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Water Saving Irrigation Decision-Making Method based on Big Data Fusion

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Abstract

In order to realize the intelligence of irrigation management and the wisdom of irrigation decision-making, improve the efficiency of water resource utilization, and introduce information fusion technology into the field of farmland irrigation, an irrigation decision-making method based on multi-source information fusion is proposed. Firstly, according to the actual situation and specific needs of the study area, the multi-objective irrigation water quantity optimization configuration model is constructed, and the multi-objective intelligent algorithm is used to solve the model. Then, using the adaptive weighted average fusion algorithm, the weight coefficient of soil moisture of millet in different growth stages and different soil layers is constructed, and the fusion of soil moisture in the data layer is realized. Finally, in order to meet different irrigation requirements, the multi-objective particle algorithm is used to solve the multi-object canal optimal water allocation model based on the optimized configuration of irrigation water volume. The experimental results show that the fusion results obtained by the multi-source large data adaptive weighted fusion algorithm are more reasonable, the uncertainty of irrigation decision-making is greatly reduced, the reliability of irrigation decision-making is improved, and the water consumption can be saved by 25.61% by using the multi-objective optimal allocation model.

Keywords: decision-making; big data fusion; irrigation water resources; optimized configuration; multi-source information fusion

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1. Introduction

At present, water shortage has become a worldwide problem, and water safety, efficiency, and rational use have become the focus of global attention [1]. Therefore, strengthening the management and rational allocation of water resources and realizing the intelligence of agricultural water-saving irrigation management and the wisdom of irrigation decision-making are of great strategic significance for improving water use efficiency, alleviating water shortage, and realizing sustainable agricultural development [2].

To achieve precise irrigation, fast and accurate access to information is the foundation, and the key is to make timely and scientific irrigation decisions [3]. The arrival of the big data era has changed the prospects of many scientific and engineering fields, including agricultural water-saving irrigation. Big data has promoted the technological development of agricultural water-saving irrigation and has brought opportunities and challenges to agricultural water-saving irrigation management and decision-making paradigm innovation. In the era of big data, traditional management and decision-making have gradually changed [4], from a linear paradigm based on management processes to a flat paradigm with data as the center. At the same time, the participation roles and information flow of management and decision-making are all diversified, and the interaction is more intensive and frequent. Eliminating the redundancy of big data information, extracting valuable information, realizing the complementary advantages of multi-source irrigation information, using certain methods to integrate and process each decision factor on time and effectively, and solving the problem of convergence to improve the reliability of irrigation management and decision-making are the challenges faced by multi-source information fusion in the field of farmland irrigation [5]. At the same time, achieving rapid processing of big data information and extracting valuable information from irrigation decision big data are especially serious challenges.

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In this paper, in order to eliminate the possible redundancy and contradiction between the information, utilize massive agricultural big data as the basic support to reduce the uncertainty of irrigation decision information and the degree of fuzzy decision-making reasoning, and improve the accuracy of irrigation decision-making, a systematic method to comprehensively reflect the quality of agricultural water-saving irrigation is established. Information fusion methods applicable to agricultural water-saving irrigation are studied to solve some difficulties and key problems in the current decision-making process of agricultural water-saving irrigation as well as improve the utilization rate of agricultural water-saving irrigation information and the ability to make correct decisions in a changing environment. Overall, the value of agricultural water-saving irrigation information is increased, creating an efficient and convenient new-generation irrigation management model.

2. Multi-Objective Optimization of Agricultural Water-Saving Irrigation Water Quantity

2.1. Multi-Objective Optimal Allocation of Irrigation Water

In the optimal allocation of irrigation water in irrigation areas, we should take into account not only the highest increase in crop yield and the greatest economic benefits of farmers, but also the economic benefits of water supply departments in irrigation areas [6]. Only in this way can we maintain the normal and healthy operation of irrigation areas and ensure their sustainable development, so as to achieve maximum comprehensive benefits [7-8]. For an irrigation activity in an irrigation area, when the available irrigation amount is different and when there are different stakeholders, the optimized irrigation water quantity allocation model and the optimization goal to be achieved are not the same. From a mathematical point of view, two or more aspects that constitute the above contradiction form an objective function of multi-objective optimization, so the above problem is a multi-objective optimization problem.

