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Optimization of the agricultural and forestry biomass power generation supply chain considering multi-period inventory

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ABSTRACT

Biomass fuel supply fluctuates due to seasonal effects, making stocks unstable. In this study, a multi-cycle inventory optimization model of agricultural and forestry biomass power supply chain was constructed based on mixed integer linear programming, considering the cooperative supply of agricultural and forestry biomass and the dynamic change of inventory. Based on case study and sensitivity analysis, the dominant model and inventory size suitable for this supply chain are discussed. The results of case study show that the broker-led model is more suitable for the supply chain of collaborative supply of agricultural and forestry biomass. After optimization, the warehouse area of the power plant is 0.83 hm^2, and the warehouse area of the five acquisition stations is 4.81 hm^2. Compared with the unoptimized state, the operating cost of the supply chain is reduced by 9.77 %, saving about 850,000 *CNY* per year. Further sensitivity analysis of the factors affecting the inventory cost shows that reducing the footprint of the warehouse and increasing the biomass supply can reduce the cost of the warehouse and improve the economic benefit. This study solves the problem of inventory overstocking caused by seasonal fluctuations of biomass fuel supply and improves supply chain stability.

1. Introduction

With the escalating global energy demand and the intensification of environmental challenges, the pursuit of renewable energy alternatives to traditional fossil fuels has emerged as a paramount objective for nations worldwide [1]. As a low-carbon, clean renewable energy, biomass energy consumption is second only to coal, oil and natural gas. It can meet about 35 % of the energy needs of most developing countries [2]. With its wide source of raw materials and environmental protection characteristics, biomass power generation has become a new type of clean power generation advocated by various countries [3,4].

Despite the numerous advantages of biomass power generation, current biomass power plants predominantly rely on a single type of biomass feedstock, such as agricultural or forestry biomass, for electricity production [5]. This reliance is subject to seasonal fluctuations, which in turn affects the stability of the fuel supply for these power plants [6]. Consequently, the exploration of mixed biomass feedstock supplies to enhance the stability and diversity of biomass provision has become a focal point of contemporary research.

The supply of agricultural and forestry biomass is inherently seasonal and regional, leading to volatility and increased uncertainty in inventory management [7]. The challenge lies in reducing inventory costs and improving resource utilization efficiency while ensuring a consistent energy supply, which has become a critical issue in the optimization of the agricultural and forestry biomass power supply chain. Presently, the majority of research on inventory optimization within existing supply chains concentrates on fixed inventory within a single cycle [8]. However, biomass inventory levels exhibit significant dynamic fluctuations in response to seasonal variations, rendering traditional static inventory management approaches inadequate for practical operational requirements. This necessitates the urgent development of a multi-period dynamic inventory optimization strategy based on seasonal characteristics [9]. This strategy enables accurate identification of periodic patterns in resource supply and establishes a dynamic inventory adjustment mechanism, thereby significantly enhancing the economic efficiency and operational stability of the supply chain.

The sustainability of the biomass supply chain is a central focus of current research, aiming to achieve profit maximization, environmental pollution minimization, and employment maximization across the social, environmental, and economic dimensions [10]. Mixed integer

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linear programming (MILP) offers significant advantages in resolving complex dynamic optimization problems, thereby facilitating the attainment of these objectives [11]. This paper primarily examines the sustainability of the agricultural and forestry biomass power supply chain from an economic perspective. By considering the variations in the collection, storage, and transportation of different biomass raw materials and the characteristics of multi-cycle inventory, the biomass power supply chain is optimized through the construction of a MILP model aimed at cost minimization.

Three distinct contributions have been provided to this field. Firstly, according to the seasonal supply characteristics of agricultural and forestry biomass, the collaborative supply can make up for the loss of power plants caused by the interrupted supply period of agricultural biomass. Secondly, according to the characteristics of dynamic inventory fluctuation of acquisition station and power plant caused by seasonal changes, the multi-period inventory dynamic planning is carried out. Lastly, a multi- period supply chain inventory optimization model for agricultural and forestry biomass power generation was established by using mixed integer linear programming method. The model is verified and verified by numerical analysis and sensitivity analysis. The organization of this paper is as follows: Section 2 summarizes the relevant literature. In Section 3, the method is analyzed and the model is constructed. Section 4 presents a case study, Section 5 presents a sensitivity analysis, Section 6 discusses the results, and Section 7 presents conclusions.

2. Literature review

Supply chain optimization encompasses the entire process from raw material procurement to energy production and distribution. In recent years, the dual objectives of enhancing economic efficiency while ensuring supply chain sustainability have emerged as critical research priorities in supply chain optimization [10]. Zahraee et al. [12] demonstrated that Mixed-Integer Linear Programming (MILP) has become a predominant methodology for addressing supply chain optimization challenges. Within the fossil fuel sector, Kim et al. [13] optimized the entire hydrogen supply chain from overseas supply to domestic consumption through MILP, demonstrating the unique advantages of MILP in addressing complex supply chain issues. Given the substantial economic, environmental, and social consequences of supply chain disruptions, Emenike et al. [14] developed an innovative MILP model to design resilient and sustainable gas supply chain networks. In the agricultural and food supply chain domain, Ying et al. [15] proposed a bi-objective MILP model that simultaneously considers economic and environmental factors, incorporating the effects of straw return and deep tillage practices on crop yield and greenhouse gas emissions, thereby expanding the application of MILP in agri-food supply chains. Alexander et al. [16] established a two-stage fuzzy-possibilistic MILP model to optimize material flow distances within supply chain networks. The application of MILP extends to various supply chain contexts, as evidenced by Cheng et al. [17]., who integrated consumer green preferences and financial constraints into a profit-maximization MILP model, effectively addressing decision-making challenges in carbon reduction investments, raw material procurement, production planning, and distribution logistics.

The optimization of biomass-powered electricity supply chains has garnered significant research attention due to its complexity. These supply chains require simultaneous consideration of biomass collection, storage, transportation, energy conversion processes, and dynamic market fluctuations in pricing and supply availability. To enhance supply chain sustainability, numerous studies have implemented MILP in biomass power supply chain optimization. Gonela et al. [18] developed a stochastic MILP model for optimizing hybrid coal-biomass co-generation supply chains under carbon emission constraints and uncertainty conditions. Ransikarbum et al. [19] proposed a multi-objective MILP model combined with fuzzy analytic hierarchy process to address multiple uncertainties in wood fuel supply chains. In response to climate change mitigation and power generation demands, Masum et al. [20] formulated a price-exogenous MILP model capable of balancing traditional wood product needs with additional bioenergy requirements for coal replacement in power plants. Ardliana et al. [21] introduced a MILP model optimizing production and transportation decisions while minimizing total costs and carbon emissions. Eric et al. [22] developed a comprehensive stochastic MILP model that accounts for biomass yield uncertainty, spatial raw material availability, and environmental impacts to optimize power supply chain configurations under uncertain conditions. These studies collectively demonstrate the efficacy of MILP in addressing the dynamic complexities of biomass power generation supply chains.

Despite these advancements, current research has largely overlooked the critical seasonal supply characteristics of biomass, which significantly impact storage requirements and supply fluctuations. To address this gap, this study proposes a novel multi-cycle inventory optimization model that explicitly incorporates seasonal supply characteristics. Through the application of MILP technology, this paper established an optimization model for agricultural and forestry biomass power supply chains based on dynamic inventory variations. The model focuses on optimizing inventory coordination between acquisition stations and power plants, determining optimal inventory levels within the planning horizon to effectively respond to seasonal variations and dynamic market demands. This optimization framework enables more precise supply chain structural adjustments and enhances resource utilization efficiency, thereby contributing to the development of more robust and sustainable biomass power supply chains.

3. Method and modeling

3.1. Problem description

A 3-level agricultural and forestry biomass power supply chain is studied, including farmers, acquisition stations and power plants. Farmers are the suppliers of biomass raw materials. The acquisition station is in the middle. Power plants are consumers of biomass. The supply chain mainly includes five steps: harvest, transportation, preprocessing, storage and energy conversion. Its operation flow is shown in Fig. 1.

