and on solutions obtained by them. α = β = 1 will bring good results in most problems. However, these two coefficients can be changed for other problems so that better results can be gained.

(b) How pheromones are renewed: In the ACS algorithm, the pheromones are renewed in two ways. One is local renewal in which moving ants deposit pheromones on the edges they are moving on. This sort of pheromone deposition is carried out by Equation (7):

$$\tau_{ij} \leftarrow (1 - \rho).\tau_{ij} + \rho \tau_0, \tag{7}$$

in which τ_0 is the initial amount of pheromones on the paths and ρ is the evaporation rate.

The other type is global renewal, which is deposited only on the best path found in each iteration, i.e., Ψ^+. If $l_{ij} \in \Psi^+$ and J^+ represent the length and cost of the path Ψ^+, respectively, the pheromone of edge l_{ij} is changed as represented by Equation (8):

$$\tau_{ij} \leftarrow (1 - \rho).\tau_{ij} + \frac{\rho}{J^+}, \tag{8}$$

Of course, evaporation has been included in Equation (8). If it is eliminated, Equation (9) will be obtained, which only states the global pheromone renewal.

$$\tau_{ij} \leftarrow \tau_{ij} + \frac{\rho}{(1 - \rho).\ J^+}, \tag{9}$$

The reason for classifying the action of pheromone deposition into two steps was to create a balance between search and operation—in other words, a balance between diversification and intensification. To obtain a good solution, α and β must be matched. Therefore, the higher the amount of α, the higher the weight of the ants' findings; the higher the amount of β, the higher the weight of the environment. In other words, the experience of the ants is stored as τ_{ij} and the effect of the environment on them as η_{ij}. There must be a balance between these two parameters.

2.2. The General Parameters of the ACO Algorithm

The ants in the colony have the following properties:

- An ant looks for the least costly solution.
  This cost can be defined as $J^* = \min \top \Psi \; [\![J_\Psi \; (L,t)]\!]$.
- The kth ant has a personal memory M^k where the path traveled is stored. This memory is used for the path inversely.
- The kth ant that is in state $s_r = \langle s_{r-1}, i \rangle$ can go to a node like j that is a member of the set $N_i^k = \vdash \mathrm{j} \dashv \| j \in N_i$ and $\langle s_r, i \rangle \in \widetilde{s}$. N_i is a set of nodes that are in the neighborhood of the ith node and is defined as $N_i = \vdash j \dashv \| l_{ij} \; \in L$.
- The kth ant starts working from the initial state S_0^k.
- The kth ant has a set of specific termination conditions as e^k.
- Ants start moving from their initial state. In each move, they go to a feasible neighboring state. This creates a feasible solution for the problem. The movement of an ant continues as long as at least one termination condition e^k is satisfied.
- The kth ant, which is located at the ith node, can move to one of the nodes located in N_i^k. The destination is selected based on a certain probability rule.
- The probability rule of the ants is a function of (a) problem constraints, (b) each ant's memory, and (c) the local information stored in each node. The local information of each node is a composition of the pheromone information τ_{ij} and the mental information η_{ij}. This information is systematically stored in a so-called routing table.
- As moving from the ith node to the jth node, each ant changes the amount of pheromone τ_{ij} on edge l_{ij}, which is called an online step-by-step pheromone update.

If an ant moves back in the path it has found and changes the pheromone of its constituting edges, it is called a delayed pheromone update.

Table 1 presents a summary of parameters in the ACO algorithm.

Table 1. The parameters of the ACO algorithm.

Parameters	Description	Consideration
K	Ant population	-
t	Maximum number of iterations	-
τ_0	Initial quantity of pheromone on the paths	Not applied in the MMAS algorithm
ρ	Evaporation rate	-
α	Pheromone information	Assuming $\alpha = 1$ in the ACS algorithm
β	Mental information	Not applied in the ANTS and SACO algorithms

In Table 1, the parameter "ant population" means the number of ants considered when running the model, the number of which can be changed and the optimal value of which is obtained when running the model. The "maximum number of iterations" parameter is also obtained when running the model in terms of other variables and objectives. The maximum number of iterations in the model is placed at an interval and obtains the value of the objective function in different iterations in that interval. The parameter "initial quantity of pheromones on the paths" is used to determine the initial path. The "evaporation rate" parameter is determined based on the evaporation level of the study area. The "pheromone information" parameter stores the mental information of the ant population, and the "mental information" parameter transfers this mental information to the next steps. The study area is shown in Figure 3.

