RESEARCH ARTICLE

Agricultural industry supply chain optimization method based on improved hybrid PSO algorithm under the concept of circular economy

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The development of agricultural circular economy plays a vital role in enhancing the returns to scale and ensuring the steady growth of related industries. This study chose the sugar sector as its target industry and developed a supply chain optimization technique using an enhanced hybrid particle swarm optimization algorithm to lower supply chain costs and increase the percentage of resources participating in the circular economy. The results indicated that the optimization by the improved hybrid particle swarm algorithm could well carry out the industry related decision making for the construction and procurement of each project plant and facility accordingly. The optimal value of the improved algorithm was obtained at about 30 iterations, which clearly allowed the population to continue to evolve and obtain the global optimal solution. When the sugar processing volume increased by 20%, the total profit was the highest, reaching ¥27.014 billion when the sugar deep processing coefficient was set to 0.94 and the other utilization coefficients were set to 1.0. Compared to the scheme with a sucrose deep processing coefficient of 0.5, the total profit increased by 162.5%, indicating the existence of practicality and feasibility of the method, which could effectively improve industrial profits, enhance efficiency, and save resource utilization. This study provided a certain theoretical foundation for encouraging the agricultural industry's modernization.

Keywords: circular economy; improved hybrid PSO algorithm; supply chain optimization; industry profit; sugar industry.

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Introduction

Resource conservation and recycling are the hallmarks of the circular economy (C-Eco), also known as a resource-cycling economy. This model promotes economic growth while maintaining environmental sustainability. All resources including energy can be used wisely and sustainably in this cycle of economic activity to reduce the negative effects of economic activity on the environment [1]. The particle swarm optimization (PSO) algorithm uses a population approach to search and makes it possible to search simultaneously for a larger number of regions in the solution space of the objective function to be optimized [2]. Combining the best aspects of both local and global particle swarm algorithms, hybrid particle swarm optimization (HPSO) outperforms traditional optimization techniques and can rapidly converge to the optimal solution, particularly in high-dimensional optimization problems. In addition, the HPSO algorithm can enhance its performance by adding new optimization strategies to adapt to the changing problem environment [3].

The agricultural industry supply chain (AISC) still faces many challenges. To complete the determination of the optimal supply chain (SC) configuration, Jonkman *et al*. designed a generalized model formulation incorporating stochastic versions to improve economic and environmental performance by considering the uncertainty of demand and harvest yields [4]. Federgruen *et al*. constructed a Stackelberg game model to determine the degree of heterogeneity of farmer groups for aggregate supply and price risk management for SC analysis of contract farming with the model's optimality gap less than 1% [5]. To expand the bioeconomy, Dahmen *et al*. adjusted perennial biomass crop quality through crop breeding and management to support the need for integration of the lignocellulosic value chain, providing an economically and environmentally efficient way to produce and utilize lignocellulosic for chemical products, energy production, and utilization with flexibility [6]. Ruan *et al*. addressed the problem of excessive investment costs in green agriculture, considering the premise of the life cycle of agricultural products, combining the Internet of Things (IoT) agricultural system to improve agricultural production and unify management of finances and operations, and solving the technical difficulties of energy and farmers' use of the network [7]. To determine the traceability of food products, Kittipanya-Ngam *et al*. built a food SC digitalization framework to ensure the safety and sustainability of food products with better connectivity performance and the ability to respond positively to customer needs and regulatory requirements [8]. Mogale *et al*. constructed a bi-objective decision support model for sustainable food SC network design to minimize costs and CO_2 emissions simultaneously [9].

The application of the improved PSO algorithm provides more efficient optimization means for the solution of practical problems, for which many researchers have provided some feasible and effective methods. Deng *et al*. designed a method combining enhanced PSO algorithm and small habitat co-evolutionary strategy for aircraft gate resource allocation to optimize the most balanced idle time and passenger walking distance of each gate and reduce the cost [10]. To realize 3D flight self-organizing network for emergency communication, Sun *et al*. conceived an improved PSO algorithm to improve the UAV positioning accuracy based on variable neighborhood search, while the cluster head determination relied on node residual energy and weighted intra-cluster distance to complete [11]. Yang *et al*. suggested a stock price prediction model that included an upgraded PSO algorithm and neural network to increase the accuracy of stock price predictions and their capacity to seek for better stock price prediction effects [12]. Ji *et al*. created a fuzzy PID cross-coupled controller to optimize the controller parameters using the improved PSO algorithm as the foundation to address the tracking error in CNC machining, which greatly increased the contouring accuracy and enabled the contouring tracking of the free curve [13]. An improved PSO-ANN for energy-efficient robust resource allocation was proposed by Srivastava *et al*., lowered cloud system costs, shortened typical startup times, and increased the effectiveness of scheduling algorithms in real-time cloud applications. The results showed that the method improved the energy efficiency by 12% and reduced the average completion time by 20% [14]. To investigate the application of variable substitution elasticity production function, scientists designed an extended variable substitution elasticity production function model in conjunction with the improved PSO algorithm with good applicability [15].