According to the division of responsibilities and profit distribution of supply chain, two operating modes are proposed. The first model is the equal leadership model, in which the farmer is responsible for the initial collection and transportation. The broker is responsible for further processing, storing and transporting the biomass to the power plant at the acquisition station. The power plant is responsible for its own storage management and electricity generation. The second model is broker-dominated. Under this model, farmers are only responsible for providing biomass feedstock. Power plants focus on warehouse management and generation tasks. Brokers are responsible for all aspects of collection, processing and transportation.

The model assumes each month as a period, according to the seasonal supply characteristics of biomass, starting from the fifth month is the first period, until the end of the following April is the last period. In each period, biomass raw materials are transported from fields or agricultural processing plants to the acquisition station, where the biomass is processed, and some of the processed biomass is transported to the power plant, and the other part is used as inventory. The power plant generates electricity from the biomass shipped in according to the demand, and the rest is kept as a stock for use in the next period. A power plant with Pc installed capacity is equipped with a warehouse and m acquisition stations. The size of the acquisition station and warehouse is Wi. All the acquired biomass will enter the power plant through the acquisition station, and if the acquired biomass exceeds the storage scale of the acquisition station, the excess part will be sent to the power plant for storage in advance. The mathematical symbols and instructions

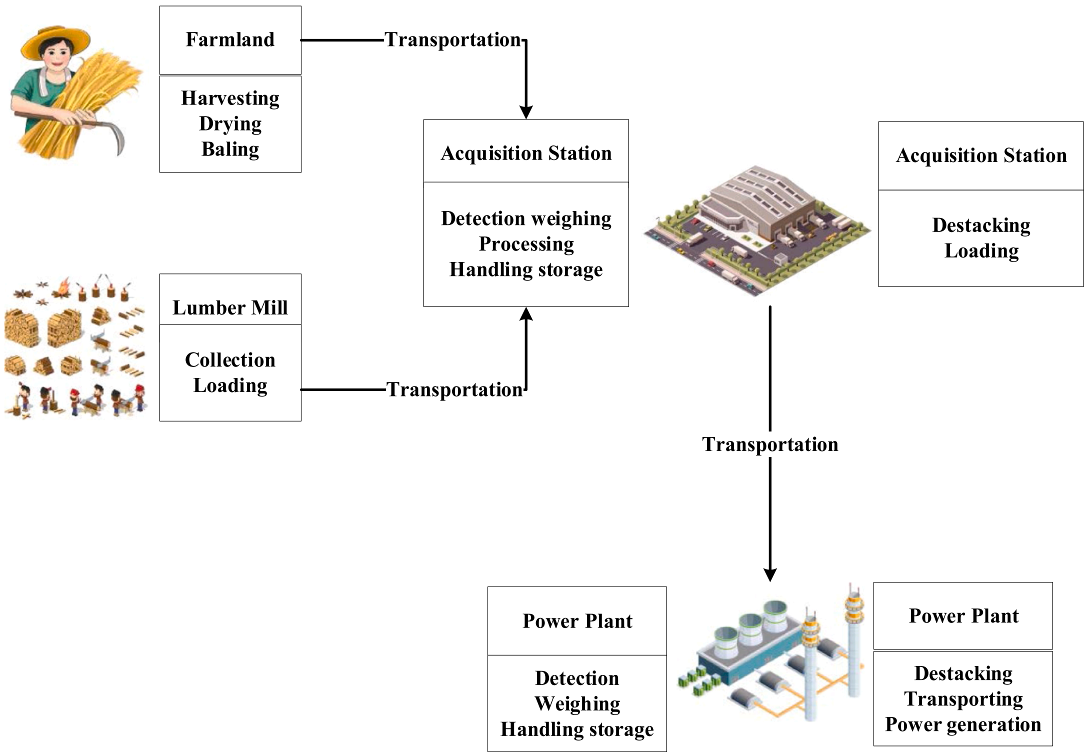

Fig. 1. Operation flow chart.

involved in this section are shown in Table 1.

3.2. Supply and demand analysis

3.2.1. Analysis of supply chain demand

The power plant uses a mixture of forestry biomass and agricultural biomass, and the annual demand for biomass in the supply chain is as shown in Eq. (1).

$$D_f = \frac{3.6 * 10^3 * P_f * T_f}{\eta * \left(\sum_{j=1}^{n} r_j * L_j\right)} \tag{1}$$

where, $D_f(t)$ represents the annual biomass demand of the power plant. $P_f(MW)$ denotes the rated power of the power plant's generating unit. $T_f(h)$ indicates the annual operating time of the power plant. $\eta(\%)$ represents the overall efficiency of the power plant. $r_j(\%)$ signifies the proportion of the j-th type of biomass used for combustion in power generation. and $L_j(kJ{\cdot}kg^{-1})$ stands for the lower heating value of the *j-th* type of biomass.

3.2.2. Analysis of supply chain supply

(1) Agricultural biomass primarily originates from the residues left after the harvest of field crops, which are naturally produced during the agricultural production process [23]. Forestry biomass mainly consists of by-products from forestry preprocessing, such as residues from timber preprocessing plants and discarded wooden materials from the furniture manufacturing industry. The biomass coefficient method was used to calculate the amount of agricultural and forestry biomass collected by Eq. (2).

$$S_{ij} = \pi * \sigma_{ij} * \zeta_{ij} * \rho_{ij} * R_{ij}^2 + Q_{ij} \tag{2}$$

where, S_{ij}(t) represents the annual supply of the *j-th* type of biomass to the *i-th* Acquisition station. $\zeta_{ij}(\%)$ indicates the proportion of the actual harvestable area around the *i-th* Acquisition station. $\rho_{ij}(t{\cdot}km^{-2})$ represents the average biomass resource density of the *j-th* type of biomass near the *i-th*Acquisition station. $R_{ij}(km)$ denotes the collection radius of the *j-th* type of biomass around the *i-th* Acquisition station. $Q_{ij}(t)$ indicates the amount of the *j-th* type of biomass provided to the *i-th* Acquisition station annually in forms other than harvesting. and σ_{ij} represents the annual harvest frequency of the *j-th* type of biomass at the *j-th* Acquisition station.

Forest biomass is supplied every month, but agricultural biomass is only supplied in the 5th-7th and 9th-11th months. The supply is affected by the seasons, geographical environment and weather, and its supply has a certain volatility. This paper assumes that the biomass supply follows a normal distribution, denoted $N\left(\mu_j, \sigma_j^2\right)$.

3.3. Analysis of supply chain costs

3.3.1. Harvesting cost

(1) Agricultural biomass

Using harvesters to collect agricultural biomass incurs a mechanical harvesting cost of 20 yuan per ton [24] . It is important to clarify that agricultural biomass, being a by-product of crops, does not require separate production costs during its production process; instead, it is treated and utilized as an incidental product of the crops [25].

(2) Forestry biomass

Forestry biomass is a by-product of forest preprocessing. It primarily comes from the wood preprocessing industry and furniture manufacturing industry, and these by-products are incidental products of the manufacturing process, thus incurring no harvesting cost [26].

3.3.2. Transportation cost

The transportation process of biomass raw materials is divided into two stages [27,28]. During primary transportation, biomass raw materials are transported from the collection point (field or wood processing

Table 1
Model symbol description.