Figure 3. The location of the Pishin Dam in the south of Sistan and Baluchestan province.

3. Results

3.1. Results of the ACO Algorithm

The first step to solving a problem with the ACO algorithm is to determine a suitable graph. In determining the graph when considering the sequential constraints, if the discretization distance is too long, it may happen that after an ant passes some decision points and makes decision choices, there exists no node within the range of decision choices that the ant can make in the next decision point (the distance between two solid circles in Figure 4). However, if the discretization constraints are not considered, the discretization can be performed so that the distance between the nodes increases. This research study set the distance of the nodes at 0.5 million m^3.

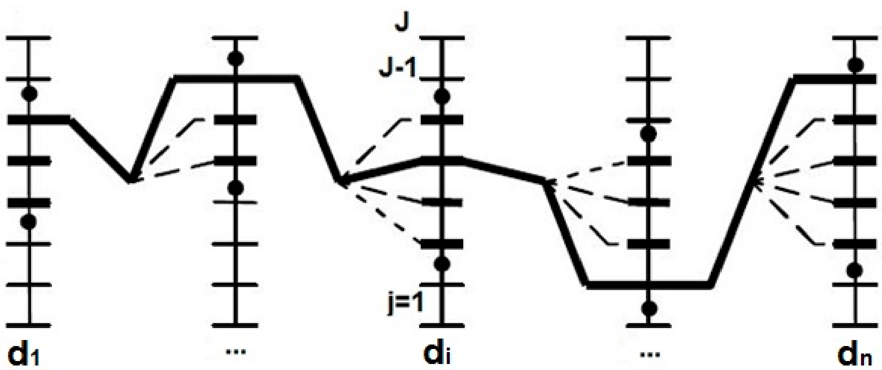

Figure 4. The graph defined for the problem of dam reservoir operation considering the sequential constraints.

Other parameters have been defined for the algorithm, too. Changing these parameters will influence the algorithm's performance. Thus, the most appropriate values should be determined for all parameters and coefficients to solve the problem. The best value for each parameter is determined by trial and error, for which the value is changed while other parameters are kept fixed as long as the most appropriate value is found. The conditions for stopping the algorithm from running are defined by various methods. Example conditions include:

1. The elapse of a certain time or iteration;
2. The elapse of a certain time or iteration with no specific improvement in the results;
3. The achievement of an acceptable level in the response.

Achieving a Certain Number of Function Evaluation (NFE)

This study considered two termination conditions: the elapse of a certain number of iterations and the elapse of a certain number of iterations with no significant improvement in the result. The condition for the ACO algorithm to stop running was that if the objective function did not change (decrease) by over 0.1 in 50 consecutive iterations, the program would stop running.

Table 2 shows changes in the number of ants. If there are few ants, there will be a lot of paths that are not passed by the ants. As a result, there will be a large set of unexamined answers. On the other hand, the program will take a longer time to run if there are many ants, which is not optimal. Given the low distance of the nodes and the application of sequential constraints, 350 ants generate the best answer of 82.529.

Table 2. The effect of ant population on the objective function in the ACO algorithm.

Ant Population	Number of Iterations	Value of the Objective Function
50	90	84.6578
100	90	85.1114
150	102	84.5897
200	89	83.7458
250	90	83.2544
300	97	84.8777
350	88	82.3658
400	91	83.4785
450	85	87.1258
500	89	84.3258
550	85	84.7748

Source: research findings. Unit: million m^3 (MCM).