On the basis of acquiring, processing, researching, and analyzing data such as irrigation data and spatial information in the study area, a balance of supply and demand analysis was conducted in the area to clarify the interrelationships between irrigation systems in the study area. The optimal allocation of irrigation water resources is a systematic project, and the optimization objectives to be achieved can be expressed and simulated by mathematical models [9], as shown in Equation (1).

$$\begin{cases} \max\ y = \max[f_1(x), f_2(x), \cdots, f_n(x)] \\ s.t.\ g_i(x) \le 0,\ i = 1,2,3,\cdots,k \\ s.t.\ h_j(x) = 0,\ j = 1,2,3,\cdots,n \end{cases} \tag{1}$$

Where x is a decision variable, generally referring to the amount of irrigation water; $f(x)$ represents the objective function, such as the largest increase in crop yield, the highest income in the water supply sector, and the highest economic income of farmers; $g(x)$ represents the set of constraints, such as the total water irrigation and water flow constraints; and $h(x)$ represents a set of equality constraints, such as crop plan wetness. Optimizing the irrigation water resources in the irrigation area requires the following steps: (1) identify the issues that need to be addressed, and identify the main influencing factors. According to the actual work situation, comprehensively consider the multi-party demand to determine the optimization goal. In this study, the two objectives are optimized at the same time, and the constraint conditions of the function are determined according to the actual situation. (2) Form a mathematical model. The problem of the previous step is expressed in mathematical language. Mathematical functions are used to represent the objectives and different constraints that need to be optimized. These functions combine to form a multi-objective optimal configuration model of irrigation water in the study area. (3) Instantiate the model. On the basis of collecting and processing the data of the study area space and attributes, the above multi-objective optimization configuration model is instantiated and expressed by the algorithm. (4) Solve the model. According to the characteristics of the multi-objective irrigation water quantity optimization configuration model after instantiation, the appropriate multi-objective intelligent algorithm is selected to solve the problem, and the reliability of the solution result is analyzed. (5) Optimize the program for decision-making. As a result of the previous step, since a set of Pareto solutions is obtained, it is necessary to select the optimal irrigation water allocation scheme among the numerous optimization schemes according to the actual situation and the personal will of the decision maker.

2.2. Multi-Objective Optimization Model for Irrigation Water Quantity

Firstly, according to the specific characteristics of the water resources system in the study area, calculate the partitioning of the irrigation water supply and determine the allocation unit for irrigation water resources through abstraction and generalization. We aim to achieve the highest efficiency of the water supply sector and establish the following objective function:

$$\max\ f_1(X) = \sum_{i=1}^{n}\sum_{j=1}^{m} QF(i) \times Q(j) \times X(j) \tag{2}$$

Where $QF(i)$ is the unit water price of the water supply department to send the irrigation water to the i bucket of the study area, and the unit is yuan/m^3. $Q(j)$ is the planting area of the *j* crop in the *i* sub-region of the study area, expressed in hectares (hm^2) [6]. $X(j)$ is the irrigation quota of the *j* crop in the *i* sub-region of the study area, and the unit is m^3/hm^2. n refers to the number of sub-areas divided into study areas, and *m* is the number of all crop types planted in the *i* sub-area of the study area [8]. If the maximum economic income of farmers is taken as the second optimization object, the second objective function is established.

$$\max\ f_2(X) = \sum_{i=1}^{n}\sum_{j=1}^{m} [\Delta Y(j) \times Q(j) \times W(j) - QF'(i) \times Q(j) \times X(j)] \tag{3}$$

Where $W(j)$ is the market price of the *j* crop in the *i* sub-region of the study area, in units of yuan/kg. $QF'(i)$ is the water price after the unit water volume is delivered to the field through the end canal system, and the unit is yuan/m^3. $Y(j)$ is the irrigation yield increase of crops under irrigation conditions in the *k* period, expressed in kg/hm^2. The constraints of the above two objective functions are as follows:

(1) The water source is available for water quantity constraints:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} [Q(j) \times X(j)] \le W \tag{4}$$

Where *W* is the total amount of irrigation water that can be provided during the duration of this irrigation.

(2) Irrigation area restriction. In the irrigated area under the jurisdiction of each water distribution outlet in the study area, the irrigated area of all crops should not be larger than the planted area, that is:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} [Q(j)] \le C \tag{5}$$

Where $Q(j)$ is the planting area of the *j* crop in the *i* sub-region of the study area, in hectares (hm^2), and C is the total crop planting area in the study area, also in hectares (hm^2).

3. Fusion of Multi-Source Irrigation Information in Data Layer

Soil moisture information is an important basis for irrigation decision-making. The real-time and accuracy of soil moisture information will have a direct impact on the final decision-making [10]. The soil moisture data used in this paper is mainly obtained by three methods: one is layered soil data, another is real-time monitoring data collected by installing moisture sensors, and the third is soil moisture data obtained through hyperspectral inversion. For the collected data, the most commonly used data processing method is the arithmetic averaging method, which is an ideal method for measuring multiple times of normal distribution characteristics.