The three C-Eco concepts including waste recycling, product reuse, and reduced resource use are all included in the agricultural industry's manufacturing process. At the initial stage of production, the use of natural resources should be input as little as possible, while the finished products should have a longer life cycle and be used in various applications. Meanwhile, the waste generated in the production process should be minimized, the chances of harmless discharge should be increased, and resource recycling should be completed. Moreover, the utilization of more recyclable and renewable resources such as solar, wind, and farmyard fertilizer in lieu of non-renewable ones would facilitate a more accurate alignment of production with the natural biological cycle, which allows humans to produce and live in a good environment, thereby improving people's quality of life overall [16]. The C-Eco development model is realized by targeting the extraction and production of resources, manufacturing them into products for the customer's consumer market, and when waste is generated, certain recycling is carried out. The safe release of primary waste and the effective and recyclable use of resources are two of the three technological trajectories of C-Eco development. In the field of agricultural production, crop cultivation and livestock breeding follow the laws of natural ecology, and some advanced technologies can be used to complete the organic coupling agricultural recycling industry chain and organize effective production according to economic laws. Livestock eco-farming methods implement clean farming, and through biogas fermentation technology, the manure produced by livestock and poultry farming is processed, turning harm into benefit, and producing and manufacturing biogas and organic agricultural fertilizer [17]

However, previous studies fail to simultaneously consider the relationship between the C-Eco concept and the total industry profit. Considering that the development of agricultural industry will bring certain ecological benefits and promote the construction of C-Eco, this study chose the sugar industry as the research target to optimize AISC for the sugarcane industry to improve its efficiency and sustainable development. Combined with the concept of C-Eco, the study adopted binary decision variable (BDV)s to analyze complex multivariate quantities and constructed an AISC optimization model incorporating improved hybrid PSO (IHPSO) algorithm. This study introduced the C-Eco concept into AISC, which emphasized resource conservation and recycling to reduce the negative impact on the environment. By studying the method of selecting BDVs, complex multivariate problems could be analyzed and handled in AISC. In addition, the study proposed IHPSO, which combined the advantages of global and local PSO with higher global search ability and fast convergence characteristics and suitable for high-dimensional optimization problems with fewer parameters. The results of this study would not only provide a new perspective and method for the agricultural field, but also help to promote the practice of C-Eco and the sustainable use of resources. The specific models and methods developed through this study would optimize the SC of the sugarcane industry, which also had reference significance for the optimization management of other agricultural SCs and contributed to the enhancement of the efficiency and sustainable development of the entire agricultural industry.

Materials and methods

AISC model incorporating the concept of C-Eco

The study chose the sugar industry SC as the research target, where the C-Eco of the sugar industry SC was shown schematically in Figure 1. The reverse logistics flow was the delivery of soil fertilizer material resources from biogas generation facility (*f*) and fertilizer plant (*g*) to parcel (*l*). The forward logistics flow was the sucrose raw material making products at the sugar factory (*w*) and entering the customer area, i.e., the final product market. The sugar production process also included three major by-products as molasses, bagasse, and filter sludge. Molasses was distributed to the distillery (*j*) to participate in the molasses alcohol market (*e*), and the materials generated by the production process were used for irrigation of agricultural land. Bagasse was transported to thermal power plant (*o*) to generate energy that could be provided to sugar mills for utilization. The filtered mud was transported to a fertilizer plant to be

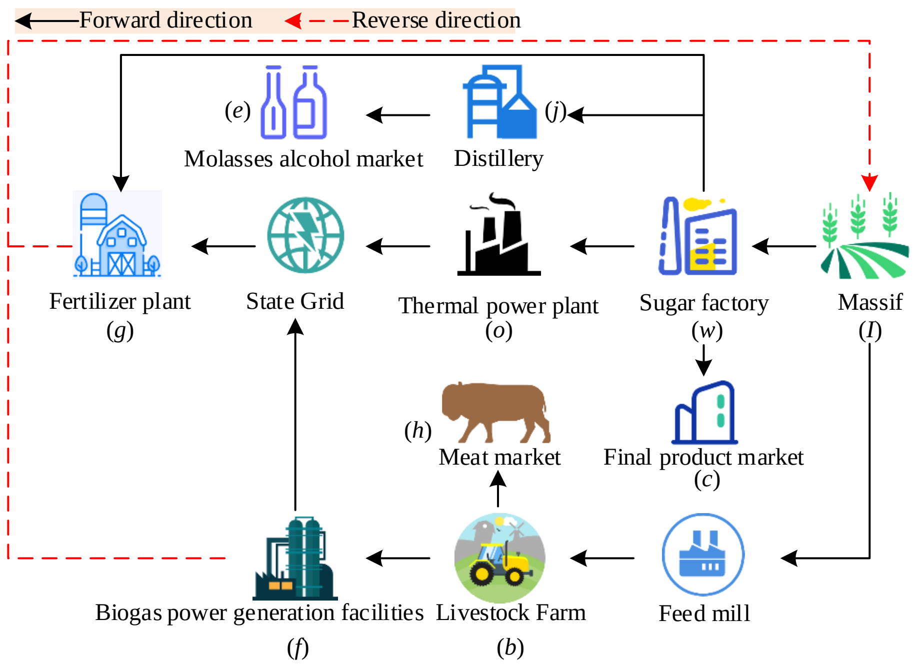

Figure 1. Circular economy in the sugar industry supply chain. The designation of each industry involved in the SC was facilitated by lowercase italicized letters.