Based on the results, with a population of 50 ants and 90 repetitions, the value of the objective function is 84.6578. Meanwhile, for an ant population of 100 and the same number of repetitions (90), the objective function has reached 85.1114. The results showed that if the population is 150 ants and the repetitions are 102, the objective function is 84.5897, which is lower than the population states of 50 and 100 ants. The highest ant populations were considered to be 500 and 550. For them, 89 and 85 repetitions were carried out, respectively, and the objective functions were 84.3258 and 84.7748, respectively. The results showed that the highest value of the objective function, 87.1258, occurred with a population of ants of 450 and 85 repetitions.

Table 3 presents the results of changing the pheromone evaporation rate. The pheromone evaporation rate varied in a range from 0.1 to 0.9, with an optimal value of 0.9. Considering a coefficient of 0.2 and 140 repetitions, the objective function was 83.3332, but with a coefficient of 0.3 and 105 repetitions, the objective function decreased, and it reached 82.6587. Examining the different coefficients shows that the highest and the lowest values of the objective function were obtained for 0.2 and 0.9, respectively.

Table 3. The effect of various ρ values on the objective function in the ACO algorithm.

ρ Coefficient	Number of Iterations	Value of the Objective Function
0.1	70	*
0.2	140	83.3332
0.3	105	82.6587
0.4	90	82.6500
0.5	78	82.6523
0.6	83	82.1254
0.7	65	82.9874
0.8	64	82.1112
0.9	61	82.1020

Source: research findings. *: The algorithm failed to find an unviolated solution. Unit: million m^3.

Since the value for the objective function was the lowest at the pheromone rate of 0.9 in the 61st iteration, it was selected as the optimal pheromone rate in the ACO algorithm.

Table 4 presents the proper parameters in the ACO algorithm to solve the operation problem considering the sequential constraints.

Table 4. The proper values of the parameters in the ACO algorithm.

Ant Population	Initial Pheromone	Penalty Coefficient (C)	Pheromone Evaporation Rate (ρ)
280	90	9	0.89

Source: research findings (unit: million m^3).

It is observed in Table 4 that the proper values for the ACO algorithm were 280 for the ant population, 90 for the initial pheromone, 9 for the penalty coefficient, and 0.89 for the pheromone evaporation rate (ρ). Table 5 presents the results of running the ACO algorithm five times with the values reported in Table 4. The results include the mean, best, and worst values of the objective functions.

Table 5. The results of running the ACO algorithm five times.

Run	1	2	3	4	5
Objective function value	82.2587	83.8002	83.3658	83.6587	82.7854
Number of iterations	80	100	70	60	65

Source: research findings (unit: million m^3).

Table 5 reveals that when the algorithm was run five times, the iteration was 80 and the objective function was 82.2587 in the first run, the iteration was 100 and the objective function was 83.8002 in the second run, and the iteration was 70, 60, and 65 and the objective function was 83.3658, 83.6587, and 82.7854 in the third, fourth, and fifth runs, respectively. At this stage, the results show that the lowest objective function occurred in the execution of the first step and the highest in the execution of the second step with 100 repetitions.

Based on the final results according to the ant algorithm, the average objective function was 83.2587. Also, the best objective function value was 82.6587 and the weakest objective function value was 83.8002 (Table 6).

Table 6. The statistical data on the performance of the ACO algorithm in five runs.

Algorithm	Mean Value of the Objective Function	Best Value of the Objective Function	Worst Value of the Objective Function
ACO	83.2587	82.6587	83.8002

Source: research findings (unit: million m^3).

Figure 5 displays the algorithm's performance considering the sequential constraints.

