International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 5346-5357

https://doi.org/10.70517/ijhsa463461

Data factor-driven resource allocation optimization for green economy: a study based on multi-objective particle swarm algorithm

Jingwen Fang[1,2], Mengyu Ruan[1,*] and Zhenghao Chang[1]
[1] School of Business Administration, Zhongnan University of Economics and Law, Wuhan, Hubei, 430073, China
[2] School of E-commerce, Wuhan Technology and Business University, Wuhan, Hubei, 430065, China
Corresponding authors: (e-mail: ruanmengyu@stu.zuel.edu.cn).

Abstract The rational allocation of resources will promote the continuous forward development of green economy. This paper designs a multi-objective linear programming model based on regional green development efficiency. Considering the comprehensive multi-objective resource allocation scheme to minimize the green resource input and maximize the economic output. The multi-objective particle swarm optimization algorithm (MOPSO) is introduced to explore the non-inferior solution set of regional resource allocation by combining the non-dominated sorting and congestion comparison strategies. The results show that the multi-objective particle swarm optimization algorithm has faster convergence speed and smaller objective function values among the three standard test functions. The algorithm was used to optimize crop water allocation and 180 sets of non-inferior allocation solutions were obtained. Among them, with the increase of water allocation, the net irrigation benefits of three crops increased continuously to 26.37*103 yuan/hm², 30.54*103 yuan/hm², and 18.57*103 yuan/hm².

Index Terms MOPSO, multi-objective linear programming, non-dominated sorting, congestion comparison, green resource allocation

I. Introduction

Since the reform and opening up of China, China's socialist modernization has made great achievements, but the accompanying problems of tightening resource and environmental constraints and environmental pollution are becoming more and more prominent. In order to realize the coordination and unity of environmental protection and economic growth, China has actively planned to solve the dilemma of ecological and environmental governance, and made a series of strategic plans around the realization of green development. Accompanied by the in-depth development of the new round of scientific and technological revolution, digital technologies such as artificial intelligence, cloud computing, big data and blockchain have had a profound impact on China's social, economic and industrial development [1]. In the era of digital economy, data elements have become a new type of innovation elements, and with the wide application of big data technology, the innovation-driven role of data elements can no longer be ignored [2], [3].

In the stage of digital industrialization, data elements are embedded in green economic activities to provide real and accurate economic information, and promote urban green economic efficiency by improving the matching efficiency of innovation elements [4], [5]. Data elements belong to digital information, and in the stage of industrial digitization, data elements are gradually integrated into economic activities in an independent form, and data elements become the core link to link the green transformation of different industries [6]-[8]. Therefore, data elements do not exist in isolation; they carry a large amount of real and reliable economic information, and their application value comes from “circulation and sharing” [9]. In addition, data elements have a multiplier effect on green total factor productivity, the factor flow environment and factor scale effect determines the factor productivity, and the data element flow environment is the basis for guaranteeing the orderly flow of data elements according to the law [10]-[12]. “Effective flow” is to stimulate the potential of data factors and fully release the data factor dividends of the prerequisites, the market has a decisive role in the allocation of data factors, but the market is not omnipotent, the market allocation of data factors at the same time need to be guaranteed by a good resource allocation methods [13]-[16]. Thus to information technology as the support, institutional construction as a guarantee to promote the whole process of data factor market-oriented transactions that is the process of data factor market-oriented configuration, a new generation of information technology can effectively alleviate the problem of market information asymmetry [17]-[19]. It can be said that data elements in the economy is not only an important path to help industrial transformation and upgrading, creating new business forms and new models, but also an important breakthrough point for cracking the double dilemma of resources and growth, and realizing the green transformation of the economy [20]-[22].

This paper centers on the multi-objective resource allocation problem of regional green development, proposes a MOLP model integrating integrated data envelopment analysis (DEA) efficiency evaluation, and introduces the MOPSO algorithm for solving. The model is designed with hierarchical constraints and variable scale efficiency to ensure the fairness and feasibility of resource allocation, and the MOPSO algorithm combines the non-dominated sorting and congestion comparison strategies to effectively balance the global search and local optimization ability, and generate the Pareto frontier solution set. By dynamically adjusting the target weights, it improves the ability of the model to adapt to different decision-making preferences. At the same time, it meets the requirements of green resource saving, economic benefit maximization and decision-making unit fairness.

II. Realization of green resource allocation based on multi-objective particle swarm algorithm

This chapter designs the MOLP resource allocation model based on regional green development efficiency. It also introduces the multi-objective particle swarm optimization algorithm for the optimization search of multiple allocation schemes.

II. A.MOLP resource allocation model based on regional green development efficiency

In this section, in order to efficiently allocate additional green resources, we design a DEA-based MOLP (Multi-Objective Linear Programming) model while considering maximizing the total change in outputs and minimizing the total green resource consumption of allocable inputs.