In a multi-sensor monitoring system, when a sensor fails, directly compiling the collected data without data consistency check will affect the accuracy of data fusion [11-12]. Therefore, the consistency of the information collected by the sensor needs to be checked before the fusion. In the past, group decision-making systems generally only performed simple arithmetic or weighted averaging on the data given by each participating evaluator. Such processing often only emphasizes the commonality of the group and ignores the differences existing in the group. To solve this problem, before aggregating group decision-making data, we must consider the personality of the group to correct the consistency of the data, so as to make the group opinion converge to a certain extent, so as to ensure that the group decision is basically in line with the objective reality.

Assuming that there are *n* sensors to measure the same monitoring object, $X_i = (i = 1, 2, 3, \cdots, n)$ is first detected for consistency. The inspection principle is that the difference between two adjacent numbers is less than or equal to the threshold value ε (the threshold value of soil moisture is ε < 3%), and the specific calculation formula is shown in Equation (6).

$$\begin{aligned} &\left|X_2 - X_1\right| \le \varepsilon \\ &\left|X_3 - X_2\right| \le \varepsilon \\ &\left|X_n - X_{n-1}\right| \le \varepsilon \end{aligned} \tag{6}$$

Since the soil moisture sensors of the test arrangement are located in different spatial locations, there is a certain difference in the monitoring data between the sensors. According to the principle of consistency check, if the difference is greater than the set threshold, the monitored data is considered to be abnormal data and cannot participate in the fusion process. In order to ensure the consistency of the monitoring data, the data of the abnormality is replaced by the average value in the period. Adaptive weighted fusion can only be performed after the monitoring data passes the consistency check.

For the group consistency correction method, we propose a comprehensive judgment matrix and consistency adjustment method for group decision. The steps for the method are as follows:

Step 1 For a decision-making problem, there are m experts ($E_k, k = 1,2,3,\cdots,m$) involved in the decision-making, and there are *n* schemes $F_j, j = 1,2,3,\cdots,n$ to choose from. Under a certain criterion, each expert uses two scales to compare the n schemes in pairs and obtain the judgment matrix.

$$C_k = (a_{ij}^{(k)})_{m\times n},\ k = 1,2,\cdots,m \tag{7}$$

Step 2 Determine the comprehensive interval judgment matrix $D = \left[\left[d_{ij}, \overline{d_{ij}}\right]\right] m\times n$ of the group decision generated by C_k of the following method, and obtain the interval $\left[d_{ij}, \overline{d_{ij}}\right]$ corresponding to ij of $\frac{\sum_{k=1}^{m} c_{ij}^{(k)}}{m} \ge \frac{\sum_{k=1}^{m} c_{ji}^{(k)}}{m}$.

Step 3 For Step 2, generate ij corresponding to interval $\left[d_{ij}, \overline{d_{ij}}\right]$. Let $A_k = \frac{d_{ij} + \overline{d_{ij}}}{2}, A_{ij} = (A_{ij})^{-1}$, and the initial comprehensive judgment matrix can be obtained.

$$A = (A_{ij})_{m\times n} \tag{8}$$

Then, use the iterative method to find the maximum eigenvalue $\lambda_{\max}$ of A and the corresponding normalized eigenvector $U = (U_1,\cdots,U_n)$ as the initial weight vector under a single criterion. This method corrects the main elements that cause inconsistency in the initial comprehensive judgment matrix and gives a method to determine the comprehensive judgment matrix of the group decision and adjust it consistently.

4. Multi-Source Big Data Fusion Algorithm

4.1. Multi-Source Big Data Adaptive Weighted Fusion Algorithm

Suppose the variance of the *n* sensors is $\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2, \cdots, \sigma_n^2$, the true value of the sensor to be estimated is X, the measured values of the respective sensors are $X_1, X_2, X_3, \cdots, X_n$, and the sensors are independent of each other and are unbiased estimates of X. The weighting factors of each sensor are $\omega_1, \omega_2, \omega_3, \cdots, \omega_n$, respectively, and the true value $\overline{X}$ and weighting factor after fusion should satisfy Equations (9) and (10) [13].

$$\overline{X} = \sum_{i=1}^{n} \omega_i X_i \tag{9}$$

$$\sum_{i=1}^{n} \omega_i = 1 \tag{10}$$

The total mean square error is shown in Equation (11).

$$\sigma^2 = E\left[(X-\overline{X})^2\right] = E\left[\sum_{i=1}^{n} \omega_i^2 (X - X_i)^2\right] \tag{11}$$

4.2. Multi-Source Irrigation Information Fusion based on D-S Evidence Theory

The D-S evidence theory, also known as the Dempster-Shafer theory, was proposed by A.P. Dempster in 1967 and is an important tool for dealing with uncertainty [14]. The main advantage is that no prior information is needed, and the description of the uncertain information is based on the "interval" method. Resolving the representation of uncertainty information shows great flexibility in distinguishing between "do not know" and "uncertainty" and accurately reflecting evidence aggregation.