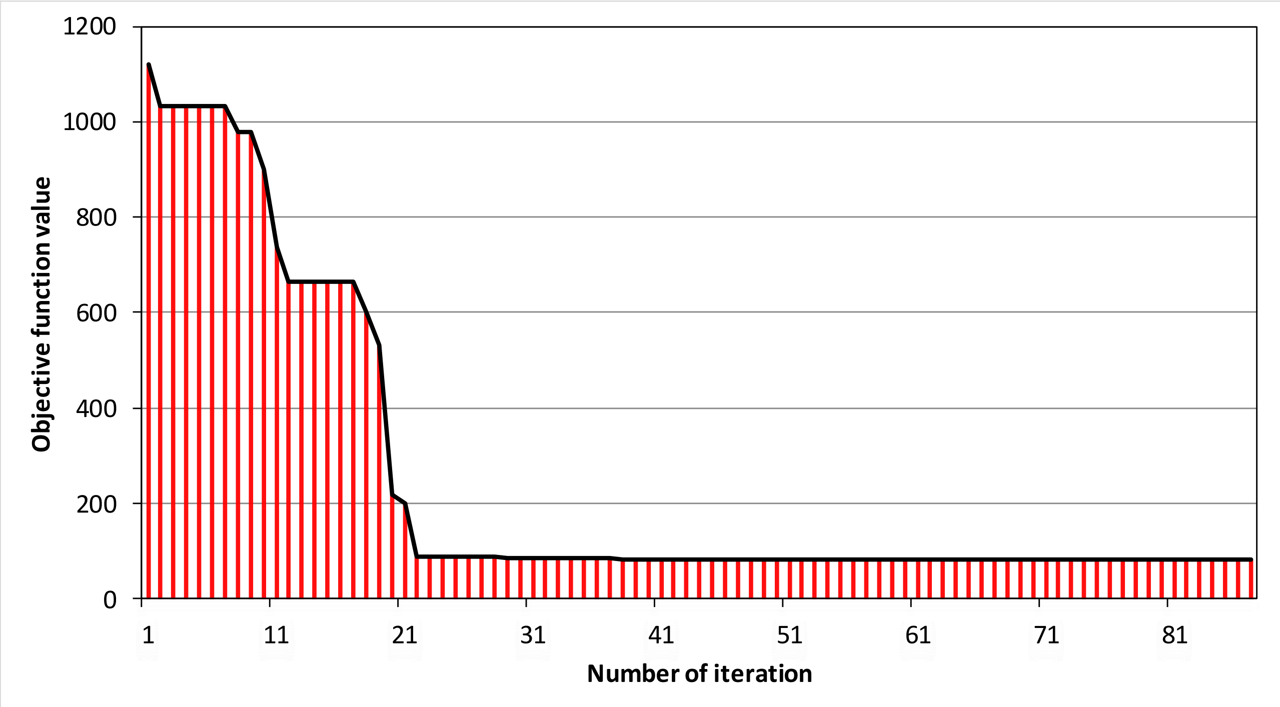

Figure 5. How the ACO algorithm performs considering the sequential constraints.

Figure 5 displays that the objective function was high when the algorithm started to run, but as the iteration increased, it started to decrease and no further improvement was observed in the objective function from a certain iteration on. As is clear in Figure 5, for iteration 1, the value of the objective function was very high and was between 1000 and 1200. With more iterations up to iteration 11, this decreasing trend continued, and the objective function was 600 to 800. A steady trend was predicted between the 12th and 17th repetitions, and from the 21st repetition onwards the decreasing trend was very high. The results show that from the 22nd and 23rd iterations onwards, the objective function followed a relatively stable path.

Figure 6 shows the optimal release rate as the output of the ACO algorithm and the demand rate.

Based on Figure 6, the release rate satisfied the demand rate in a few months, and there was a significant difference between them in most months. In many of the months under review, there was a lack of supply of demand. But in some months, the algorithm was able to allocate a large amount of demand. According to the figure, the amount of demand was between 0 and about 200 MCM, and the amount of water release was on average in the range of 0 to 140 MCM.

As seen in Figure 7, the objective function increased in the initial iterations, but after a certain iteration, no changes were observed in the objective function, which is related to the increase in the demand due to the increase in the cultivation area.

The objective function in this scenario had significant changes compared to the base case (Figure 5). In the initial iterations, the rate of decrease was very high, but gradually the process slowed down and became stable. Applying the acreage scenario and implementing the basic algorithm affects the required amount of demand.