reprocessed into an organic composite fertilizer and delivered soil fertilizer material resources to the plots. Leaves left behind from sugarcane cultivation in the plots were fed to livestock farms (*b*) in cooperation with the livestock farms, realizing an increase in revenue from the meat market (*h*). The biomass present in the farm farming in the biogas power generation facility could generate biogas to supply to the national grid to participate in the alcohol market and the national grid to realize the synergistic development of multiple industries such as sugar, feed, and animal husbandry. Combining the agricultural and sugar industries completed the construction of a closed-loop production system and maximized the value-added by-products. It was assumed that, in the model, each factory on the candidate address was newly built including sugar mill, feed mill, thermoelectric power plant, and distillery, *etc*. Moreover, the sugarcane from parcel (*I*) was transported to the sugar mill. It was required that the transportation raw material of each facility was lower than the capacity of the facility, and if there was a case of insufficient capacity of the facility, the same facility of the hierarchy of the second priority of the next node was selected as the target, and all the transportation raw material was still transported from the previous node of the SC. It was finally determined that the yield of the plot, the production of the sugar mill, and the demand of each type of market were known without the influence of other external factors. To ensure that profit maximization was achieved, it was indicated that both total sales revenue and total costs could be optimized. The total sales revenue consisted of sugar and alcohol products, electricity, meat, and fertilizers. Costs included fixed costs of industrial facilities, costs of transportation between facilities, costs of energy use in the sugar production process, and costs of operation, production, processing packaging and reprocessing [18]. To simulate the total profit in AISC and the utilization efficiency in the sucrose production process, the values of the control variables were modified in accordance with the principles of C-Eco. The utilization coefficients in AISC with three Schemes A, B, and C were studied (Table 1). The sucrose deep processing coefficient was the degree of precision

Table 1. Industrial chain regulation production parameters.

Scheme	Sucrose deep processing coefficient	Molasses utilization coefficient	Bagasse utilization coefficient	Sugarcane leaf utilization coefficient	Filter sludge utilization coefficient
A	0.50	0.00	0.00	0.00	0.00
B	0.75	0.50	0.50	0.50	0.50
C	0.94	1.00	1.00	1.00	1.00

processing. Scheme A, B, and C represented the lowest level of processing, moderate level of processing, and near complete processing, respectively. The study determined the values of the deep processing coefficient of sucrose as well as the utilization coefficients of bagasse, molasses, filter sludge, and sugarcane leaves through the study of best practices and relevant literature in the sugar industry [19]. The utilization coefficients of bagasse, molasses, filter sludge, and sugarcane leaves all indicated the degree of reuse of by-products. For these four coefficients, scheme A was set to 0.0 to indicate that the by-product had not been utilized. Scheme B was set to 0.5 to indicate that half of the by-product had been utilized. Scheme C was set to 1.0 to indicate that the by-product had been fully utilized. This was situated within the context of the C-Eco concept, which was predicated on the principle of optimizing the utilization of resources. In the SC model, let *s* be the starting point and *e* be the ending point, and the transportation distance $d_{s,e}$ between any two nodes was generated by the ratio of Euclidean metrics as shown in Equation (1).

$$d_{s,e} = \sqrt{\left(a_s - a_e\right)^2 + \left(b_s - b_e\right)^2} \times 1000 \quad (1)$$

For each product, the average demand D_{cp}^{avg} for each sales market was shown in Equation (2).

$$D_{cp}^{avg} = mean\left(\theta_{w,p} QS_i\right) \times |I| / |C| \times |P| \quad (2)$$

The sales market demand was illustrated by Equation (3).

$$D_{c,p} = U\left[\left\lceil 0.4 \times D_{cp}^{avg} - 0.5\right\rceil, \left\lceil 1.6 \times D_{cp}^{avg} - 0.5\right\rceil\right] \quad (3)$$

Molasses alcohol market demand D_s was shown in Equation (4).

$$D_s = U\left[\left\lceil 0.4 \times mean\left(\sigma_j Q_j\right) \times |J| / |S| - 0.5\right\rceil, \left\lceil 1.6 \times mean\left(\sigma_j Q_j\right) \times |J| / |S| - 0.5\right\rceil\right] \quad (4)$$

where $mean\left(\sigma_j Q_j\right)$ was the average value of sucrose degree of treated sugar. σ_j was the coefficient of raw material consumption to produce alcohol per unit of alcohol in the alcohol production center. Livestock meat market demand D_h was shown in Equation (5).