D-S evidence theory is an extension of classical probability theory. As an uncertain reasoning method, it has the ability to express uncertainty. The theory measures the uncertainty, is closer to people's thinking habits, can reduce the set of hypotheses through evidence accumulation and synthesis rules, and can integrate multi-source information. D-S evidence theory uses mathematical reasoning to carry out the fusion of incomplete and uncertain information [15]. In the D-S evidence theory fusion algorithm, the framework of the whole judgment is the recognition framework. The basis of the fusion is to determine the basic probability distribution function, the synthesis rule is the fusion process, and the likelihood function and the trust function are used to express the fusion result. The hypothesis supports the upper and lower limits of the strength.

For a discriminant problem, assume that all the results obtained are represented by the set Θ, and each sub problem of the question corresponds to a subset of Θ. Then, it is called the collection of Θ as the frame of discernment, that is, $\Theta = \{a_1, a_2, \cdots, a_M\}$. All possible sets in Θ are represented by a power set 2^Θ, and when there are M elements in Θ, the number of elements of the Θ power set 2^Θ is 2^M. It can be specifically expressed as

$$2^\Theta = \{\varnothing, \{a_1\}, \cdots, \{a_M\}, \{a_1, a_2\}, \cdots, \{a_1, a_m\}, \cdots, \Theta\} \tag{12}$$

Given that a recognition framework is Θ and set function m is a mapping $m: 2^\Theta \to [0,1]$ on the power set 2^Θ of Θ, then the following is satisfied: $m(\varnothing) = 0$ and $\sum_{A \subset \Theta} m(A) = 1$, and m is called the basic probability assignment. $m(A)$ is called the basic trustworthy number or mass function of *A*, which reflects the extent to which evidence supports the occurrence of proposition *A*. 2^Θ represents a collection of all subsets of Θ. If $A \subseteq \Theta$ and $m(A) > 0$, then *A* is called the focal element of the evidence, and the collection of all the focal elements is called the core [16].

The fusion result of D-S evidence theory needs to express the support for any hypothesis through the interval. The lower limit of this interval is called the trust function. Given a recognition framework Θ, the set function $m: 2^\Theta \to [0,1]$ identifies the basic credibility assignment on the framework Θ [10].

$$Bel(X) = \sum_{Y \subseteq X} m(Y), \ \forall X, Y \subseteq \Theta \tag{13}$$

The function Bel: $2^\Theta \to [0,1]$ is the trust function on the recognition framework Θ. As can be seen from the definition, *Bel*(*X*) represents the sum of the basic probabilities for all subsets of *X*, indicating that *X* is true trust [17].

5. Multi-Objective Decision-Making Optimization Algorithm for Agricultural Water-Saving Irrigation

In engineering practice and scientific research, many specific problems can ultimately be attributed to optimization problems. It is always the pursuit of human beings to obtain the maximum benefit at the lowest cost. The same is true in the field of irrigation water resource optimization. Obtaining the maximum crop yield or the highest economic benefit with the least amount of irrigation water is one of the goals pursued by irrigation district managers. The basic theories and technical methods for solving these optimization problems are an important research direction, involving many fields. Researching efficient optimization techniques and methods has received great attention from researchers in many fields. With the progress of the times and the development of science and technology, the scale of research objects is getting larger and larger, the degree of no linearization of the system is becoming more serious, more goals need to be considered, and constraints are also increasing. Target optimization theory and methods are very necessary.

Through the discussion of multi-objective optimization problems, it can be concluded that the optimal solution satisfying the multi-objective optimization problem is not unique but rather a set of solutions, the so-called Pareto optimal solution set, and the Pareto optimal solution set is usually composed of a large number of Pareto optimal solutions. At the same time, there is no dominant relationship between Pareto optimal solutions. Improving the performance of any one of these targets will inevitably reduce the performance of other targets.

5.1. Multi-Objective Particle Swarm Optimization

From the perspective of bio-sociology, swarm intelligence refers to a collective form of intelligence that is expressed by social animals such as bees, birds, and ants when they are engaged in nesting and foraging. Based on the social group behavior, researchers proposed swarm intelligence. The group intelligence algorithm mainly includes two kinds of methods: particle swarm optimization (PSO), which was proposed by Kennedy et al., and the MOP mathematical model, which is described as follows:

$$\begin{cases} Maximize\ \ y = f(x) = (f_1(x), \cdots, f_n(x))^{\mathrm{T}} \\ s.t.\ \ g_i(x) \le 0,\ i = 1, 2, \cdots, p \\ h_j(x) = 0,\ i = 1, 2, \cdots, q \end{cases} \tag{14}$$

Where $g_i(x) \le 0$ is the inequality constraint, $x = (x_1, \cdots, x_m) \in X, X \subseteq R^m$, and $y = (y_1, y_2, \cdots, y_m) \in Y$.