Symbols	Description
Collections	Description
I	The set of warehouses i, $i=0$, is the power plant; $i=1,2,\cdots m$, for the acquisition station.
J	The set of the *j-th* type of biomass, when $j=1$, is agricultural biomass; When $j=2$, it is forestry biomass.
Parameters	Description
s_{ij}^{s}	The safety stock of the *i-th* acquisition station (t).
s_{0j}^{s}	The safety stock of the power plant (t).
s_i	The maximum preprocessing capacity of the *i-th* acquisition station (t).
s_0	The maximum receiving capacity of the power plant (t).
d_{0t}	The minimum biomass demand of power plant in the *t-th* period (t).
g_{jt}	The maximum collectable amount of the *j-th* type of biomass in the *t-th* period (t).
y_{ij}	Amount of the *j-th* type of biomass that can be stored in the *i-th* acquisition station (t).
y_{0j}	Amount of the *j-th* type of biomass that can be stored in the power plant (t).
g_{it}	Maximum collection capacity of biomass at the *i-th* acquisition station in the *t-th* period (t).
Z_t	Difference between cost and revenue of the agricultural and forestry biomass power supply chain in the *t-th* period (CNY).
Z_{pt}	Difference between cost and revenue of farmers in the *t-th* period (CNY).
Z_{bt}	Difference between cost and revenue of acquisition stations in the *t-th* period (CNY).
Z_{ft}	Difference between cost and revenue of the power plant in the *t-th* period (CNY).
c_j^a	Unit harvesting cost for the *j-th* type of biomass ($CNY \cdot t^{-1}$).
c_j^b	Unit preprocessing cost in the field for the *j-th* type of biomass ($CNY \cdot t^{-1}$).
c_{ij}^m	Unit raw material procurement price paid by the *i-th* acquisition station to farmers for the *j-th* type of biomass ($CNY \cdot t^{-1}$).
c_{0j}^m	Unit raw material procurement price paid by the power plant to the *j-th* acquisition station for the *j-th* type of biomass ($CNY \cdot t^{-1}$).
c_{ij}^b	Unit preprocessing cost of the *j-th* type of biomass at the *i-th* acquisition station ($CNY \cdot t^{-1}$).
c_{0j}^s	Unit power generation cost when the power plant uses the *j-th* type of biomass ($CNY \cdot t^{-1}$).
c_{ij}^{t1}	Unit primary transportation cost for farmers to transport the *j-th* type of biomass to the *i-th* acquisition station ($CNY \cdot t^{-1}$).
c_{ij}^{t2}	Unit Secondary transportation cost for transporting the *j-th* type of biomass to the power plant at the *i-th* acquisition station ($CNY \cdot t^{-1}$).
c_{ij}^v	Unit inventory variable cost per the *j-th* type of biomass at the acquisition station ($CNY \cdot t^{-1}$).
c_{0j}^v	Unit inventory variable cost per the *j-th* type of biomass at the power plant ($CNY \cdot t^{-1}$).
c_{0j}^e	Electricity price for the *j-th* type of biomass when generating electricity ($CNY \cdot kwh^{-1}$).
c_{ij}^f	The unit mass fixed cost for the *j-th* type of biomass in the *i-th* acquisition station, occupying the total capacity ($CNY \cdot t^{-1}$).
c_{ij}^p	The unit mass construction cost for the *j-th* type of biomass in the *i-th* acquisition station, including facilities ($CNY \cdot t^{-1}$).
c_{0j}^f	The unit mass fixed cost for the *j-th* type of biomass in the power plant warehouse, occupying the total capacity ($CNY \cdot t^{-1}$).
c_{0j}^p	The unit mass construction cost for the *j-th* type of biomass in the power plant warehouse, including facilities ($CNY \cdot t^{-1}$).
k_j^a	The loss rate during loading, unloading, and transportation from the field to the *i-th* acquisition station (%).
k_j^b	The loss rate during loading, unloading, and transportation from the *i-th* acquisition station to the power plant (%).
λ_j^a	The farmer's collection loss rate for the *j-th* type of biomass during preprocessing (%).
λ_j^b	The acquisition station's preprocessing loss rate for the *j-th* type of biomass (%).
γ_j	The conversion coefficient for the quantity of the *j-th* type of biomass to electricity(kWh/t).
θ_j	The collection ratio of the *j-th* type of biomass, excluding harvesting (%).
η	The power plant's generation efficiency (%).

Table 1 (*continued*)

Symbols	Description
Decision Variables	Description
y_t	If $(y_{ijt}-y_{ij})$ is positive, take 1; if $(y_{ijt}-y_{ij})$ is negative, take 0.
d_m	If ($c_{ij}^m \neq 20$), take 1; if ($c_{ij}^m = 20$), take 0.
d_{ijt}	The amount of the *j-th* type of biomass sent to the *i-th* acquisition station in the *t-th* period (t).
t_{ijt}	The amount of the *j-th* type of biomass sent from the *i-th* acquisition station to Power Plant in the *t-th* period (t).
t_{0jt}	The amount of the *j-th* type of biomass required by power plant for power generation in the *t-th* period (t).
y_{ijt}	The inventory of the *j-th* type of biomass at the *i-th* acquisition station after the *t-th* period (t).
y_{0jt}	The inventory of the *j-th* type of biomass at power plant after the *t-th* period (t).

plant) to a nearby purchase station using a small agricultural tractor. The secondary transportation uses large trucks to transport the collected biomass raw materials from the purchase station to the power plant. During the outbound journey, the agricultural biomass is near its full load, while the density of forestry biomass is greater than that of agricultural biomass, resulting in a full load situation as well. During the return journey, the vehicle is unloaded. The ratio of full-load to empty-load travel is 1:1. The detailed transportation cost calculation is as follows:

$$c_{ij}^{tn} = c^T * l_{ij}^n * \beta \tag{3}$$

The unit fuel cost is:

$$c^T = \frac{(q_k/v_k + q_m/v_m)N_m p_o}{2\rho_o} \tag{4}$$

where, c_{ij}^{tn} ($CNY \cdot t^{-1}$) represents the unit transportation cost. When n=1, is the unit primary transportation cost of the *j-th* biomass from the collection point to the *i-th* acquisition station; When n=2, is the unit secondary transportation cost of the *j-th* biomass from the *i-th* acquisition station to the power plant. $l_{ij}^n(km)$ represents the transportation distance. βrepresents the road tortuosity factor. It is generally set to $\sqrt{2}$. $c^T(CNY \cdot t^{-1} \cdot km^{-1})$ represents the unit fuel cost. $q_k(kg \cdot kwh^{-1})$ represents the fuel consumption rate when the vehicle is empty. $q_m(kg \cdot kwh^{-1})$ represents the fuel consumption rate when the vehicle is fully loaded. $v_k(km \cdot h^{-1})$ represents the average speed of the vehicle when it is empty. $v_m(km \cdot h^{-1})$ represents the average speed of the vehicle when it is fully loaded. $N_m(kw \cdot t^{-1})$ represents the power-to-load ratio of the vehicle (rated power/vehicle load). $p_o(CNY \cdot L^{-1})$ represents the price of diesel. $\rho_o(kg \cdot L^{-1})$ represents the density of diesel fuel.

3.3.3. Preprocessing cost

(1) Agricultural biomass

Agricultural biomass, due to its large volume and low density, is typically dried and windrowed to reduce moisture content for ease and efficiency of transport [29]. After reaching appropriate moisture levels, it is often preprocessed and baled directly in the field, then loaded by grab machines and transported to acquisition stations. The total cost of agricultural biomass preprocessing mainly includes baling costs and loading costs.

$$C_1^b = C_1^k + C_1^l \tag{5}$$

The cost of baling the biomass is:

$$C_1^k = \frac{ptn + qtp_o + p_w/12}{tQ} + \frac{\left(p_g - p_z\right)/12t_p}{tQ} \tag{6}$$

where, $C_1^b(CNY{\cdot}t^{-1})$ represents the total cost of the agricultural biomass preprocessing process. $C_1^k(CNY{\cdot}t^{-1})$ represents the mechanical baling cost of agricultural biomass. $C_1^l(CNY{\cdot}t^{-1})$ represents the mechanical loading cost of agricultural biomass. p (CNY) represents the daily wage of each operator. t represents the operating duration per period for each machine. n represents the number of workers required per machine. $q(L)$ represents the daily fuel consumption per machine. $p_g(CNY)$ represents the purchase price per machine. $p_z(CNY)$ represents the residual value after scrapping each machine. $p_w(CNY)$ represents the annual maintenance cost per machine.t_p represents the depreciation period per machine. Q(t) represents the daily biomass processing capacity per machine.