Suppose there are n decision units under a centralized decision maker in the organization. For each j, decision unit j uses w non-reallocable invariant inputs $X_J=(x_{1j},x_{2j},\cdots x_{wj})^T$, m reallocable invariant inputs $F_J=(f_{1j},f_{2j},\cdots f_{mj})^T$, and t reallocable The variable inputs $U_J=(u_{1j},u_{2j},\cdots u_{tj})^T$ are used to generate s desired outputs $Y_J=(y_{1j},y_{2j},\cdots y_{sj})^T$. Suppose that in the next production cycle, the central decision maker provides additional total inputs of R_i, $i=1,2,\cdots m$, for each allocable variable input green resource. The total allocated input provided for each allocable variable input green resource is E_i, $i=1,2,\cdots t$. The central decision maker wishes to allocate these green resources to each decision unit in appropriate proportions. In this section, we assume that the set of production possibilities does not change after the allocation of green resources. where $L(k)$ denotes the set of observed decision units belonging to layer k. Here Δf_{iq}, Δu_{iq}, and Δy_{iq} denote the amount of change in constant inputs i, variable inputs i, and outputs r.

$$Max\sum_{q=1}^{n}\sum_{r=1}^{s}\Delta y_{rq}(I) \tag{1}$$

$$Min\sum_{q=1}^{n}\sum_{i=1}^{t}\Delta u_{iq}(II) \tag{2}$$

$$s.t.\ \sum_{j\in L(k)}\lambda_{jq}x_{ij}\le x_{iq} i=1,\cdots,w k=1,\cdots,p,q\in L(k) \tag{3}$$

$$\sum_{j\in L(k)}\lambda_{jq}f_{ij}\le f_{iq}+\Delta f_{iq} i=1,\cdots,m k=1,\cdots,p,q\in L(k) \tag{4}$$

$$\sum_{j\in L(k)}\lambda_{jq}u_{ij}\le \Delta u_{iq} i=1,\cdots,t k=1,\cdots,p,q\in L(k) \tag{5}$$

$$\sum_{j\in L(k)}\lambda_{jq}y_{rj}\ge y_{rq}+\Delta y_{rq} r=1,\cdots,s k=1,\cdots,p,q\in L(k) \tag{6}$$

$$\Delta f_{iq}=0\ when\ f_{iq}\ge f_{iq}^{Mpss} i=1,\cdots,m,q=1,\cdots,n \tag{7}$$

$$f_{iq}+\Delta f_{iq}\le f_{iq}^{Mpss}\ when\ f_{iq}\le f_{iq}^{Mpss} i=1,\cdots,m,q=1,\cdots,n \tag{8}$$

$$\sum_{q=1}^{n}\Delta f_{iq} = R_i i = 1,\cdots,m \tag{9}$$

$$\sum_{q=1}^{n}\Delta u_{iq} \le E_i i = 1,\cdots,t \tag{10}$$

$$\sum_{j\in L(k)}\lambda_{jq} = 1 k = 1,\cdots,p \in L(k) \tag{11}$$

$$\Delta f_{iq} \le \beta_i f_{iq} i = 1,\cdots,m, q = 1,\cdots,n \tag{12}$$

$$\lambda_{jq} \ge 0 \Delta u_{iq} \ge 0 \forall j \in L(k) k = 1,\cdots,p i = 1,\cdots,m \tag{13}$$

In models (1)-(2), maximizing the sum of changes in total output of all decision-making units in the model in the next period to bring about the highest production is the primary objective of the central decision maker in making green resource allocation. While minimizing the sum of reallocable variable inputs allocated to all decision-making units in the next period, because the secondary objective of the central decision maker is to consider saving as much as possible green resource inputs while maintaining the maximum organizational output. (The constraints of (3)-(6) ensure that new production by each decision cell is feasible in its own altered set of production possibilities. Constraints (9) and (10) in model (1)-(2) indicate that the total amount of green resources allocated in all decision cells cannot exceed the total additional input green resources. Constraint (11) indicates that economies of scale are assumed to be variable in this model. To ensure that proportional scaling is managerially feasible, following Korhonen et al. we restrict the variation in constant inputs to $\Delta f_{iq} \le \beta_i f_{iq}$. This constraint eliminates the solution where all green resources are allocated to only a few decision units using advanced technology, thus reflecting the fairness of the central decision maker to all decision units.

Assume that the allocated constant input green resource F is very valuable for production but scarce due to cost and availability. The central decision maker has spent a lot of effort and money to acquire these green resources, so it is natural for the decision maker to want to get a return on that investment as soon as possible. Therefore, we hypothesize that this type of green resource should be fully allocated. Recognizing the great value of allocated constant-input green resources makes us want to ensure that they are allocated to those decision-making units that really need them, thus applying the concept of the new MPSS Zhu et al. which consists of constraints (7) and (8). The f_{iq}^{Mpss} denotes the maximum value of inputs $i = 1,2,\cdots m$ in the decision unit q in the new MPSS domain. For each layer, there is only one such maximum, i.e., the decision cells in the same layer have the same maximum. The maximum value for each layer can be calculated by Zhu et al.

In addition, to maximize satisfaction within the organization, the input of an additional unit should be allocated to the DMU that brings greater satisfaction to the organization, while still maintaining the maximum output. Based on this setting, we define this output growth rate as the effectiveness of DMUs, and the effectiveness of the organization is expressed as follows.