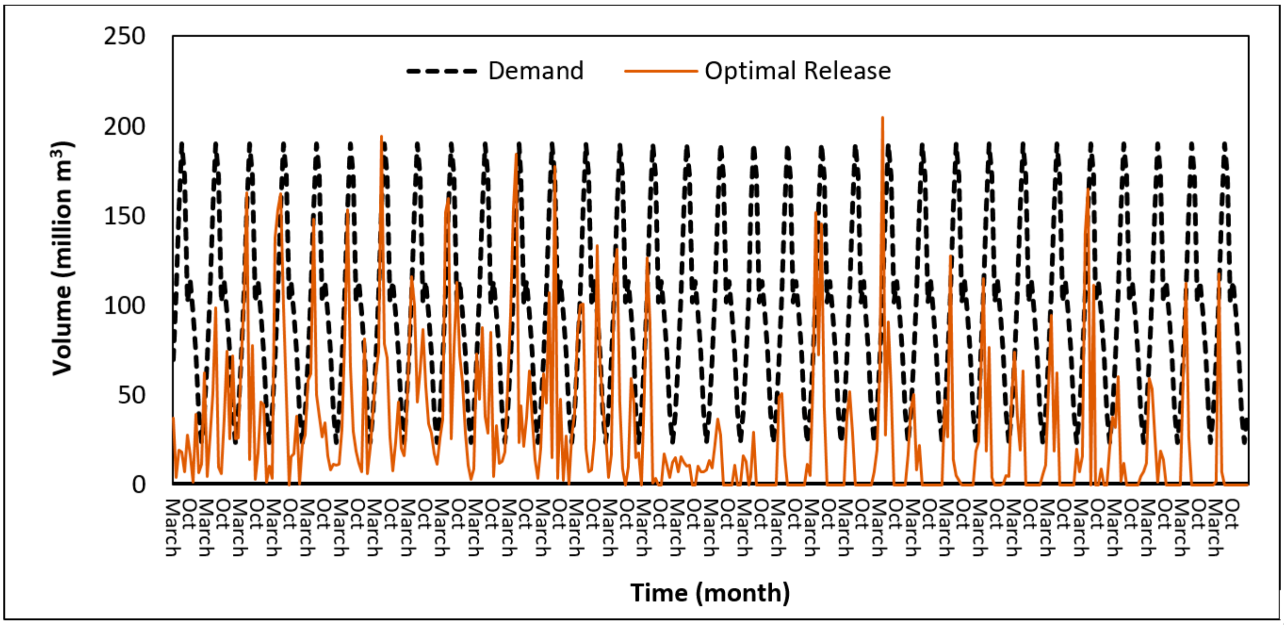

Figure 6. The optimal release rate as the output of the ACO algorithm and the demand rate.