(2) Forestry biomass

There is no suitable site and equipment for processing forestry biomass in forest product processing plants, and it is generally transported to the acquisition station for centralized processing [30]. The unit preprocessing cost of forestry biomass is the same as the baling cost of agricultural biomass.

3.3.4. Inventory cost

After being processed and stored in the acquisition stations warehouse, agricultural and forestry biomass are kept in separate storage areas. In power plants, agricultural biomass is stored indoors, while forestry biomass is stored outdoors. Inventory costs are mainly composed of fixed inventory costs and variable inventory costs.

(1) Fixed cost

The fixed cost per period of the warehouse refers to the necessary fixed cost expenditure to maintain the normal operation of the warehouse within a period. Within the scope of meeting specific inventory requirements, the fixed cost of the warehouse has nothing to do with the entry and exit of goods, and mainly includes the fixed cost under the total storage capacity (personnel compensation, fixed lighting costs, and fixed equipment maintenance costs) and depreciation costs. The formula for this can be expressed as:

$$c_{ij}^F = c_{ij}^f + c_{ij}^p \tag{7}$$

Fixed cost per unit mass of biomass in terms of the total warehouse capacity occupied by the biomass:

$$c_{ij}^f = \frac{f_{Fij}v_j}{12n_{Ni}h_i(1-\alpha_i)\delta_{ij}} \tag{8}$$

Unit cost of construction for the warehouse (including equipment) used for biomass per unit mass:

$$c_{ij}^p = \frac{P_{Fi}v_j}{12n_{Ni}n_{ci}h_i(1-\alpha_i)\delta_{ij}} \tag{9}$$

where, $c_{ij}^F(CNY{\cdot}t^{-1})$ represents the fixed cost required for storing the *j-th* biomass in the *i-th* warehouse. n_{Ni} represents the inventory turnover rate. $v_j(m^3{\cdot}t^{-1})$ represents the unit weight volume of the *j-th* biomass. $h_i(m)$ represents the stackable height of the *i-th* warehouse. $\alpha_i(\%)$ represents the lane occupancy ratio of the *i-th* warehouse. $\delta_{ij}(\%)$ represents the storage capacity utilization ratio of the *i-th* warehouse used for the *j-th* biomass. $f_{Fij}(CNY{\cdot}m^{-2})$ represents the unit area fixed cost under the total storage capacity of the *i-th* warehouse occupied by the *j-th* biomass. and $p_{Fi}(CNY{\cdot}m^{-2})$ represents the construction cost of the *i-th* warehouse. n_{ci} represents the depreciation period of the *i-th* warehouse.

(2) Variable cost

Warehouse variable cost refers to the costs associated with the inventory in and out of the warehouse during its operation, denoted as $c_{ij}^v(CNY{\cdot}t^{-1})$. It mainly involves water, electricity, gas costs, equipment maintenance costs, workers' overtime costs and goods damage costs, etc., which are generated with changes in inventory.

3.3.5. Power generation cost

Power generation cost is the cost consumed in the process of biomass power generation, recorded as $c_{0j}^s(CNY{\cdot}kwh^{-1})$. It mainly involves combustion costs, equipment maintenance costs, labor costs, management costs and other expenses directly related to the power generation process.

3.4. Model construction

Based on mixed integer linear programming, a multi-cycle supply chain inventory optimization model for agricultural and forestry biomass power generation was constructed. In the t period ($t=1,2,\cdots,12$), the difference between the cost and income of the supply chain of agricultural and forestry biomass power generation is the sum of the difference between the cost and income of farmers, acquisition stations and power plants. Farmers ' costs include collection costs, field processing costs, and primary transportation costs (broker-led model has no cost). Income is only biomass raw material income. The cost of the acquisition station includes collection cost, field processing cost, primary transportation cost (broker-led model has the first three costs), raw material cost, acquisition station processing cost, inventory cost and secondary transportation cost. The income is biomass sales revenue. The cost of power plant includes acquisition cost, inventory cost and power generation cost. Income only includes power generation income. Z_t, Z_{pt}, Z_{bt},and Z_{ft} are all the difference between costs and incomes.

$$\min Z_t = Z_{pt} + Z_{bt} + Z_{ft} \tag{10}$$

$$\begin{aligned} Z_{pt} = {} & \sum_{i=1}^{m}\sum_{j=1}^{2}\frac{c_j^a d_m}{\left(1-k_j^a\right)\left(1-\lambda_j^a\right)}d_{ijt} + \sum_{i=1}^{m}\sum_{j=1}^{2}\frac{c_j^b d_m}{\left(1-k_j^a\right)}d_{ijt} \\ & + \sum_{i=1}^{m}\sum_{j=1}^{2}\frac{c_{ij}^{t1} d_m}{\left(1-k_j^a\right)}d_{ijt} - \sum_{i=1}^{m}\sum_{j=1}^{2}\left(c_{ij}^m d_m + \frac{c_{ij}^m(1-d_m)}{\left(1-k_j^a\right)\left(1-\lambda_j^a\right)}\right)d_{ijt} \end{aligned} \tag{11}$$

$$Z_{bt} = \left[\begin{aligned} & \sum_{i=1}^{m}\sum_{j=1}^{2}\frac{c_j^a(1-d_m)}{\left(1-k_j^a\right)\left(1-\lambda_j^a\right)}d_{ijt} + \sum_{i=1}^{m}\sum_{j=1}^{2}\frac{c_j^b(1-d_m)}{\left(1-k_j^a\right)}d_{ijt} \\ & + \sum_{i=1}^{m}\sum_{j=1}^{2}\frac{c_{ij}^{t1}(1-d_m)}{\left(1-k_j^a\right)}d_{ijt} + \sum_{i=1}^{m}\sum_{j=1}^{2}\left(c_{ij}^m d_m + \frac{c_{ij}^m(1-d_m)}{\left(1-k_j^a\right)\left(1-\lambda_j^a\right)}\right)d_{ijt} \\ & + \sum_{i=1}^{m}\sum_{j=1}^{2}\left(c_{ij}^f + c_{ij}^p\right)y_{ij} + \left(1 - y_t\frac{y_{ijt}-y_{ij}}{y_{ijt}}\right)c_{ij}^v y_{ijt} \\ & + \sum_{i=1}^{m}\sum_{j=1}^{2}\left(1-\lambda_j^b\right)c_{ij}^b d_{ijt} + \sum_{i=1}^{m}\sum_{j=1}^{2}c_{ij}^{t2}\left(t_{ijt} + y_t\left(y_{ijt}-y_{ij}\right)\right) \\ & - \sum_{i=1}^{m}\sum_{j=1}^{2}\left(1-k_j^b\right)c_{0j}^m\left(t_{ijt} + y_t\left(y_{ijt}-y_{ij}\right)\right) \end{aligned}\right] \tag{12}$$

$$\begin{aligned} Z_{ft} = {} & \sum_{i=1}^{m}\sum_{j=1}^{2}\left(1-k_j^b\right)c_{0j}^m\left(t_{ijt} + y_t\left(y_{ijt}-y_{ij}\right)\right) + \sum_{j=1}^{2}\left(c_{0j}^f + c_{0j}^p\right)y_{0j} \\ & + \left(1 - y_t\frac{y_{0jt}-y_{0j}}{y_{0jt}}\right)c_{0j}^v y_{0jt} - \sum_{j=1}^{2}\eta\gamma_j\left(t_{0jt} + y_t\left(y_{0jt}-y_{0j}\right)\right)\left(c_{0j}^e - c_{0j}^s\right) \end{aligned} \tag{13}$$

$$\sum_{j=1}^{2}y_{ijt}=\sum_{j=1}^{2}\left(1-\lambda_j^b\right)d_{ijt}+\sum_{j=1}^{2}y_{ij(t-1)}\left(1-y_{(t-1)}\frac{y_{ij(t-1)}-y_{ij}}{y_{ij(t-1)}}\right)-\sum_{j=1}^{2}t_{ijt} \tag{14}$$