Definition 1 The effectiveness of an organization is defined as the output growth rate of all its DMUs. This is a welfare index that can be calculated as follows:

$$\psi = \sum_{q=1}^{n}\sum_{r=1}^{s}\frac{\Delta y_{rq}}{y_{rq}} \tag{14}$$

The organization should consider not only the change in total output and consumption of input green resources, but also the effectiveness of green resource allocation. Therefore, the objective function in the above model (1)-(2) should be transformed into

$$\begin{aligned} &Max\sum_{q=1}^{n}\sum_{r=1}^{s}\Delta y_{rq} \quad (I) \\ &Min\sum_{q=1}^{n}\sum_{i=1}^{t}\Delta u_{iq} \quad (II) \\ &Max\sum_{q=1}^{n}\sum_{r=1}^{s}\frac{\Delta y_{rq}}{y_{rq}} \quad (III) \end{aligned} \tag{15}$$

Models (1)-(2) are multi-objective planning problems in DEA. Following the multi-objective planning approach, we can convert the multi-objective models (1)-(2) into the following single-objective model (27):

$$Max\sum_{q=1}^{n}\sum_{r=1}^{s}\Delta y_{rq}-w_1\sum_{q=1}^{n}\sum_{i=1}^{t}\Delta u_{iq}+w_2\sum_{q=1}^{n}\sum_{r=1}^{s}\frac{\Delta y_{rq}}{y_{rq}} \tag{16}$$

$$s.t.\sum_{j\in L(k)}\lambda_{jq}x_{ij},, x_{iq}i=1,\cdots,wk=1,\cdots,p,q\in L(k) \tag{17}$$

$$\sum_{j\in L(k)}\lambda_{jq}f_{ij}\le f_{iq}+\Delta f_{iq}i=1,\cdots,mk=1,\cdots,p,q\in L(k) \tag{18}$$

$$\sum_{j\in L(k)}\lambda_{jq}u_{ij}\le \Delta u_{iq}i=1,\cdots,tk=1,\cdots,p,q\in L(k) \tag{19}$$

$$\sum_{j\in L(k)}\lambda_{jq}y_{rj}\ge y_{rq}+\Delta y_{rq}r=1,\cdots,sk=1,\cdots,p,q\in L(k) \tag{20}$$

$$\Delta f_{iq}=0whenf_{iq}\ge f_{iq}^{Mpss}i=1,\cdots,m,q=1,\cdots,n \tag{21}$$

$$f_{iq}+\Delta f_{iq}\le f_{iq}^{Mpss}whenf_{iq}\le f_{iq}^{Mpss}i=1,\cdots,m,q=1,\cdots,n \tag{22}$$

$$\sum_{q=1}^{n}\Delta f_{iq}=R_i i=1,\cdots,m \tag{23}$$

$$\sum_{q=1}^{n}\Delta u_{iq}\le E_i i=1,\cdots,t \tag{24}$$

$$\sum_{j\in L(k)}\lambda_{jq}=1k=1,\cdots,p\in L(k) \tag{25}$$

$$\Delta f_{iq}\le \beta_i f_{iq}i=1,\cdots,m,q=1,\cdots,n \tag{26}$$

$$\lambda_{jq}\ge 0\Delta u_{iq}\ge 0\forall j\in L(k)k=1,\cdots,pi=1,\cdots,m \tag{27}$$

The single-objective model (27) has the same constraints as models (1)-(2), with $w_1(0<w_1<1)$ and $w_2(0<w_2<1)$ being the weights for the objective of minimization of the input green resources and the objective of maximization of the organization's effectiveness, respectively, in the objective function of model (27). Since the weight selection has a great impact on the optimal solution. Different studies use different methods to select the weights. In this section, we assume $w_1>w_2$ as the main objective considering the reality factor, the objective of minimizing input green resources as the secondary objective considering the importance of green development, and organizational effectiveness as the third objective. It is worth noting that different weights can be set when different central decision makers have different preferences for input green resources and effectiveness. In this chapter, in the model analysis part, the effect of different weights is also considered, and the settings of w_1, w_2, and numerical analysis is done. In summary, we use the model (27) to establish a comprehensive scheme of green resource allocation according to the needs of the central decision maker, considering multiple objectives, this model has applicability, and can be used to establish a model that meets the reality according to the difference of the central decision maker's objective selection, so as to give a more scientific and reasonable scheme of green resource allocation.

II. B.Particle Swarm Algorithm

II. B. 1) Particle Swarm Algorithm Fundamentals

The core concept of particle swarm optimization algorithm (PSO) is to consider each individual in the population as a particle and search for the optimal solution in a multidimensional space. Each particle initializes its own position and velocity and is updated during iterations until the optimal solution is found. In each iteration, the particle adjusts its moving direction according to its own position and the optimal position of the whole population as well as its own historical optimal position to find the next more optimal position. The fitness value of the particle indicates the distance of the particle from the real solution, and the fitness value is used to determine whether the particle finds the real solution, in which the updating formula of the particle speed and position in each iteration is affected by many factors, and the calculation formula is as follows:

$$v_i(t+1)=w\cdot v_i(t)+c_1r_1(Pbest_i-x_i(t))+c_2r_2(Gbest_i-x_i(t)) \tag{28}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{29}$$

where $x_i(t+1)$ and $v_i(t+1)$ denote the position and velocity of particle i at the $t+1$ th iteration, and $x_i(t)$ and $v_i(t)$ denote the position and velocity of particle i at the t th iteration; w is the inertia weight, c_1 and c_2 are the individual and global acceleration factors, respectively, and r_1 and r_2 are normally distributed random numbers between 0 and 1, $Pbest_i$ denotes the individual pole position of particle i, and $Gbest_i$ denotes the population pole position.