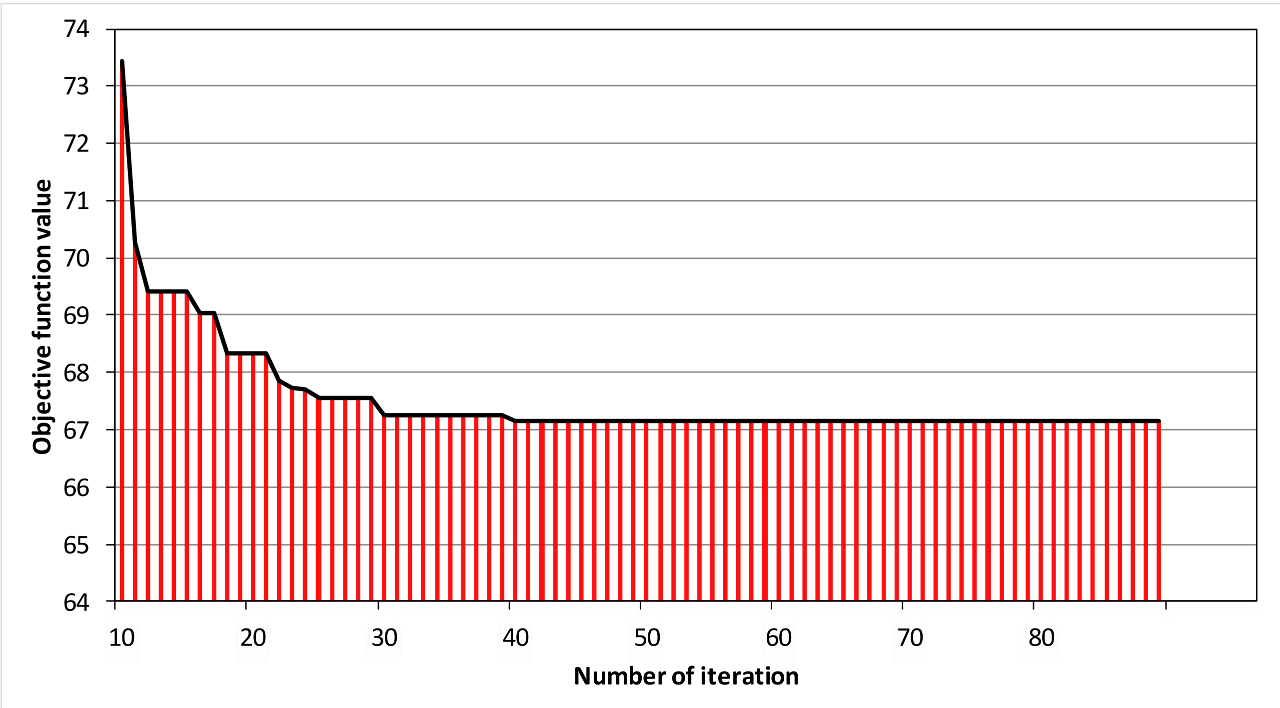

Figure 7. The performance of the ACO algorithm considering the sequential constraints for the scenario.

Figure 8 displays the optimal release rate related to the ACO algorithm and the demand rate.

Figure 8 reveals that the demand was low at the beginning of the period, but as agriculture gradually developed in the region, it increased, and after some time, it reached a plateau. According to the scenario of the cultivated area, the amount of demand faced an upward trend in the first few months from 100 to 240 MCM, but in the following months, due to planning in the development of the cultivated area based on upstream documents and planning horizons, it became stable in the range of 250 to 300 MCM. The results show that the optimal release value was very low at the beginning, but it improved later.