$$\sum_{j=1}^{2}y_{0jt}=\sum_{i=1}^{m}\sum_{j=1}^{2}\left(1-k_j^b\right)\left[t_{ijt}+y_t\left(y_{ijt}-y_{ij}\right)\right]+\sum_{j=1}^{2}y_{0j(t-1)}\left(1-y_{(t-1)}\frac{y_{0j(t-1)}-y_{0j}}{y_{0j(t-1)}}\right)-\sum_{j=1}^{2}t_{0jt} \tag{15}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{2}\sum_{t=1}^{12}\left(1-\lambda_j^b\right)d_{ijt}=\sum_{i=1}^{m}\sum_{j=1}^{2}y_{ij12}+\sum_{i=1}^{m}\sum_{j=1}^{2}\sum_{t=1}^{12}t_{ijt}+\sum_{i=1}^{m}\sum_{j=1}^{2}\times\sum_{t=1}^{12}y_t\left(y_{ijt}-y_{ij}\right)-\sum_{i=1}^{m}\sum_{j=1}^{2}s_{ij}^s \tag{16}$$

$$\sum_{i=1}^{m}\frac{d_{ijt}}{\left(1-\lambda_j^a\right)\left(1-k_j^a\right)}\le g_{jt}, j=1,2; t=1,2,\cdots 12 \tag{17}$$

$$\sum_{j=1}^{2}d_{ijt}\le g_{it}, i=1,2\cdots m; t=1,2,\cdots 12 \tag{18}$$

$$\sum_{j=1}^{2}\left(1-\lambda_j^b\right)d_{ijt}\le s_i,\ i=1,2\cdots m; t=1,2,\cdots 12 \tag{19}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{2}\left(1-k_j^b\right)t_{ijt}\le s_0\ , t=1,2,\cdots 12 \tag{20}$$

$$\sum_{j=1}^{2}t_{0jt}\ge d_{0t}, t=1,2,\cdots 12 \tag{21}$$

$$\sum_{i=1}^{m}\left(1-\lambda_j^a\right)d_{ijt}\ge 0, j=1,2; t=1,2,\cdots 12 \tag{22}$$

Eqs. (10)–(13) are the objective functions, where Eq. (10) represents overall objective function of the model, aiming to minimize the difference between the expected cost and income of the agricultural and forestry biomass power generation supply chain for each period, and Eqs. (11)–(13) represent the differences between the expected costs and incomes of farmers, acquisition stations, and power plants, respectively. Eq. (14) represents the inventory balance constraint for the collection station. Eq. (15) represents the inventory balance constraint for the power plant. Eq. (16) states that the total amount of biomass fuel transported from the acquisition station to the power plant in a year is equal to the amount of biomass fuel received by the power plant. Eq. (17) limits the maximum collection quantity of biomass fuel. Eqs. (18) and (19) limit the maximum collection and preprocessing capacity of each acquisition station. Eq. (20) limits the maximum receiving capacity of the power plant. Eq. (21) limits the minimum required amount of biomass fuel for power generation at the power plant. Eq. (22) represents the seasonal entry limit of biomass fuel into the acquisition station warehouse.

The inventory balance constraints for the acquisition station and power plant in the first period are affected by the initial safe inventory, and are expressed as Eqs. (23) and (24).

$$\sum_{j=1}^{2}y_{ij1}+\sum_{j=1}^{2}t_{ij1}=\sum_{j=1}^{2}\left(1-\lambda_j^b\right)d_{ij1}+\sum_{j=1}^{2}s_{ij}^s \tag{23}$$

$$\sum_{j=1}^{2}y_{0j1}+\sum_{j=1}^{2}t_{0j1}=\sum_{i=1}^{m}\sum_{j=1}^{2}\left(1-k_j^b\right)t_{ij1}+\sum_{j=1}^{2}s_{0j}^s+\sum_{i=1}^{m}\sum_{j=1}^{2}y_1\left(y_{ij1}-y_{ij}\right) \tag{24}$$

4. Case study

4.1. Parameter settings

In this study, for a 30MW biomass power plant, the ratio of forestry biomass to agricultural biomass is 8:2 annually. The annual operating time is 7200 h, and the overall efficiency of power generation is 19 % [31]. To more intuitively reflect the impact of supply quantity, procurement price, and inventory quantity of biomass fuel in the power generation supply chain on the final income of farmers, traders, and power plants, the following will perform data simulation on the model built in the previous text, with some parameters as shown in Tables 2–5:

The residual value of the scrapped equipment and the daily maintenance cost of the equipment are calculated at 5 % of the purchase price [24]. In the treatment of loading and baling costs, assuming they are equivalent. The working hours of each baler and the operator are synchronized, working 8 h a day. In the loading stage, in addition to one person operating the grass grabbing machine, one person is required to carry out loading and site sorting.

The primary transportation is completed by tractors. Assuming that the acquisition station is evenly distributed, the collection range of biomass can be regarded as a circular area centered on the acquisition station with a radius of R. Based on geometric derivation, the average collection distance of primary transportation is 2/3R [37]. The acquisition station collects biomass at a field and forest product processing plant with a radiation radius of about 10km [36]. The average resource density of agricultural biomass is 88.55$t{\cdot}km^{-1}$ [33]. The secondary transportation uses large trucks for transportation, and the acquisition stations are scattered around the power plant, about 15~50km [35].

The height of the warehouse of the acquisition station is 7 m, of which 40 % is the roadway. When stored, agricultural biomass is packaged in bales. The size of each bundle is 1.5m×1.0m×0.9m, the weight is 260kg and the volume is 0.192$t{\cdot}m^{-3}$ [24]. The actual capacity utilization rate is 70 %. The accumulation weight of forestry biomass is about 0.4$t{\cdot}m^{-3}$ [31]. The accumulation utilization coefficient is 80 %. When stored in power plants, agricultural biomass is stored in closed warehouses. The pile height is 7m, and 40 % is roadway. and the actual storage capacity utilization rate is 70 %. Forestry biomass often exists in open field. The accumulation utilization coefficient is 80 %.

In the equal leadership model, the acquisition station acquires 180 $CNY{\cdot}t^{-1}$ of forestry biomass and 160 $CNY{\cdot}t^{-1}$ of agricultural biomass [24,38], while in the broker-led model, It costs only 20 $CNY{\cdot}t^{-1}$ to acquire biomass from farmers and processing plants. The acquisition of forestry biomass by power plants is 350 $CNY{\cdot}t^{-1}$ and that of agricultural biomass is 330 $CNY{\cdot}t^{-1}$ [24,38].

4.2. Selection of model

The profits of farmers, acquisition stations and power plants are affected by the cyclicality of biomass supply. The 1-3 and 5-7 periods are the agricultural biomass supply period, and the two biomasses of agriculture and forestry are purchased. Other periods are supply breaks, and farmers only collect forestry biomass. The advantages and disadvantages of the equal leadership model and broker-led model in different periods are shown in Fig. 3. The upper and lower parts are the profit line charts of the equal leadership model and the broker-led model respectively. The specific numerical changes can be referred to Tables 6 and 7.

As shown in Fig. 2, Tables 6 and 7, in the equal leadership model, farmers ' profits are maintained at about 3.35 million CNY in the 1-3 and 5-7 periods. The 4th and 8th periods beat. Other periods fluctuate around 2.68 million CNY. The profit of the acquisition station decreased from 930,000 CNY to 420,000 CNY in the 1-3 and 5-7 periods. It rises in the 4th and 8th periods, and fluctuates around 2.3 million CNY in other periods. The profit of the power plant is stable at 6million CNY in the 1-3

Table 2
Parameter assignment of model in preprocessing stage.