Equation (28) is the core expression of the particle swarm algorithm, which describes the way the particles update their velocity during the search process, the process of updating the velocity takes into account three factors:

1) Inertia: the particle will maintain its current velocity tendency, this part characterizes the particle's motion inertia.

2) Individual experience: particles tend to fly to the best position they have already searched for, i.e. the influence of individual experience.

3) Group sharing: the particle tends to fly to the best position it has already searched in the whole group, which reflects the sharing and utilization of information in the group.

The above factors together affect the velocity update of the particles, which enables the particles to efficiently search for the optimal solution of the problem. All the above three components show the PSO's maintenance of exploration and exploitation capabilities.

II. B. 2) Particle Swarm Algorithm Flow

Figure 1 shows the particle swarm algorithm algorithm flow, the basic particle swarm algorithm contains the following steps:

1) Initialization: randomly assign position and velocity to each particle to initialize the whole particle swarm.

2) Evaluate the fitness: according to the fitness function, calculate the fitness of each particle.

3) Update individual best position: for each particle, compare the current fitness with its historical best fitness, if the current fitness is higher, update its individual best position.

4) Update group best position: compare the fitness of each particle with the best fitness in the whole group memory, if the fitness of a particle is better than the group best fitness, then update the group best fitness.

5) Update velocity and position: update the velocity and position of each particle according to the inertia of the particle, individual memory and group sharing information.

6) Iteration termination conditions: determine whether to end the iteration according to the set number of iterations or other termination conditions. If the iteration continues, return to step (2); otherwise, end the algorithm.

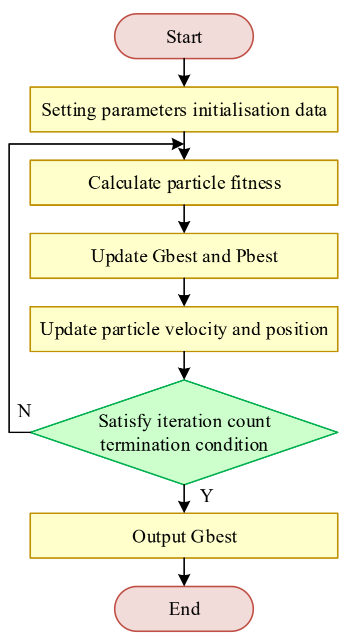

Figure 1: Flowchart of particle swarm algorithm

II. C.Multi-objective particle swarm optimization algorithm (MOPSO)

Multi-Objective Particle Swarm Optimization (MOPSO) is a particle swarm optimization based algorithm designed to solve complex problems with multiple optimization objectives. MOPSO searches for optimal solutions by simulating the social behavior of a flock of birds, and is suitable for dealing with high-dimensional data spaces and multi-objective problems. The algorithm searches for the Pareto optimal set of solutions satisfying all objective functions by directing the flight of particles in the solution space.

II. C. 1) Particle Update Strategy

In MOPSO, the update strategy of particles is one of its core mechanisms. Each particle represents a potential solution in the solution space and adjusts its position in the solution space according to individual and social experiences. The rules for updating the velocity and position of a particle are as follows:

Velocity update: The velocity of a particle is adjusted according to its own historical best position (individual experience), as well as the historical best positions of all particles in the population it belongs to (social experience). In addition, considering the characteristics of multi-objective optimization, the velocity update also needs to combine multiple Pareto optimal solutions to guide the particle's moving direction.

Position update: Based on the updated velocity, the positions of the particles are adjusted in each generation to explore new potential solutions.

This update strategy not only utilizes the search experience of the particle itself, but also draws on the successful experience of other particles in the population, thus finding a balance between global search and local fine search.

II. C. 2) Particle Selection Strategy

In MOPSO, the particle selection strategy is the process of deciding which particles will be retained into the next generation. The key to this process is how to select the optimal particles from the current population and the newly generated particles to form the new population. The main steps include:

Non-dominated sorting: the particles are sorted according to the Pareto dominance relation and the non-dominated particles are selected into the next generation.

Crowding Comparison: further select particles among the non-dominated particles based on crowding, and preferentially keep the particles located in the sparse region of the Pareto front to maintain the diversity of the solutions.

II. C. 3) Multi-objective particle swarm algorithm flow

Step1: Initialization, set the position and velocity of each particle in the particle swarm randomly.

Step2: Adaptation calculation, assessing an adaptation value for each particle.

Step3: Optimal solution update, update the personal best historical position of each particle; meanwhile, use non-dominated sorting and congestion sorting to refresh the global optimal solution set.

Step4: Velocity and position update: Adjust the velocity and position of particles according to the particle update policy.

Step5: Particle selection, according to the particle selection strategy, select the optimal particles from the current particle swarm and newly generated particles to form a new population.

Step6: Termination condition, repeat steps 2 to 5 until the termination condition is satisfied, the maximum number of iterations is reached or the improvement of the Pareto front is lower than the specified threshold.