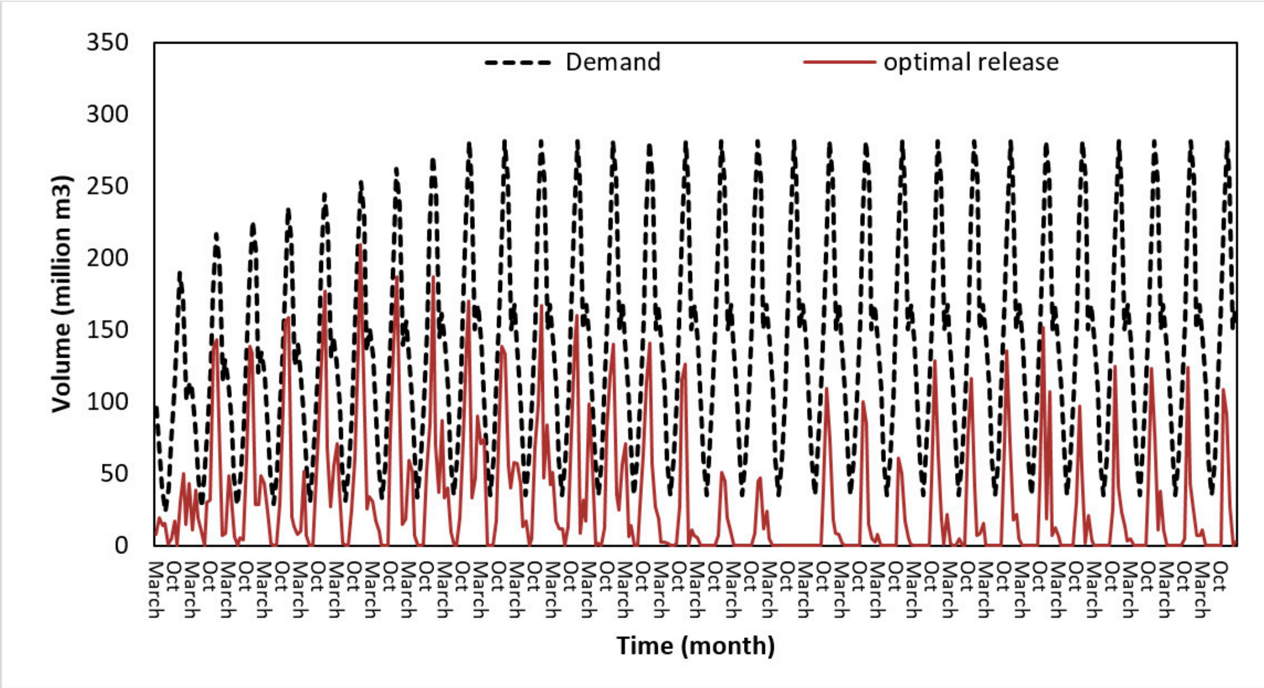

Figure 8. The optimal release rate as the output of the ACO algorithm and the demand under the scenario.

4. Discussion and Conclusions

The research aimed to optimally allocate the water resources of the Pishin Dam using the ACO algorithm based on a comparison with the base year and the management scenario of developing the cultivation area. The results showed that the ACO algorithm is a robust metaheuristic algorithm that can optimally allocate water in the Pishin Dam.

Given the arid and semi-arid climatic conditions of Iran, the limitation of water resources is considered the most important obstacle in the development of sustainable agriculture in a large part of the country. In addition to slowing down the process of agricultural development, the lack of water resources will also cause losses in the future. The implementation of an agricultural water productivity system in the water management structure of the country is one of the recommended solutions. Therefore, in order to prevent crisis, it is necessary to move towards the management of water demand, including a change in the cultivation patterns. Changing the current cultivation patterns to optimal cultivation patterns is one of the main axes of the strategy of improving agricultural management practices for the strategic management of agricultural water shortages. Therefore, it is necessary to plan the cultivated areas and determine the optimal patterns for managing agricultural production systems, especially in arid and semi-arid areas that suffer from water shortages and where the uncertainty of cropping plans is more likely.

Water management is considered the main possible solution to solve the problems caused by the quantity and quality of water. Sustainable management of water resources has to consider two goals at the same time: sustainable aquaculture to ensure food security and environmental protection. It is necessary to create a stable interaction between these two goals now and in the future; at the same time, potential conflicts between these two goals with the help of methods such as using new irrigation methods, preventing water loss in the transmission routes, changing the cultivation patterns towards crops, low consumption, and development of cultivation should be discounted.

Water has long been the most important development factor in the world. Due to successive droughts, sustainable use of water in the world, especially in Iran, is of particular importance. In this study, the effects of various economic, social, physical, institutional, and management factors on the amount of agricultural water loss have been determined. This study showed that the development of economic plans in the agricultural sector is very important. These scenarios in less developed areas can help improve the economic situation in different ways and increase the economic well-being of the society. The development of the agricultural sector in these areas should be given a lot of attention. But what is important in this section is the water section and its allocation. Allocation of water is a very serious matter to prevent water wastage and save it.

In many regions of the world, especially the studied region, there is a shortage of water, and drought has caused water crises and tension. The aim of this article was to use one of the meta-heuristic algorithms to solve the optimal allocation of water in a less developed area with the aim of sustainability. Therefore, the ant algorithm was used for this purpose. The results showed that this algorithm can cover the scenarios considered in this study well and provide good optimal points for water allocation.