Parameter		Value			Refs.
		Baling Machine	Grass Grabbing Machine	Crusher	
The amount of biomass processed per machine per day	$Q(t)$	20.00	32.00	32.00	[32,33]
The daily wage of each operator	$p(CNY)$	200.00	200.00	200.00	Field Research
The daily fuel consumption of each machine	$q(L)$	21.60	20.00	22.40	[32,33]
Diesel prices	$p_o(CNY{\cdot}L^{-1})$	7.55	7.55	7.55	Average annual price in 2023
Purchase price of each equipment	$p_g(CNY)$	48,000.00	29,000.00	8000.00	[32,33]
Depreciation age	$t_p(y)$	15.00	12.00	10.00	[32,33]

Table 3
Parameter assignment of model in transportation stage.

Parameter		Value		Refs.
		Large Truck	Tractor	
No-load fuel consumption	$q_k(kg{\cdot}kwh^{-1})$	0.30	0.24	[24, 33]
Full load fuel consumption	$q_m(kg{\cdot}kwh^{-1})$	0.40	0.28	[24, 32]
Power-to-load ratio (power/ load)	$N_m(kw{\cdot}t^{-1})$	6.10	9.10	[24, 34]
Diesel density	$\rho_o(kg{\cdot}L^{-1})$	0.84	0.84	[35, 34]
No-load average driving speed	$v_k(km{\cdot}h^{-1})$	45.00	25.00	[24, 36]
Average speed at full load	$v_m(km{\cdot}h^{-1})$	35.00	20.00	[24, 36]

Table 4
Parameter assignment of model in storage stage.

Parameter		Value		Refs.
		Acquisition Station	Power Plant	
Annual fixed cost per unit area	$f_{Fi}(CNY{\cdot}m^{-2})$	3.54	3.54	[31, 24]
Depreciation age	n_{ci}	20.00	20.00	[24, 36]
Utilization ratio of roadway	$\alpha_i(\%)$	0.40	0.40	[31, 36]
Unit area cost (shed)	$P_{Fi1}(CNY{\cdot}m^{-2})$	19.50	64.00	[31, 35]
Unit area cost (open)	$P_{Fi2}(CNY{\cdot}m^{-2})$	–	28.00	[31]
Warehouse variable cost	$c^v_{ij}(CNY{\cdot}t^{-1})$	27.90	32.42	[31]

Table 5
Parameter assignment of model in power generation stage.

Parameter		Value		Refs.
		Forestry Biomass	Agricultural Biomass	
Biomass loss rate in primary transport	$k^a_j(\%)$	6.00	6.00	Field Research
Biomass loss rate in secondary transport	$k^b_j(\%)$	2.00	2.00	[35,36]
Preprocessing rate in the field	$\lambda^a_j(\%)$	0.00	4.00	[36]
Preprocessing rate in the acquisition station	$\lambda^b_j(\%)$	7.50	0.00	Field Research
Conversion rate of biomass quantity into electricity	$\gamma_j(kwh{\cdot}t^{-1})$	5.20×10^3	$4.62{\times}10^3$	[31,24]
Low heat value of pull	$L_j(kJ{\cdot}kg^{-1})$	18,709.25	16,640.00	[31,24]
Unit cost of biomass power generation	$c^s_{0j}(CNY{\cdot}kwh^{-1})$	0.29	0.12	[38,24]

and 5-7 periods. The rest of the period is about 1.65million *CNY*. The total profit of the whole supply chain decreased slightly from 6.92million *CNY* to 6.37million *CNY* in the 1-3 and 5-7 periods. The rest of the period rose from 6.38million *CNY* to 6.79million *CNY*.

However, in the broker-led model, farmers ' profits fluctuate between 35 and 50million *CNY*, which is significantly lower than the multi-agent model. The profit of the acquisition station in the 1-3 and 5-7 periods decreased from 3.76 million *CNY* to 3.23 million *CNY*. The 4th and 8th periods jumped to 4.6 million *CNY*, and other periods fluctuated around this. The profit fluctuates greatly, which is significantly higher than the multi-agent model. The profit of the power plant is basically maintained between 1.65 and 2.62 million *CNY*. The total profit of the whole supply chain is consistent with the multi-agent model.

In summary, in the equal leadership model, the profits of each subject are not much different. Among them, farmers have the highest profits. The profit of the acquisition station is low. In the broker-led model, the profit of the power plant remains unchanged. The profit of the acquisition station has increased significantly. Farmers ' profits become smaller. Under the two modes, the profit of each subject changes greatly, but the overall profit of the supply chain remains unchanged. It shows that different models only affect the profit distribution of supply chain participants, and have no effect on their overall income. The broker-led model transfers the responsibility of farmers ' collection and transportation to the acquisition station. Although the cost of the acquisition station increases, the purchase price of raw materials decreases. Farmers do not have to bear the responsibility of collecting and transporting while obtaining income. The broker-led model has not changed the overall efficiency. However, this distribution model enhances the rights and interests of the acquisition station and reduces the burden on farmers. More conducive to the stable operation of the supply chain.

4.3. Comparison of inventory optimization results

The optimized warehouse area of the acquisition station and the power plant is smaller than the unoptimized warehouse area. The warehouse operation cost is mainly composed of inventory fixed cost and inventory variable cost. The fixed cost of inventory is mainly related to the area of warehouse land, which decreases with the decrease of warehouse land area. The variable cost of inventory is only related to the amount of inventory, which increases with the increase of inventory in each period. The warehouse land and warehouse operation cost before and after optimization are shown in Table 8 below.

Table 6
Changes in biomass profit across different periods in the equal leadership model.

Period \ Profit	Farmers (Equal Leadership Model)	5 Acquisition Stations (Equal Leadership Model)	Power Plant (Equal Leadership Model)	Supply Chain (Equal Leadership Model)
1	336. 65	93. 63	262. 71	692. 99
2	332. 55	86. 35	262. 34	681. 23
3	336. 96	66. 85	261. 96	665. 77
4	269. 08	230. 30	168. 79	668. 17
5	334. 57	67. 99	260. 96	663. 53
6	335. 04	55. 03	260. 59	650. 66
7	334. 34	42. 89	260. 22	637. 45
8	268. 98	202. 43	167. 04	638. 45
9	266. 81	215. 99	166. 42	649. 23
10	265. 50	228. 68	165. 80	659. 98
11	268. 18	235. 87	165. 17	669. 22
12	268. 20	246. 43	164. 55	679. 18

Table 7
Changes in biomass profit across different periods in the broker-led model.

Period \ Profit	Farmers (Broker-led Model)	5 Acquisition Stations (Broker-led Model)	Power Plant (Broker-led Model)	Supply Chain (Broker-led Model)
1	54. 22	376. 06	262. 71	692. 99
2	53. 66	365. 23	262. 34	681. 23
3	54. 35	349. 46	261. 96	665. 77
4	35. 59	463. 79	168. 79	668. 17
5	53. 93	348. 63	260. 96	663. 53
6	53. 90	336. 17	260. 59	650. 66
7	53. 86	323. 37	260. 22	637. 45
8	35. 58	435. 83	167. 04	638. 45
9	35. 29	447. 51	166. 42	649. 23
10	35. 12	459. 06	165. 80	659. 98
11	35. 47	468. 58	165. 17	669. 22
12	35. 48	479. 16	164. 55	679. 18

By comparing the warehouse land and warehouse operation cost before and after optimization, it is found that the optimized warehouse covers an area of 5.63 hm^2, which is 75.99 % less than the unoptimized warehouse. The significant reduction in the area of warehouse land reduces the operating cost of the warehouse. The operating cost of the optimized warehouse scale saves 9.77 % compared with the unoptimized warehouse operating cost, saving about 850,000 *CNY* per year, as shown in Fig. 3.

5. Sensitivity analysis

Inventory cost is composed of fixed cost and variable cost. Fixed inventory cost is directly related to the actual storage area of the warehouse. The variable cost of inventory is only related to the actual amount of incoming and outgoing inventory, and is affected by both supply and demand. In the case of constant demand, it is directly affected by supply. In the broker-led model, inventory changes are discussed by regulating supply and storage space.