$$D_h = U\left[\left\lceil 0.4 \times mean\left(w_b Q_b\right) \times |B| / |H| - 0.5\right\rceil, \left\lceil 1.6 \times mean\left(w_b Q_b\right) \times |B| / |H| - 0.5\right\rceil\right] \quad (5)$$

where w_b was the biomass emission coefficient put out by livestock after consuming units of feed in the process of raising livestock in the feeding center. Fertilizer demand D_{1i} for plot $1i$ was shown in Equation (6).

$$D_{1i} = U\left[\left\lceil 0.4 \times mean\left(\varphi_g Q_g\right) \times |G| / |I| - 0.5\right\rceil, \left\lceil 1.6 \times mean\left(\varphi_g Q_g\right) \times |G| / |I| - 0.5\right\rceil\right] \quad (6)$$

where φ_g was the fertilizer filter sludge consumption factor for fertilizer production unit in the fertilizer center. The demand for fertilizer D_{2i} in plot $2i$ was shown in Equation (7).

$$D_{1i} = U\left[\left\lceil 0.4 \times mean\left(\phi_f Q_f\right) \times |F| / |I| - 0.5\right\rceil, \left\lceil 1.6 \times mean\left(\phi_f Q_f\right) \times |F| / |I| - 0.5\right\rceil\right] \quad (7)$$

where ϕ_f was the production coefficient of methane digests produced after fermentation of biomass at the biogas power generation facility.

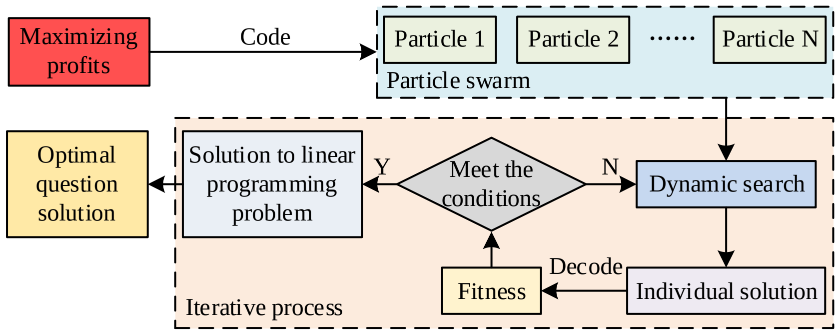

Figure 2. IHPSO algorithm framework.

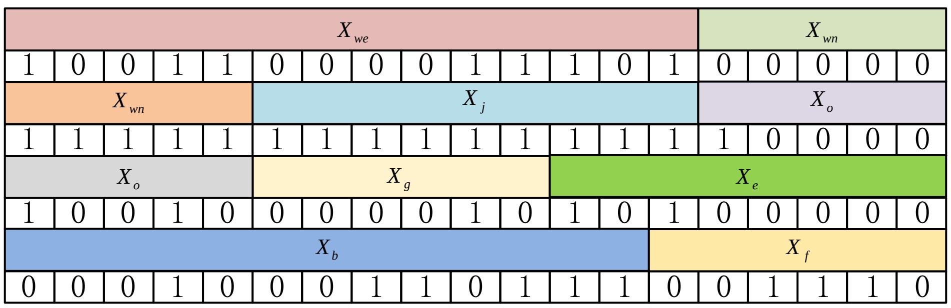

Figure 3. Binary decision variable particle coding.

AISC optimization based on IHPSO algorithm

Generally, the PSO technique was selected for the model optimization solution once the cane sugar industry's SC model had been constructed. The PSO algorithm was used in conjunction with C-Eco to maximize profit by optimizing the SC in the cane sugar sector due to the fewer adjustment parameters and simple operation. However, the PSO algorithm was not effective in models containing many variables, and the solution was more difficult and less efficient [20]. The HPSO algorithm, on the other hand, incorporated a variety of optimization strategies, including genetic algorithm (GA), local search and global search, which improved its adaptability to different problems with superior performance in theory and effectiveness in practice. However, the HPSO algorithm had some difficulties in dealing with complex and high-dimensional optimization problems, which could not efficiently tackle discrete or combinatorial optimization problems due to its tendency to fall into a local optimum while searching for the global minimum, which would lower convergence accuracy and difficulty. Therefore, to reduce the constraint limitations, an IHPSO algorithm was designed. The PSO searched for discrete decision variables in the MIP model. Then the algorithm encoding was selected, screened by the PSO algorithm, followed by a dynamic search, solving the individual, determining the fitness after decoding, and satisfying the conditions to solve the linear programming problem, thus completing the optimal problem solution (Figure 2). Finding the optimal solution focused on the development of a suitable IHPSO algorithmic coding along with speed adjustment and search position updating. BDV were firstly searched by PSO algorithm in the feasible solution by setting the dimension value of each particle to 0 - 1. BDV is a variable that can only take two values in the decision-making process, which is usually denoted by 0 and 1. The goals and restrictions of the problem must be clearly defined and transformed into a mathematical model to conduct constrained problem solving for BDV. To get the best results, it was necessary to change the model's parameters and the optimization algorithm's settings during the solution process. To make sure the solution outcome satisfied the problem's requirements, it must lastly be examined and validated. The BDV particle coding for the SC model was designed with the particle position as a 1 × 76 dimensional structure with $X=\{X_{we},X_{wn},X_j,X_o,X_g,X_e,X_b,X_f\}$, illustrating a set of feasible solutions for SC (Figure 3). The velocity v_{id} of particle i defined the structure, and the spatial position of the moving particle was $v_{id}=\{v_{i1},v_{i2},...,v_{i\xi},...,v_{i76}\},1\le\xi\le 76$. General particles were either uniformly or randomly arranged in the search space and moved. Particles traveled in accordance with their own experiences as well as those of other particles, and the dynamic improvement produced by their speed allowed them to modify their paths inside the search space. In continuous PSO, particles attracted by the current best particle p_{id} and the global best particle p_{gd}, updated the velocity v_{id} and position x_{id} expression as shown in Equation (8).