III. Algorithm effectiveness verification and resource allocation practice

In this chapter, the standard test function is utilized to test the advantages of the proposed algorithm in terms of search search performance. After that, it is applied in crop irrigation water resource allocation optimization to verify the allocation optimization effect of the algorithm in this paper.

III. A. Testing and Simulation of Algorithms

In order to verify the effectiveness of the improved multi-objective particle swarm algorithm proposed in this study in optimizing the search performance, a series of simulation experiments using three standard test functions (Rosenbrock, Schwefel, and Michalewicz) are conducted in this section. These experiments demonstrate the effectiveness and accuracy of the improved multi-objective particle swarm algorithm in accelerating the convergence speed and enhancing the local search capability. In addition, in order to comprehensively evaluate the performance of the improved multi-objective particle swarm algorithm, this study also incorporates the genetic algorithm (GA) into the comparative analysis, and conducts experimental comparisons together with the original particle swarm algorithm (PSO) and the improved particle swarm algorithm (MOPSO) in this paper. By this method, the convergence performance and optimization accuracy of these three algorithms are comprehensively evaluated to prove the value of MOPSO algorithm's contribution to the research of this paper.

The control parameters of the algorithm set in this paper are as follows: the initial population size is 55 and the maximum number of iterations is 55.

III. A. 1) Rosenbrock function and related operational data

Fig. 2 shows the time and minimum objective value used by the three algorithms to perform simulation experiments in the Rosenbrock function. Fig. 3 shows the convergence results of the three algorithms performing simulation experiments. The Rosenbrock function is characterized by a narrow parabolic shaped global minimum region, which is challenging for the algorithm as it needs to precisely move along the narrow region to the global minimum. MOPSO has the shortest computation time of 0.006s, which indicates that it outperforms the PSO (0.013s) and GA (0.011s) in terms of computational efficiency. 0.013s) and GA (0.011s). PSO has the longest computation time, probably due to the fact that it requires more computational resources during the search process. The MOPSO algorithm converges very quickly in the initial phase, quickly reaching a low objective function value (0.004) before the 5th iteration. PSO and GA also show fast convergence, but slower than the MOPSO algorithm. The MOPSO algorithm has the lowest objective function value indicating that it outperforms PSO (0.042) and GA (0.024).

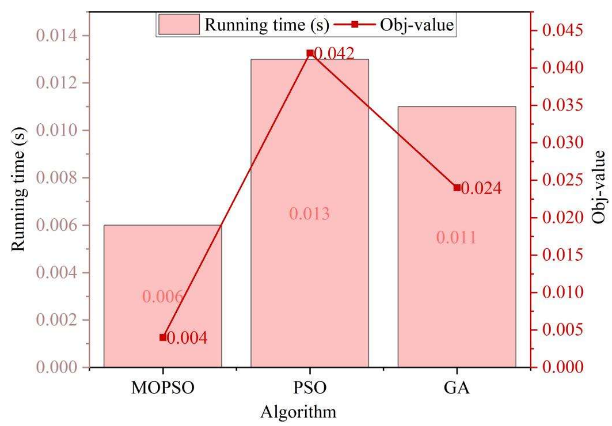

Figure 2: Time used in the simulation experiment and the minimum target value

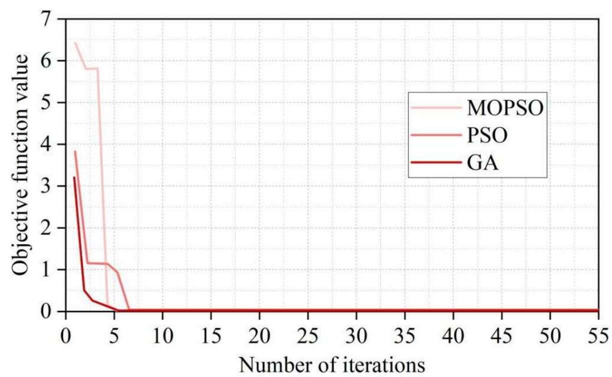

Figure 3: The convergence result of the simulation experiment

III. A. 2) Schwefe function and related operational data

Fig. 4 shows the time and minimum objective value used for simulation experiments of the three algorithms in Schwefel function. Figure 5 shows the convergence of the simulation experiments of the three algorithms.The Schwefel function is very complex and it has many local minima, which makes it difficult to find the global minimum.The MOPSO algorithm has the shortest computation time (0.005s) while the PSO algorithm has the longest (0.015s).The MOPSO algorithm reaches the lowest objective function value (3200), which shows that it finds a a superior solution.PSO (3500) and GA (3600) had similar results, but PSO slightly outperformed GA.The MOPSO algorithm showed very fast convergence, reaching a relatively low function value by the 15th iteration.The PSO algorithm converged slowly at the beginning, but its performance improved as the number of iterations increased.The GA algorithm had the slowest convergence rate and the function value decreases less throughout the iterations, basically stabilizing at around 3600.