Each particle in the particle swarm optimization algorithm represents a solution in the solution space. During the optimization process, the particle can adjust the flight state according to its own and the flight experience of its companions. For each particle, the best position in flight is the optimal solution found by the particle, and the best position of the whole group is the optimal solution of the group. In actual operation, the fitness value of each particle in the group is generally evaluated based on the fitness value determined by the value of the objective function. Each particle in the group is continuously iterated and updated by the above two extreme values, resulting in a new generation from generation to generation, as shown in Figure 1. It can be seen from Figure 1 that each particle in the group can be used as a point in the solution space. Set the group size to *N*, and then the $i(i = 1, 2, \cdots, N)$ particle position can be represented by X_i . The speed is expressed by V_i , the best position of the particle can be recorded as *Pbest*[*i*], and the position of the best particle in the group is represented by the index *g*. According to the following formula, particle *i* will update its speed and position.

$$\begin{cases} v_{ij}(t+1) = \omega.v_{ij}(t) + c_1.r_1.(p_{ij} - x_{ij}(t)) + c_2.r_2.(p_{gbestj} - x_{ij}(t)) \\ x_{ij}(t+1) + x_{ij}(t) + v_{ij}(t+1) \end{cases} \tag{15}$$

Where t represents the number of iterations, $i = 1, 2, \cdots, N,$ and $j = 1, 2, \cdots, D.$ The $c_1, c_2 > 0$ factor represents the individual learning and social learning factor, r_1 and r_2 are both in the range between the [0,1] independent random factor, and ω represents the inertia weight used to weigh the ability of the local optimum and global optimum capacity.

5.2. Multi-Objective Canal Optimization Water Distribution Particle Swarm Optimization Algorithm

For irrigation district planning and the design of irrigation canal systems, in order to maintain a balance between water distribution time and water distribution, the irrigation area controlled by the same channel should be approximately the same. However, in the actual operation and management of irrigation area, because of the changes in crop planting structure, irrigation quota, and irrigation technology, the actual water allocation amount and time between the rotation irrigation groups are quite different. At this time, it is necessary to re-divide the rotation irrigation group to distribute the flow and irrigation time. In this paper, based on the basis of PSO, the WPSO algorithm for optimizing irrigation water quantity is proposed, and the irrigation water demand is studied.

The conventional practice is to first obtain the net irrigation water demand in the area based on the actual irrigation area controlled by the study area and the irrigation quota of each crop grown.

$$M_{water} = \sum_{i=1}^{n} m_i s_i \tag{16}$$

Where M_{water} represents the amount of net irrigation water required in the area, and the unit is m^3; m_i represents the irrigation quota of the i crop planted in the area, expressed in m^3/hm^2; and s_i represents the i species in the area. The planting area of the crop is in hm^2. Reducing the duration of the whole water distribution process is key to improving the utilization of irrigation water resources in the study area. With the shortest total water distribution time as one of the objective functions, we have constructed the following optimization model:

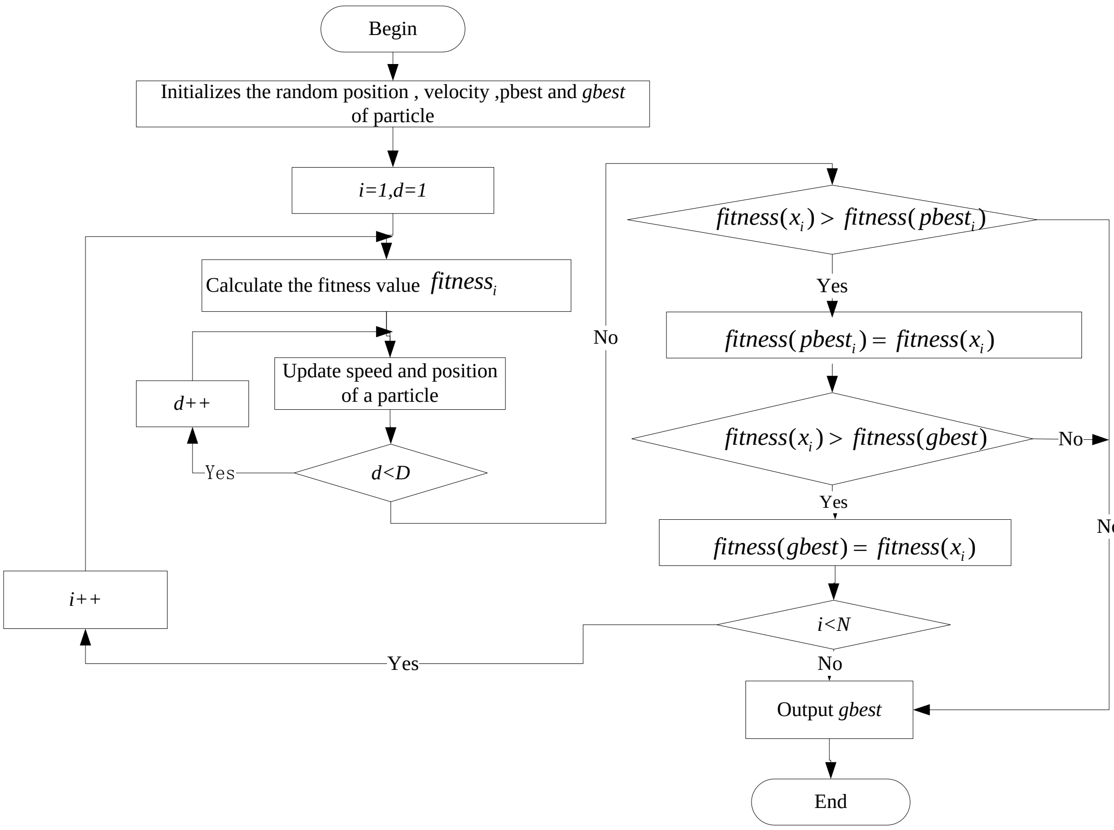

Figure 1. Particle swarm optimization process

$$\min f_1(X) = \min T = \max \sum_{j=1}^{N} x_{ij} t_i \tag{17}$$

In Equation (16), $f_1(X)$ refers to the total water distribution duration, and the unit is h; N is the total number of canals under the branch channel; x_{ij} is the decision variable $(i = 1, 2, 3, \cdots, n;\ j = 1, 2, 3, \cdots, M)$, indicating that the j in the i rotation group is the switch state of the water outlet of the bucket; and t_i is the continuous water diversion time of the j water inlet, and the unit is h.

In this study, in addition to the first optimization objective, the second optimization objective is to minimize the time difference of continuous water diversion among rotation irrigation groups, so as to minimize the time difference of continuous water diversion among rotation irrigation groups. It is of great practical significance to ensure the accuracy of water distribution and simplify the flow of water distribution.

$$\vartriangle T = \min\{\max(T_i - T_k)\},\ 1 \le i < N,\ 1 \le k < N,\ \text{and } i \ne k \tag{18}$$

In Equation (18), $\vartriangle T$ is the difference between the continuous water diversion time between each wheel irrigation group, indicating that the unit is h. T_i and T_k are the times of continuous water diversion for the i wheel irrigation group and the k wheel irrigation group, respectively, and the unit is h.

The above two optimization objectives in Equations (16) and (17) jointly construct a multi-objective optimization model for the optimal water distribution of canal system in irrigation activities.

6. Experimental Analysis

6.1. Data Fusion Analysis of Multi-Source Irrigation Information

In the experimental analysis process, we use the multi-source big data fusion algorithm proposed above to fuse the data. The first step in data fusion is to determine the weighting factor. The experimental data used in the adaptive weighted data fusion is the soil moisture data collected during the millet growing season in Yulin City, Shaanxi Province in 2017-2018 (the sensor is layered every 15 cm, totalling 15 layers). The acquisition frequency is 1 time/h, and 223,510 and 196,980 samples of data are collected in two years.

According to the principle of the above adaptive weighted average fusion algorithm, the consistency of the collected data is first checked. The results show that the difference between the two adjacent numbers is within the range of the given threshold ε = 3%, indicating that the installed sensor is running well and there is no data abnormality. On this basis, we fully consider the effects of irrigation, precipitation, and infiltration. Using the principle of water balance, calculate the water consumption of each layer of soil in the growth period, and then compare the water consumption of each layer with the total water consumption of a 1 m soil layer to obtain the weight coefficient of each layer of soil under different growth periods and water treatment conditions. The calculation results of the weighting factors for 2017-2018 are shown in Table 1.