$$\begin{cases} v_{id}(t+1)=v_{id}(t)+c_1r_1(t)\left[p_{id}(t)-x_{id}(t)\right]+c_2r_2(t)\left[p_{gd}(t)-x_{id}(t)\right] \\ x_{id}(t+1)=x_{id}(t)+v_{id}(t+1),-v_{\max}<v_{id}(t+1)<v_{\max} \end{cases} \tag{8}$$

where $i=1,2,...,N$. N were the populations. In the convergence process of a problem, the most important thing was the determination of the ratio of local and global search capabilities. It was examined to dynamically adjust the inertia weights by means of the feature adaptation of the sine-cosine function as given in Equation (9) to prevent a rise in the number of ineffective searches.

$$w=\begin{cases} w_{\min}+(w_{\max}-w_{\min})*\sin\left(\dfrac{\pi*f(t)}{f_{avg}(t)}\right) & f(t)\le f_{avg}(t) \\ \dfrac{w_{\max}-w_{\min}}{2}*\left(cos\dfrac{\pi(t-1)}{g_{\max}}+1\right) & f(t)>f_{avg}(t) \end{cases} \tag{9}$$

where the general maximum inertia weight $w_{\max}=0.9$ and the minimum inertia weight $w_{\min}=0.4$. $f(t)$ was the value of particle adaptation. $f_{avg}(t)$ was the total average of $f(t)$'s Ja at the current t-th iteration. $g_{\max}$ was the maximum number of iterations. Since the particle velocity variable was related to the learning factor (LF) of the particle, the improvement of the cognitive LF (c_1) and the social LF (c_2) were expressed in Equation (10).

$$\begin{cases} c_1=2+\dfrac{f(t)-f_{avg}(t)}{f_{avg}(t)-f_{\min}} \\ c_2=2-\dfrac{f(t)-f_{avg}(t)}{f_{avg}(t)-f_{\min}} \end{cases} \tag{10}$$

where $f_{\min}$ was the minimum of the adaptation values of all particles in the whole population. To address the issue of premature convergence, the study created a new mechanism for the velocity update that improved the synergistic effect between particles. The velocity update mechanism was expressed in Equation (11).

$$\begin{aligned} v_{id}(t+1)&=v_{id}(t)+c_1r_1(t)\left[p_{id}(t)-x_{id}(t)\right]... \\ &+c_2r_2(t)\left[p_{gd}(t)-x_{id}(t)\right]+c_3r_3(t)\left[p_{jd}(t)-x_{id}(t)\right] \end{aligned} \tag{11}$$

where p_{gd} was used to localize the iterative function and control the swarm of particles, i.e., the behavioral LF of the domain particles. c_3 was the LF of particles. r_3 was a random number between 0 and 1 [21].

Data resources and program running environment

The data used for this study was obtained from the China Agricultural Supply Chain Dataset (National Bureau of Statistics, Beijing, China). The dataset covered agricultural production data and SC data from 2019 to 2023 in Beijing, China. There were 200 people in the starting population with the maximum iterations of 50. 20 experiments were conducted, which represented the computational time and experimental