5.1. Sensitivity analysis of storage parameters of acquisition station

5.1.1. Sensitivity analysis of multi-biomass storage parameters

In Scenario A, the area occupied by the biomass acquisition station is the baseline. In Scenario B, the area is reduced by 25 %. Scenario C and Scenario D are reduced by 50 % and 75 % respectively. Throughout all these scenarios, the minimum area required for safe storage is maintained.

(1) Changes in inventory costs

The three-dimensional histogram of the inventory cost of the power plant with the period change and the line chart of the inventory cost of 5 acquisition stations with the period change under different warehouse area scenarios are shown in Fig. 4.

As shown in Fig. 3, compared with Scenario A, the inventory costs of acquisition stations under Scenarios B, C and D are reduced by 4 %, 7 % and 11 % respectively. With the gradual reduction of the warehouse area

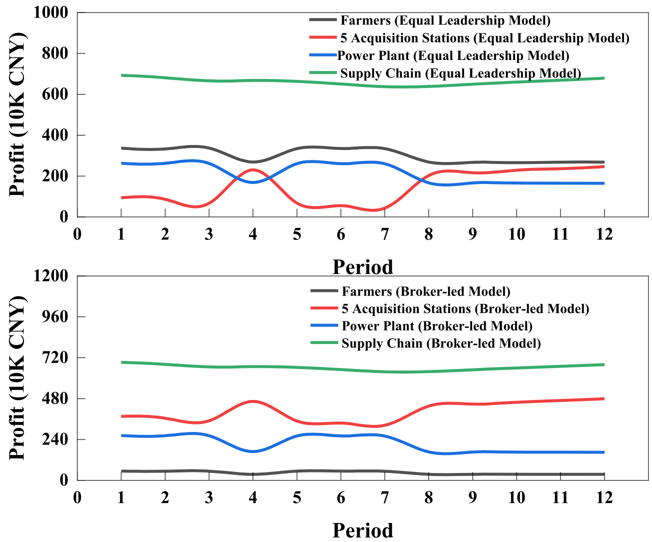

Fig. 2. Changes in biomass profit across different periods under two models.

Table 8
Warehouse land and operating costs.

	Warehouse land (hm^2)	Operating costs (10 K *CNY*)
Unoptimized the power plant warehouse	3.47	201.02
Unoptimized the acquisition station warehouse	20.01	659.52
Total	23.47	860.54
Optimized the power plant warehouse	0.83	184.99
Optimized the acquisition station warehouse	4.81	591.45
Total	5.63	776.44

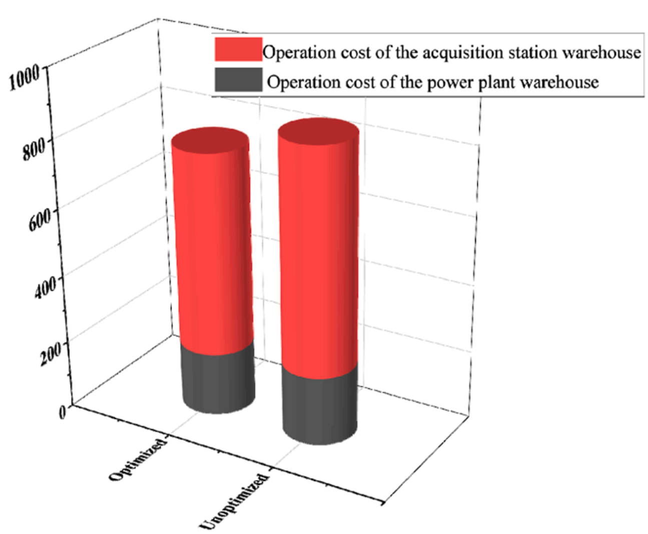

Fig. 3. Warehouse operation cost analysis.

of the acquisition station, the inventory cost of the power plant remains unchanged, while the inventory cost of the acquisition station shows a slight downward trend. This shows that reducing the area of the acquisition station within a reasonable range can reduce the construction and maintenance costs of the warehouse, thereby reducing the inventory cost without affecting the actual storage capacity and inventory management needs of the warehouse.

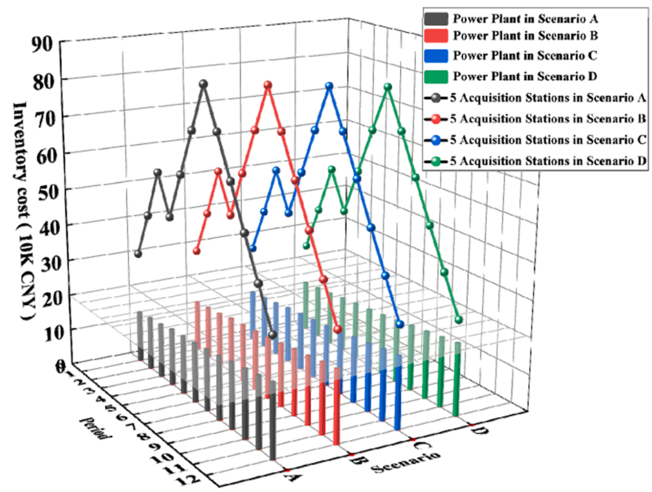

Fig. 4. The change of inventory cost when the warehouse area of acquisition station changes.

(2) Changes in profit

Under different warehouse area scenarios, the top layer is the line chart of the profits of the 5 acquisition stations changing with the period. The middle layer is the line chart of the profit of the power plant over the period. At the bottom is the line chart of farmers' profits over time, as shown in Fig. 5.

As shown in Fig. 5, from Scenario A to Scenario D, the profits of farmers and power plants remain unchanged, while the profits of acquisition stations increase slightly. Compared with scenario A, the profit of the acquisition station in scenario B, C and D increased by 0.47 %, 0.94 % and 1.41 % respectively. The reason for this trend is that farmers' income mainly comes from the sale of biomass raw materials and does not involve storage, so their profits are not affected by storage adjustments. By reducing the area of the warehouse, the acquisition station reduces the fixed cost expenditure and directly increases its profit. There is no excess inventory in the acquisition station to the power plant, and the inventory of the power plant does not change. As the core subject of the supply chain, the reasonable control of the inventory scale of the acquisition station can promote the stability and economy of the supply chain.

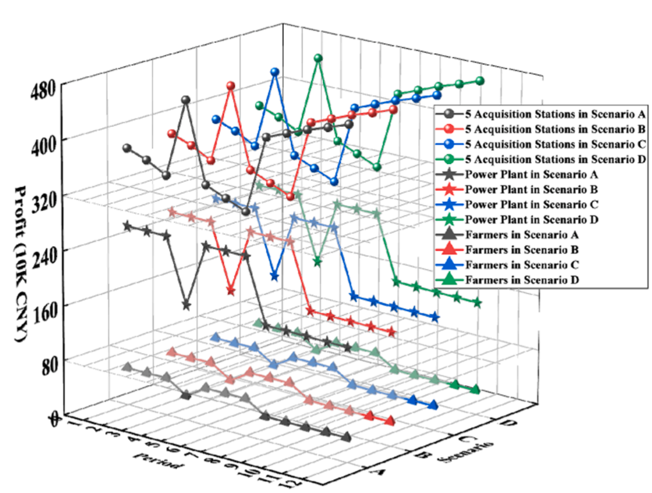

Fig. 5. Profit changes when the warehouse area of the acquisition station changes.

5.1.2. Sensitivity analysis of single biomass storage parameters

In the acquisition station, the two types of biomass are stored in different reservoir areas, so there is an option to reduce the warehouse area of only one type of biomass. Scenario A refers to the difference between the reduction of the area of a single biomass (forestry biomass or agricultural biomass) warehouse in the acquisition station by 25 % and the reduction of the area of the overall warehouse in the acquisition station by 25 %. Scenario B and scenario C are reduced by 50 % and 75 % respectively.