Table 1. Weight coefficient of soil moisture of millet crops under different water treatment conditions in 2017-2018

Growth period	Moisture treatment	5cm	10cm	20cm	30cm	50cm	80cm
Germination	High water	0.0997	0.0397	0.3268	0.3245	0.5648	0.7321
	Middle water	0.2221	0.1221	0.3219	0.3212	0.4532	0.7543
	Low water	0.3213	0.3113	0.1212	0.1321	0.4312	0.687
Heading period	High water	0.3211	0.2211	0.3468	0.4342	0.3218	0.6543
	Middle water	0.2833	0.1833	0.4389	0.4321	0.3412	0.5658
	Low water	0.3618	0.3118	0.2212	0.3221	0.2311	0.5433
Maturity	High water	0.3268	0.2268	0.2268	0.1222	0.2134	0.5432
	Middle water	0.2089	0.1089	0.2189	0.1322	0.2145	0.3090
	Low water	0.2212	0.2082	0.1212	0.0432	0.2653	0.2998

It can be seen from Table 1 that during the germination period, for high water treatment, the soil layers with weight coefficients greater than 20% are 5cm, 20cm, 30cm, and 50cm, the soil layers with weight coefficients greater than 5% in the middle water are 10cm, 30cm, and 80cm, and the soil layers with weight coefficients greater than 5% in low water treatment are 20cm and 50cm.

The calculated weight coefficient of each layer of soil moisture is multiplied by the corresponding actual monitored moisture data, and after summing the water data of the 1 m soil layer, the soil moisture value after the weight distribution is obtained. According to the arithmetic average method, the moisture data of different soil layers monitored by the sensor is calculated to obtain the average value of the moisture data of the 1 m soil layer.

Taking high water treatment as an example, the results obtained by the fusion result obtained by the adaptive weighting algorithm in 2017-2018 and the arithmetic average method are shown in Figure 2.

6.2. Multi-Objective Decision-Making Optimization Analysis of Water-Saving Irrigation

After constructing the optimized water distribution model of the irrigation canal in the study area and instantiating it, it is necessary to select an efficient and robust optimization algorithm to obtain its optimal solution. The two objectives involved in the optimal water distribution model for the canal system in the study area are mutual influence and even conflict. It is therefore difficult to find a solution that allows all objective functions to achieve global optimality and satisfy all constraints and has a set of Pareto optimal solutions. Therefore, based on Pareto optimization theory, the PSO intelligent algorithm is used to solve the multi-objective optimal water distribution model of canal system that has been constructed and instantiated.

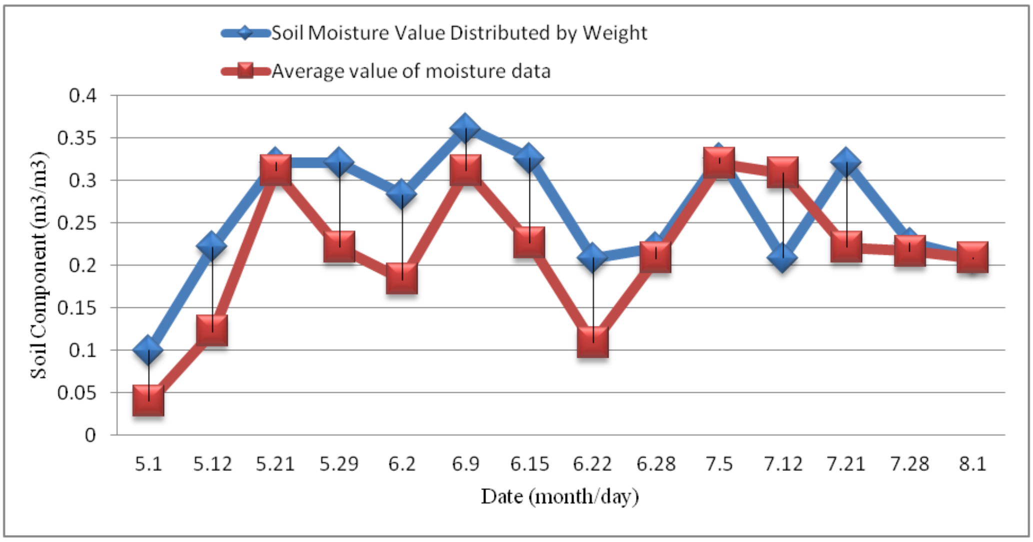

Figure 2. Adaptive weighted average method for soil moisture fusion

First, a group of random particles is initialized, and then the Pareto optimal solution set is searched through the continuous iterative optimization process. Write the instantiated multi-objective irrigation water quantity optimization configuration model into the program, and set the parameters required for the algorithm to run. Set the population N = 120, dimension D = 5, weight ω = 0.8, crossover probability ρ_c = 0.6, mutation probability ρ_m = 0.02, maximum evolution generation K = 2100, and $c_1 = c_2 = 2$. After iterative calculation, the optimal distribution of irrigation water volume is shown in Table 2. The results of the Pareto solution at the time of water distribution are shown in Figure 3.