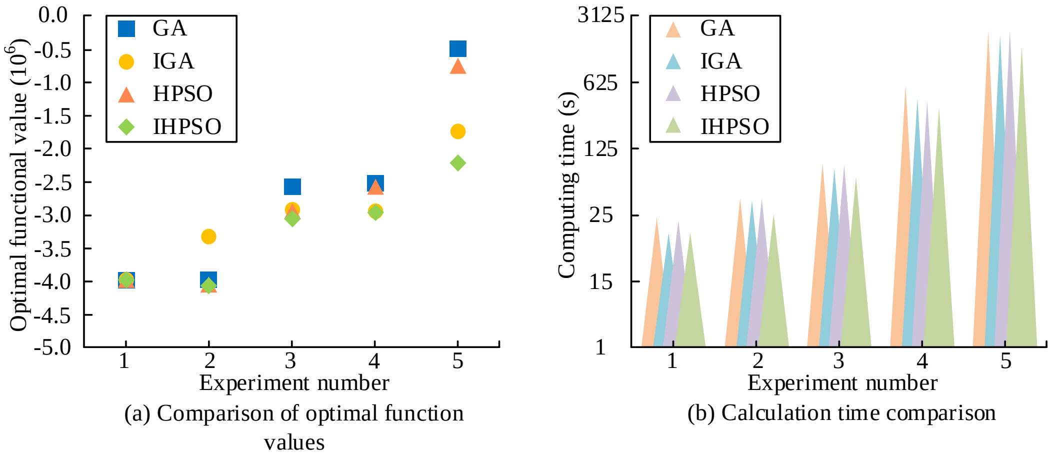

Figure 4. Comparison of optimal function values and calculation time results of different algorithms.

optimal value. AMD Ryzen7, 1.8 GHz, 8 GB RAM computer was employed with MATLAB R2019a (https://www.mathworks.com/products/matlab.html) to test the model and optimization algorithm. GA and PSO were used to optimize SC models. The study selects improved genetic algorithm (IGA), HPSO, and IHPSO for experimental comparison.

Results and discussion

Performance analysis of the IHPSO algorithm

To more accurately evaluate the effectiveness of different algorithms in SC model optimization, multiple repeated experiments were conducted with identical initial conditions and parameter settings. The discrepancies between experiments were primarily manifested in the randomness, diversity of the initial population, and random operations during the algorithmic process. The average test results were taken from 20 tests of different algorithms to reduce the fluctuation of results caused by randomness, which allowed for a more reliable evaluation of the performance of each algorithm. In SC models of different scales, the planting plots for sugarcane in tests 1 - 5 were set as 500, 1,000, 2,000, 4,000, and 6,000, respectively. The comparison of the optimal function values and the mean calculation time results of different algorithms showed that the optimal function values obtained by the IGA in tests 1 and 2 were -1.0079 × 10^6 and -0.9303 × 10^6, respectively, while the IHPSO algorithm was -1.0084 × 10^6 and -0.9325 × 10^6, respectively, while the optimal function values obtained by the IHPSO algorithm in tests 3, 4, and 5 were -1.9616 × 10^6, -2.0376 × 10^6, and -2.0376 × 10^6, respectively (Figure 4a). Taken together, the IHPSO algorithm demonstrated better optimization performance. The IGA showed the least computation time in test 1 as 15.79 s, while in tests 2 to 5 as 25.48 s, 61.00 s, 340.86 s, and 1,419.97 s, respectively (Figure 4b). The computation speed of the IHPSO algorithm was 1.4 times higher than that of the HPSO algorithm. To compare and analyze the effectiveness of the IHPSO algorithm, the convergence processes of the HPSO and IHPSO algorithms were compared. The results showed that, between 0 and 80 iterations, the mean value of the fitness function of the HPSO algorithm fluctuated significantly, and then stabilized to 1. As the iterations increased, the change in the mean value fluctuation gradually decreased, and the HPSO algorithm was in a locally optimal solution, and it failed to continue to evolve the population. The HPSO algorithm converged faster, and the optimal value was obtained at about 10 iterations (Figure 5a). The optimal value of the IHPSO algorithm was obtained in about 30 iterations. Compared with the HPSO algorithm,

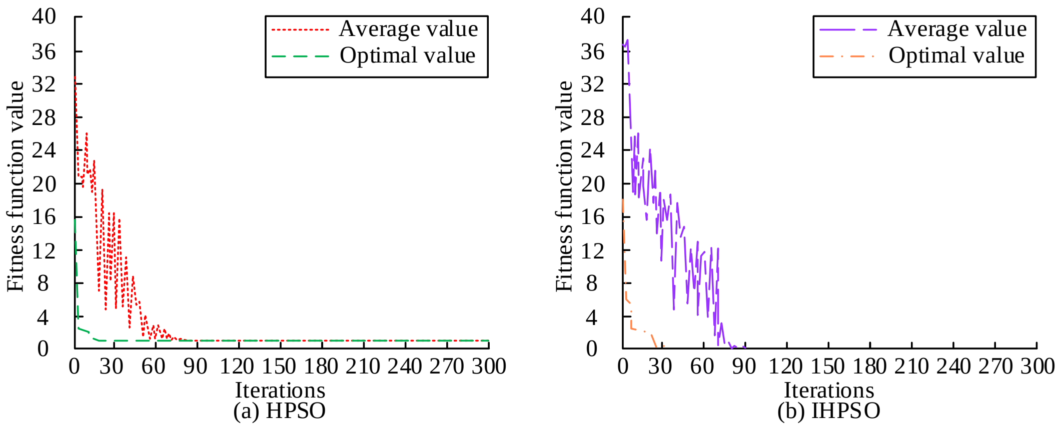

Figure 5. Comparison of convergence processes between HPSO and IHPSO algorithms.

the convergence speed was slower (Figure 5b). Moreover, the IHPSO algorithm obviously allowed the population to continue to evolve and obtain the global optimal solution 0. In contrast to the HPSO algorithm, the IHPSO algorithm could circumvent the issue of premature convergence, enabling the population to continue evolving and ultimately achieving the optimal global solution. Concurrently, the IHPSO algorithm enhanced the diversity of the population, augmented global search capability, and exhibited enhanced robustness and adaptability.