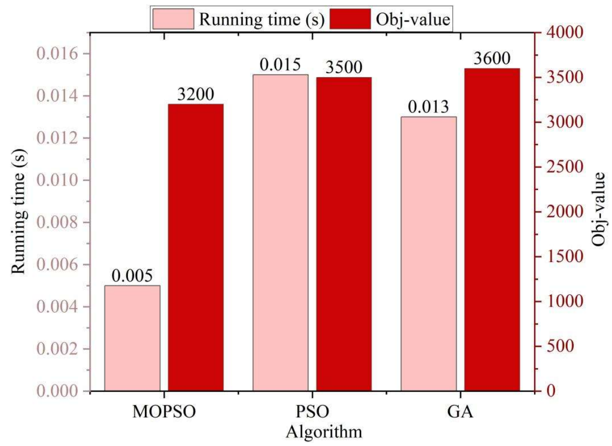

Figure 4: Time used and the minimum target value in Schwefel function

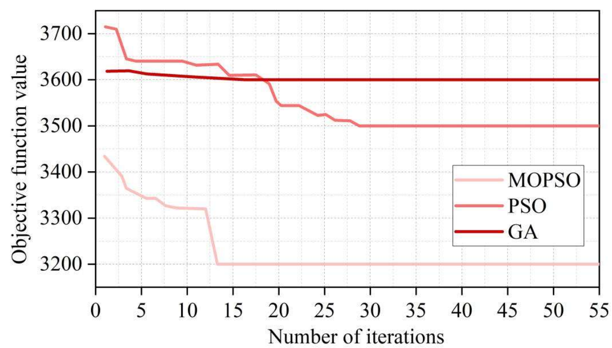

Figure 5: The convergence situation in the Schwefel function

III. A. 3) Michalewicz function and related operational data

Figure 6 shows the time plots used by the three algorithms for simulation experiments in Michalewicz function along with the minimum objective value. Figure 7 compares the convergence results of the three algorithms for simulation experiments in Michalewicz function. The Michalewicz function has multiple local minima. The MOPSO algorithm took the least amount of time, only around 0.008s, and the PSO algorithm took the most amount of time, 0.027s. The MOPSO algorithm converged faster and found the optimal solution (-8.53), followed by PSO (-5.67), while GA performed the worst. 8.53), followed by PSO (-5.67), while GA performed the worst (-3.21).

From the three standard test functions and the corresponding algorithm running results in this section, the improved multi-objective particle swarm algorithm proposed in this paper, has a faster running speed and can quickly find the lowest objective value. It can be further applied to the practice of resource allocation optimization in green economy.

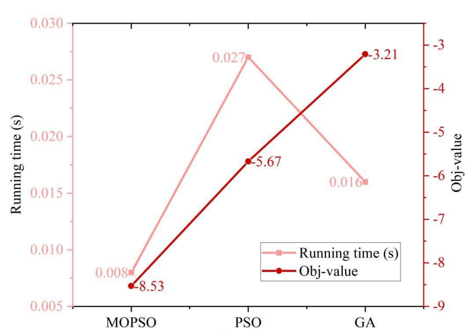

Figure 6: Time used and the minimum target value in Michalewicz function

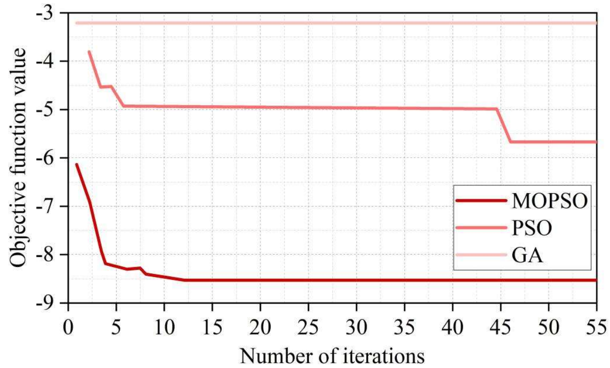

Figure 7: The convergence situation in the Michalewicz function

III. B. Statistics of experimental base data

III. B. 1) Basic data on precipitation and crop growth for each irrigation period

In this study, 10 irrigation districts in the middle reaches of the S River were selected as the study area for the optimization of green economic resource allocation, and the irrigation districts were numbered in order as A, B, ..., and J. The different flow levels were classified according to the historical data of 1948-2018 by using the percentage of the distance from the level, and the probability of the occurrence of the various flow levels were: extra-abundant flow 0.1325, the Partial Abundance Flow 0.2070, Medium Flow 0.3226, Partial Dry Flow 0.2203, and Extra Dry Flow 0.1175. Food demand is 401kg/person, and the cost of surface water and groundwater supply is 0.06 yuan and 0.09 yuan/m³, respectively. Crop water requirements were determined using the crop coefficient method, where reference crop evapotranspiration was calculated using the Penman-Monteith formula. The irrigation period was from May to October.

Table 1 summarizes the precipitation and crop growth basis data for each irrigation period in the middle reaches of the S River. A large amount of water is required for irrigation during the full life span of the crop from May to October. From the average precipitation in the table, it was found that the precipitation varied from 3.75 mm to 29.95 mm in each month, with large differences. And there are also differences in the growth data of different agricultural crops such as field corn, seed corn, wheat and vegetables. Therefore, artificial green water allocation is needed to ensure that the net benefits of irrigation for crops are maximized.