Table 2. Optimal distribution of irrigation water

Area	Total area (hm^2)	Irrigation water volume (m^3)	Water distribution (m^3)	Average irrigation volume (m^3)
Area A	366.98	16.76	500	15.21
Area B	231.23	13.21	400	14.56
Area C	321.88	19.12	560	18.32

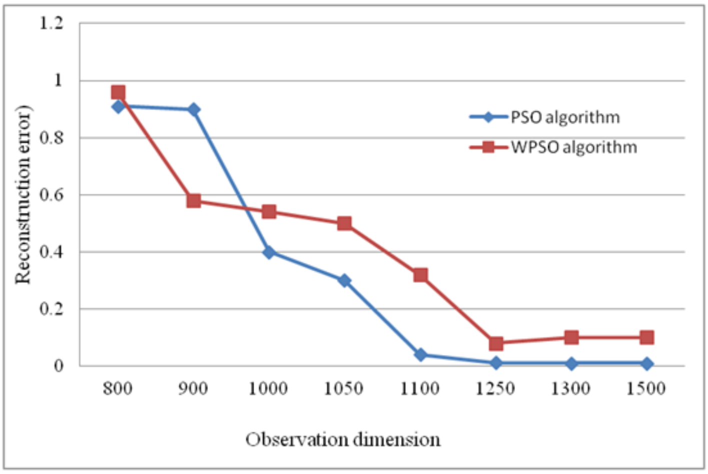

Figure 3. Comparisons of four different data fusion clustering algorithms

It is clearly evident from the Figure 3 that when comparing the results of solving the irrigation water consumption model based on multi-objective particle swarm optimization, the water consumption of crops is largest during the germination period.

As shown in Figure 4, our proposed is an optimal wheel irrigation combination obtained by using modern optimization technology to construct a multi-target canal optimal water distribution model and solved by an intelligent algorithm. We analyzed the three-dimensional space of water saving, irrigation, and time, which can greatly reduce the rotation period specified by the water distribution plan manually formulated by the irrigation district management department. It can also reduce the irrigation cycle required, save time, and lower the duration of water diversion, so as to minimize the loss of water in the process of water distribution.

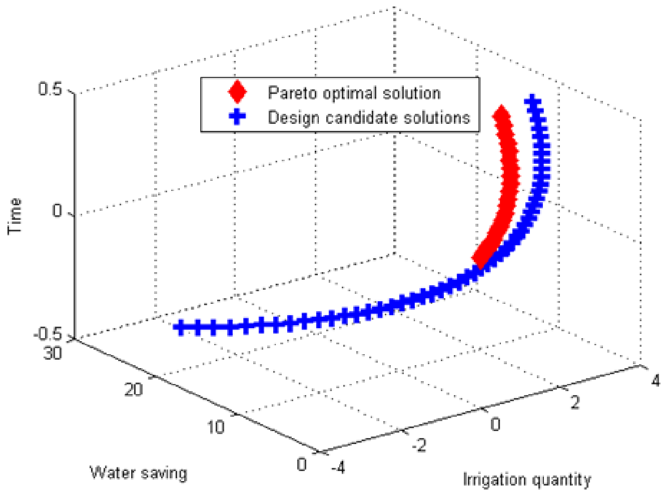

Figure 4. Pareto solution at chemical water distribution time

7. Conclusions

In this paper, aiming at the difficulties of information fusion of multi-source irrigation decision-making, information fusion technology was introduced into the field of farmland irrigation. Taking the millet crops in Yulin, Shaanxi as the main research object, the effects of climate, crop growth, and soil moisture on the crop growth process were considered, and a research irrigation strategy based on multi-source information fusion was implemented. The weighting coefficient of soil moisture in different growth stages and different soil layers of millet was determined using the adaptive weighted average fusion algorithm, and the fusion of soil moisture at point scale was completed.

At the same time, based on the crop water production function and the farmland water balance equation, according to the actual situation of the study area, the main factors affecting the irrigation income were analyzed. The relationship between system water quantities was studied, and the target that needs to be optimized was determined, so as to construct a multi-objective irrigation water quantity optimal allocation model. On the basis of optimal allocation of irrigation water, the multi-objective particle algorithm and multi-objective ant colony algorithm were used to solve the multi-object canal optimal water allocation model. In future research, with the development of multi-source information fusion technology, different fusion methods can be selected to fuse multi-source irrigation information, and the impact of different fusion methods on the reliability of final decision-making can be compared to further improve the accuracy of irrigation decision-making fusion.

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