Supply chain modeling results for IHPSO at AICE

The research set up 6,000 sugarcane planting plots, 10 existing sugar factories, and 20 newly built sugar factories, distilleries, fertilizer factories, thermal power plants, feed factories, breeding centers, and biogas power generation facilities. To analyze the optimal configuration of facilities or factories for maximizing resource utilization in this context, the IHPSO algorithm was employed for analysis and was optimized to determine the selection of 52 candidates addresses including 5 closed sugar mills, 4 new fertilizer mills, 5 sugar mills, feed mills, and biogas generation facilities, as well as 7 distilleries, cogeneration plants, and 8 feeding centers. Due to the inherently unstable and fluctuating nature of market prices, this study examined the impact of three pricing schemes defined as A, B, and C on the sugar processing industry, considering the inherent variability in volume. The study assumed that fluctuations in sugar processing yielded 20%, 10%, 0%, -10%, and -20%, respectively, so that the output values of molasses and wine, organic fertilizer, and electricity were compared through schemes. Regardless of the fluctuation of sugar processing quantity, the molasses wine output value of scheme A was 0 because the coefficient of cane sugar deep processing was 0.50 and the rest of the utilization coefficients were 0. With the gradual increase of the fluctuation of sugar processing quantity, the curves of molasses wine output value of schemes B and C showed a rising trend. When the fluctuation of sugar processing quantity was 0, the molasses wine output values of schemes B and C were ¥327 million and ¥523 million, respectively (Figure 6a). As the fluctuation of sugar processing volume gradually increased, the output value of organic fertilizer of schemes B and C gradually increased. When the fluctuation of sugar processing volume was 0, the production values of organic fertilizer in schemes B and C were ¥728 million and ¥405 million, respectively (Figure 6b). As the fluctuation of sugar processing volume gradually increased, the output value of schemes B and C electricity gradually increased too. When the fluctuation of sugar processing volume was 0, electricity output values in schemes B and C were ¥756 million and ¥439 million, respectively (Figure 6c). The value

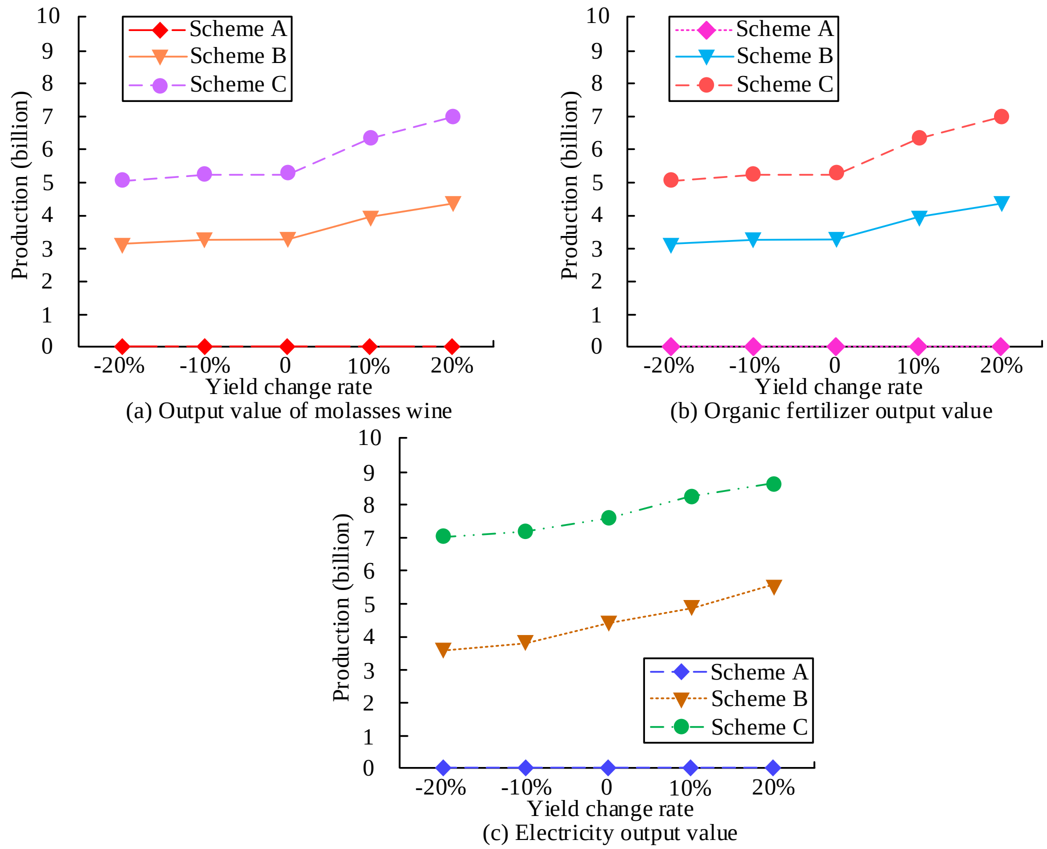

Figure 6. Comparison of output values of molasses wine, organic fertilizer, and electricity under different schemes.