Table 1: Precipitation and crop growth monthly data in the middle reaches

Month	Average precipitation/mm	Average ET/mm	Crop coefficient			
			Field corn	Seed corn	Wheat	Oil crop
May	3.75	117.05	0.21	0.21	0.32	0.36
June	3.99	150.18	0.45	0.53	1.14	0.84
July	20.16	157.44	0.52	1.17	1.16	1.02
August	24.97	159.06	1.44	1.22	0.94	1.04
September	29.95	142.54	1.12	1.21	0.42	0.61
October	20.57	100.92	1.24	0.62	1.26	0.34

Note:ET0 is the evapotranspiration of reference crop.

III. B. 2) Basic data on key indicators for irrigation areas

Table 2 summarizes the basic data of the main indicators for 10 irrigation districts in the middle reaches of the S River. It includes a total of 6 indicators, including population, crop yield per unit area, canal water utilization coefficient, field water utilization coefficient, management cost, and water productivity. It can be seen that the population of the 10 irrigation districts in the middle reaches of the S River ranges from $0.89*10^4$ to $16.43*10^4$ people, and the corresponding levels of economic development are also different. The range of crop yield per unit area is 5473kg/hm²-12523kg/hm², while the index data of canal water utilization coefficient and field water utilization coefficient also have large differences, which is in line with the optimization research demand of the multi-objective allocation scheme in this paper.

Table 2: Basic data of 10 irrigation areas in the middle reaches of Heihe River

Irrigation area	Population/104	Crop yield per unit area(kg/hm²)	Canal water use coefficient	Field water use coefficient	Management cost (yuan/m³)	Water productivity(kg/m³)
1	7.67	10200	0.66	0.86	0.0538	1.72
2	16.43	10394	0.72	0.79	0.0496	1.61
3	7.22	12523	0.66	0.83	0.0614	1.74
4	4.48	10096	0.66	0.77	0.0822	1.43
5	1.45	5473	0.63	0.73	0.0655	0.82
6	0.89	5695	0.61	0.80	0.1621	1.66
7	2.04	8167	0.64	0.83	0.0364	1.01
8	1.75	8006	0.62	0.82	0.0433	0.93
9	1.13	7940	0.57	0.85	0.0357	0.76
10	1.76	8186	0.63	0.81	0.0455	1.05

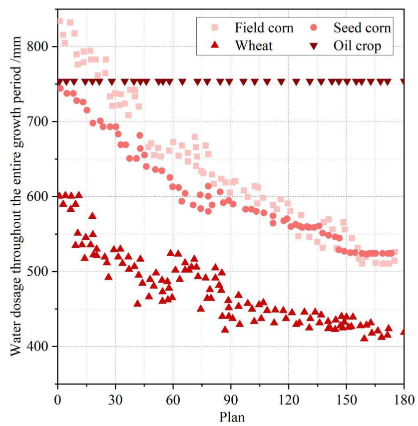

Figure 8: Non-inferior program set crop water distribution

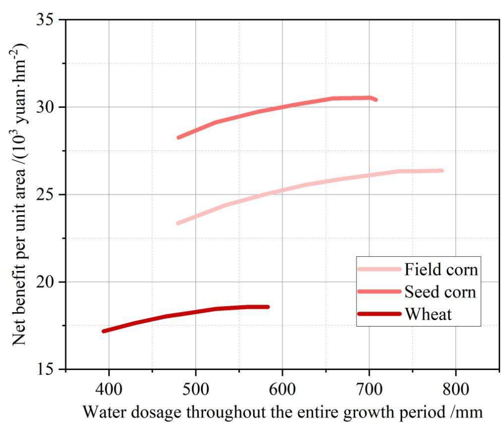

Figure 9: Crop water distribution and net benefit curve

III. C. Results of optimization of agricultural water allocation

The Pareto solution set of water allocation scenarios for different crops is solved using the resource allocation model introduced in this paper as a multi-objective particle swarm optimization algorithm. The results of water allocation for each crop for the full life cycle for 180 sets of non-inferior allocation scenarios are demonstrated in Fig. 8. Figure 9 shows the crop water allocation versus net benefit curves. As the numbering increases, the water allotment per unit area for the three crops, field corn, seed corn, and wheat, decreases gradually. Field maize decreases from 834 mm to 511 mm, seed production maize from 744 mm to 524 mm, and wheat from 601 mm to 419 mm. This is because crop water allotment has a direct effect on irrigation effectiveness and water use efficiency. The model is based on a quadratic water production function to measure the relationship between irrigation water quantity and yield for the first type of crop, and within a certain range, as the water allotment increases, the yields of field maize rice, seed maize, and wheat increase, and their net irrigation benefits per unit area continue to increase: the net irrigation benefit per unit area of field maize increases from $23.35*10^3$ yuan/hm² to $26.37*10^3$ yuan/hm², and the net irrigation benefit per unit area of field maize increases from $23.35*10^3$ yuan/hm² to $26.37*10^3$ yuan/hm², and the net irrigation benefit per unit area of field maize increases from 744mm to 524mm. The net benefit of irrigation per unit area for seed production maize increased from $28.26*10^3$ yuan/hm² to $30.54*10^3$ yuan/hm², and the net benefit of irrigation per unit area for wheat increased from $17.18*10^3$ yuan/hm² to $18.57*10^3$ yuan/hm². Thus the total modeled net irrigation benefit is maximized when the crop water allotment is close to the upper irrigation limit.