Based on the results obtained, water resource management in the study area is very necessary and can pose serious risks for the development of cultivated area in the future according to sustainability criteria. The scenarios examined in this research were developed by planners, and serious attention should be paid to their results and effects. This can greatly contribute to sustainability in the region. The results of this study confirm the findings of researchers such as Iglesias and Garrote [30], Valipour [31], Kernecker et al. [32], Bai et al. [33], Bazrafshan et al. [34], Ghaffari Moghadam et al. [35], Safari et al. [36], Mianabadi et al. [37], Madani et al. [38], Geoponic et al. [39], and Wang et al. [40]. The results showed that the objective function was 84.6578 with an ant population of 50 and 90 iterations. When the ant population was 100, the objective function was estimated at 85.1114 in the 90th iteration. When the ant population was increased to 350, the objective function was calculated at 82.3658 in the 88th interaction. Finally, under the ant population of 600, the objective function reached 83.4587 in the 86th iteration. The minimum value of the objective function was 82.3658, obtained in the 88th iteration with an ant population of 350, and the maximum value was 87.1258 in the 102nd iteration with an ant population of 450.

The results of this study confirm the ones of Margini et al. [41] and Kooshari et al. [42] showing that the ant algorithm has a high ability to optimize, especially in the management of water resources. In fact, this algorithm can estimate the defined objective functions with the least error.

Also, the objective function obtained was 84.4477 in the 140th iteration when the pheromone rate was 0.2. When the pheromone rate was changed to 0.3, the objective function decreased to 82.6587 in the 105th iteration. Also, it decreased to 82.6500 in the 90th iteration at the pheromone rate of 0.4, 82.1112 in the 64th iteration at the pheromone rate of 0.8, and 82.1020 in the 61st iteration at the pheromone rate of 0.9. The results also revealed that the mean value of the objective function was 83.2587 for the ACO algorithm, and the best and worst values were 82.6587 and 83.8002, respectively. Also, the algorithm was run five times for the scenario considered in the research. The objective function was 67.1258, 67.3258, 67.9874, 67.3256, and 67.6541 in the first to fifth runs, respectively. The comparison of the runs revealed that the objective function was the lowest in the first run.

In this regard, the following recommendations can be put forth for planning and policymaking in the region:

- The agricultural sector has the highest demand in the studied region. So, consumption variations in this sector will influence water resources and regional development significantly. Therefore, relevant officials and managers need to pay serious attention to the prosperity of this sector.
- Since the virgin environment of the Pishin region and the riverbed are crucial for the life of marsh crocodiles, investment must be made to preserve the environmental conditions.

- Interviews with experts showed that there is no formulated plan for operation based on the critical conditions of water in the region. It is therefore recommended that policies, long-term strategies, and future plans regarding water allocation and operation be formulated according to regional conditions.
- Since the present research was comprehensive and integrated, in which various scenarios of water supply and demand were considered for a 10-year long-term period in the future, it is recommended that the relevant managers especially consider the results of this research.
- Considering that the livelihood of the people of the study area is dependent on agriculture and the agricultural sector accounts for the largest share of the use of freshwater resources, it is suggested to use the experiences of the leading farmers in the region in the field of agriculture.
- Due to the lack of water resources in this region, it is suggested to use modern irrigation methods to manage and exploit water resources.
- It is suggested to increase the role of education and public participation in the exploitation of water resources.
- Effective action through the adoption of effective mechanisms to implement the proposed policies will be able to put agriculture in the study area on a sustainable path with a sustainable approach in the current situation. According to the dynamic approach of the ant algorithm, moving towards the optimal situation in the region is in line with the goal of sustainable development of agriculture with a dynamic and sustainable approach.
- Long-term planning in upstream organizations seems necessary for coherence and coordination in the field of sustainable development. It is necessary for the media to generalize the concepts and principles of sustainable development and to increase the demands of the people of the region regarding the observance of the principles and standards of sustainable agricultural development.
- Finally, ACO showed that it has the ability to optimally allocate water resources according to the conditions of this area under different scenarios. It is suggested to use this algorithm in different planning for the management of water resources in the region and draw other different scenarios based on future planning.

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