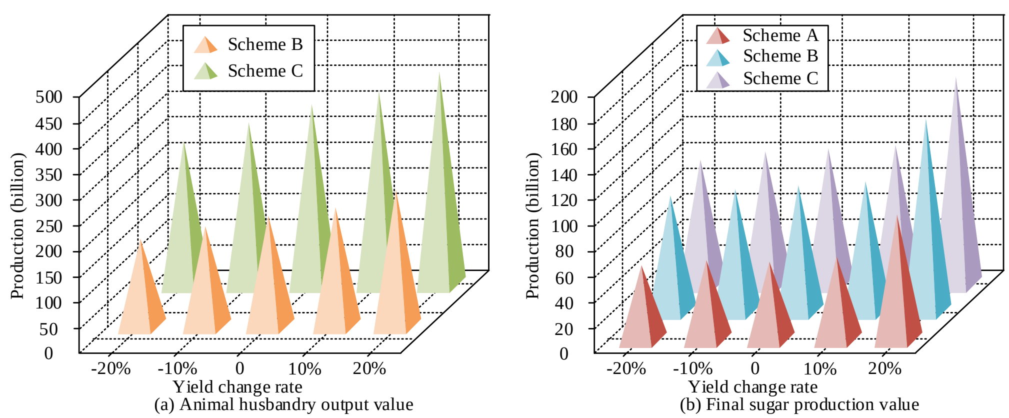

Figure 7. Comparison of animal husbandry and final sugar production value under different schemes.

of livestock production in schemes B and C gradually increased as the fluctuation in sugar processing volume gradually increased. The values of organic fertilizer production in schemes B and C were ¥36.001 billion and ¥22.503 billion, respectively (Figure 7a). When the fluctuation of sugar processing volume was 0, the final sugar production values of schemes A, B, and C were ¥6.862 billion, ¥10.293 billion, and ¥10.979 billion, respectively (Figure 7b). The total production profit changes under the three schemes were shown in Figure 8. Overall, scheme

C had the highest total profit, while the lowest was scheme A. When the fluctuation of sugar processing volume increased by 20%, the total profits of schemes A, B, and C were the highest as ¥10.292 billion, ¥20.883 billion, and ¥27.014 billion, respectively. Scheme C had an increase in total profit of 62.47% (Figure 8).

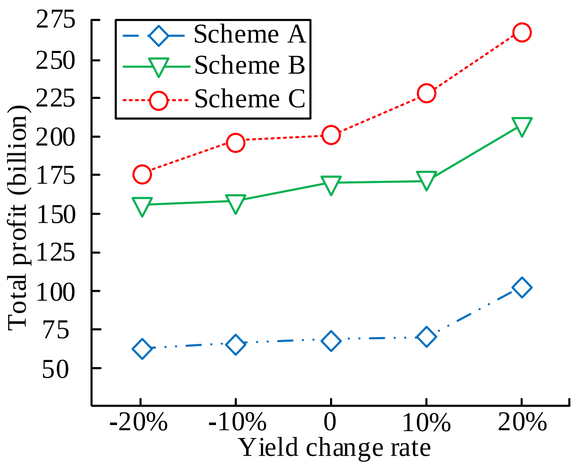

Figure 8. Changes in total production profit.

Conclusion

To increase the proportion of resources participating in C-Eco and reduce SC cost, this study took sucrose industry as the research object, considered the C-Eco concept, constructed an AISC optimization model incorporating the IHPSO algorithm, and analyzed the complex multivariate quantities using BDV. The results showed that the IHPSO algorithm performed better in avoiding local optima and improving global search ability compared with that before improvement. This optimization was of great significance for solving complex optimization problems and demonstrated the effectiveness of the IHPSO algorithm in global optimization. The improved AISC optimization model indicated that, when the sugar processing volume reached 0, the output value of scheme C, which was nearly at the point of complete processing, was ¥523 million for molasses wine, ¥405 million for organic fertilizer, and ¥439 million for electricity. It was evident that, regardless of the fluctuations in the processing volume, the total profit of scheme C was consistently higher than that of the other two plans, which indicated that the model demonstrated robust performance and could ensure efficiency improvement to achieve total profit growth. However, the study was short and failed to consider the impact of geographic location on the agricultural economy, which should be deepened in future.

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