IV. Conclusion

In this paper, by integrating the MOLP model and MOPSO algorithm, the multi-objective resource optimization allocation of green economy is realized. The running time of MOPSO in the 3 types of standard test functions is only 0.006s, 0.005s, 0.008s, and the value of the objective function decreases to 0.004, 3200, and -8.53. In the case of the S River Irrigation District, it achieves the goal of the positive increase of the crop water allocation volume and the net benefits of irrigation. The net benefits of irrigation for the three crops increased to $26.37*10^3$ yuan/hm², $30.54*10^3$ yuan/hm², and $18.57*10^3$ yuan/hm² with the increase of water allocation. In the future, the model can be extended to multi-region cooperative allocation scenarios to further enhance the universality of green resource allocation.

Funding

This work was supported by the National Social Science Fundation of China (Grant No. [24BTQ069]).

References

[1] Kolesnikov, A. V., Zernova, L. E., Degtyareva, V. V., Panko, I. V., & Sigidov, Y. I. (2020). Global trends of the digital economy development. Opción: Revista de Ciencias Humanas y Sociales, (26), 523-540.

[2] Koch, T., & Windsperger, J. (2017). Seeing through the network: Competitive advantage in the digital economy. Journal of organization design, 6, 1-30.

[3] Jiang, X. (2020). Digital economy in the post-pandemic era. Journal of Chinese Economic and Business Studies, 18(4), 333-339.

[4] Wang, Y. (2024). The Impact of Data Element Aggregation on Green Economy Development: Evidence from China. Academic Journal of Business & Management, 6(8), 184-191.

[5] Tao, C. Q., Yi, M. Y., & Wang, C. S. (2023). Coupling coordination analysis and Spatiotemporal heterogeneity between data elements and green development in China. Economic Analysis and Policy, 77, 1-15.

[6] Jing, L., Tianshu, Q., & Qing, H. (2025). Open government data and green economic growth. Economic Analysis and Policy, 85, 2207-2218.

[7] Kong, L., & Li, J. (2022). Digital economy development and green economic efficiency: Evidence from province-level empirical data in China. Sustainability, 15(1), 3.

[8] Moşteanu, N. R., Faccia, A., & Cavaliere, L. P. L. (2020, August). Digitalization and green economy-changes of business perspectives. In Proceedings of the 2020 4th International Conference on Cloud and Big Data Computing (pp. 108-112).

[9] Ge, Y., Xia, Y., & Wang, T. (2024). Digital economy, data resources and enterprise green technology innovation: Evidence from A-listed Chinese Firms. Resources Policy, 92, 105035.

[10] Ren, Y., Zhang, J., & Wang, X. (2024). How does data factor utilization stimulate corporate total factor productivity: A discussion of the productivity paradox. International Review of Economics & Finance, 96, 103681.

[11] Şeker, M., & Saliola, F. (2018). A cross-country analysis of total factor productivity using micro-level data. Central Bank Review, 18(1), 13-27.

[12] Jiang, J. (2025). The multiplier effect of data elements empowering green economic development: a mechanism examination based on innovation-driven. Applied Economics, 1-16.

[13] Guan, Y., Chen, Q., & Li, Z. (2022). Application of data resource allocation in economic management information system. Computational Intelligence and Neuroscience, 2022(1), 1346646.

[14] QIAO, H., & LI, Z. (2022). Research on market allocation efficiency of data elements. Bulletin of Chinese Academy of Sciences (chinese Version), 37(10), 1444-1456.

[15] Ximing, Y., Zhenyang, L., Jin, C., & Rong, Z. (2022). The Value Ecosystem Construction and Market Allocation Mechanism of Data Elements. Science & Technology Progress and Policy, 39(22), 1-8.

[16] Tian, J., & Liu, Y. (2021). Research on total factor productivity measurement and influencing factors of digital economy enterprises. Procedia Computer Science, 187, 390-395.

[17] Bateni, M., Chen, Y., Ciocan, D. F., & Mirrokni, V. (2022). Fair resource allocation in a volatile marketplace. Operations Research, 70(1), 288-308.

[18] LIU, J., & WANG, S. (2022). Dilemmas and suggestions on market-based data allocation. Bulletin of Chinese Academy of Sciences (Chinese Version), 37(10), 1435-1443.

[19] Fang, J., Ruan, M., & Chang, Z. (2025). Research on resource allocation optimization based on multilevel model in green economy driven by data elements. J. COMBIN. MATH. COMBIN. COMPUT, 127, 9483-9499.

[20] Ran, Q., Yang, X., Yan, H., Xu, Y., & Cao, J. (2023). Natural resource consumption and industrial green transformation: does the digital economy matter?. Resources Policy, 81, 103396.

[21] Si, H., Tian, Z., Guo, C., & Zhang, J. (2024). The driving effect of digital economy on green transformation of manufacturing. Energy & Environment, 35(5), 2636-2656.
[22] Chang, X., Su, J., & Yang, Z. (2022). The effect of digital economy on urban green transformation—An empirical study based on the Yangtze River Delta City Cluster in China. Sustainability, 14(21), 13770.