(1) Changes in the inventory cost of the acquisition station

When the upper, middle and lower layers correspond to scenarios C, B and A respectively, the difference in inventory cost between the adjustment of the area of a single biomass warehouse at the acquisition station and the adjustment of the overall warehouse area changes with the period, as shown in Fig. 6.

As shown in Fig. 6, under different scenarios, the inventory cost difference caused by only reducing the area of forestry biomass warehouse is always greater than the inventory cost difference caused by reducing the area of agricultural biomass warehouse. As the scenario gradually progresses from A to C, the adjustment of forestry biomass warehouse area produces an average of 51 % more inventory cost difference per period than agricultural biomass. This shows that forestry biomass has a high occupancy rate in storage space, resulting in less waste of storage space. Priority should be given to reducing the storage area of agricultural biomass in an appropriate amount, which can more effectively reduce space waste and inventory costs.

(2) Changes in the profit of the acquisition station

When the upper, middle and lower layers correspond to scenarios A, B and C respectively, the profit difference of the adjustment of the area of a single biomass warehouse in the acquisition station and the adjustment of the overall warehouse area changes with the period, as shown in Fig. 7.

As shown in Fig. 7, from Scenario A to Scenario C, adjusting the area of forest biomass compared to adjusting the area of agricultural biomass, the profit per period is about 51 % less. Agricultural biomass is large in volume and small in density. Reasonable reduction of agricultural biomass storage area is more effective in reducing inventory costs and increasing profits. There is no need to reduce or abandon the storage space of forest biomass to avoid the imbalance of space distribution.

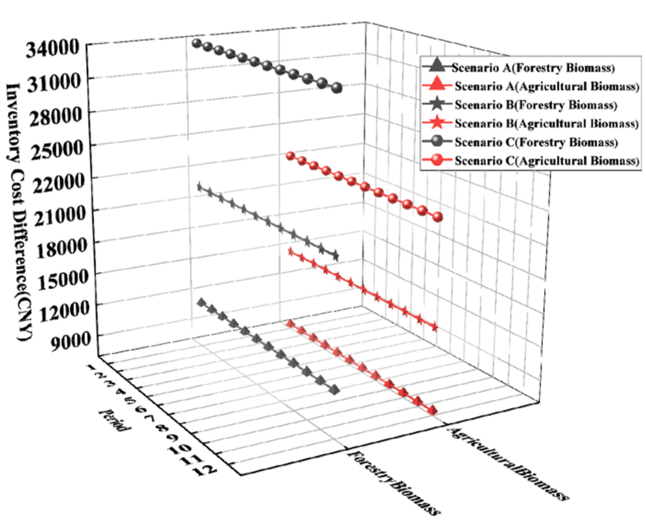

Fig. 6. The change of inventory cost difference in each period of acquisition station.

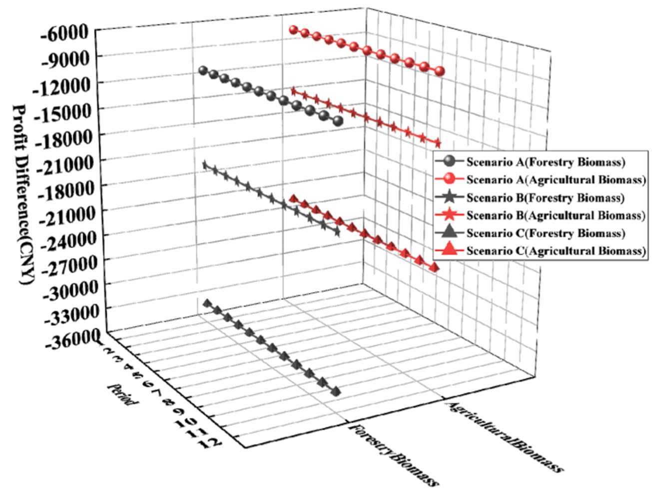

Fig. 7. The change of profit difference in each period of acquisition station.

5.2. Analysis of supply quantities sensitivity analysis of supply parameters

5.2.1. Sensitivity analysis of multi-biomass supply parameters

The change of biomass supply directly affects the storage space demand, inventory cost and profit of the acquisition station. Scenario A is the original supply of biomass, and Scenario B is the original supply of biomass increased by 25 %. Scenario C is an increase of 50 %.

(1) Changes in inventory costs

The three-dimensional histogram of the inventory cost of the power plant with the period change and the line chart of the inventory cost of 5 acquisition stations with the period change under different supply scenarios are shown in Fig. 8.

From Fig. 8, it can be seen that from scenario A to scenario C, the inventory costs of the five acquisition stations increase rapidly. Compared with scenario A, the maximum increase of inventory cost in scenario C is even 936 %. However, the inventory cost of power plants only increased slightly from the sixth cycle of scenario C, which was 64 % higher than that of scenario A. Under the condition that the quantity of outgoing storage is unchanged, the increase of incoming storage will increase the inventory. The demand for storage space and the pressure of inventory management are also rising.

(2) Changes in profit

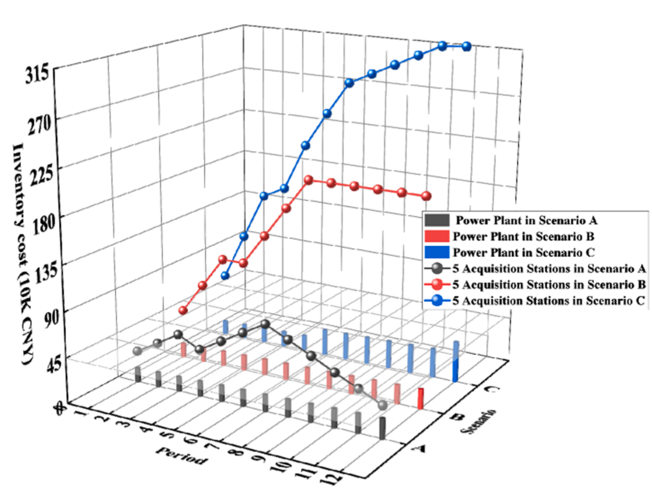

Fig. 8. Changes in inventory costs when supply changes.

In different supply scenarios, the top layer is a line chart of the profits of the 5 acquisition stations over the period. The middle layer is the line chart of the power plant profit with the change of the period; At the bottom is a line chart of farmers' profits over the period, as shown in Fig. 9.

In Fig. 9, from Scenario A to Scenario C, farmers ' profits continue to grow, and the profits of acquisition stations decline rapidly, while the profits of power plants remain basically unchanged except for fluctuations in individual cycles. Compared with Scenario A, the profit of farmers in Scenario B and Scenario C increased by 25 % and 50 % respectively, while the profit of acquisition stations decreased by 35 % and 54 % respectively. As farmers sell more biomass, the cost of stock at the acquisition station increases. After the inventory exceeds the space capacity of the acquisition station, the excess part is shipped to the power plant in advance, causing its profit fluctuation. The amount of biomass purchase should be reasonably planned according to actual demand to prevent inventory overhang caused by oversupply.

5.2.2. Sensitivity analysis of single biomass supply parameters

Agricultural and forestry biomass can be supplied separately, increasing the supply of only one biomass. Scenario A is the difference between a 25 % increase in the supply of single biomass (forestry biomass or agricultural biomass) and a 25 % increase in the supply of both biomasses. Scenario B increases by 50 %.

(1) Changes in the inventory cost of the acquisition station

When the upper and lower levels correspond to scenarios A and B respectively, the difference of inventory cost between the adjustment of single biomass supply and the adjustment of both biomass supplies changes with the period, as shown in Fig. 10.

It can be seen from Fig. 10 that the inventory cost difference caused by increasing the supply of agricultural biomass is large and the difference is negative. Compared with increasing the supply of forestry biomass, increasing the supply of agricultural biomass pays a lower inventory cost. Scenario A can pay up to 250 % less cost. The inventory cost paid less in the later stage of scenario B is even as high as 443 %. The storage demand of forestry biomass is relatively stable. Increasing the supply of agricultural biomass can better balance the liquidity of inventory and the change of demand, without increasing the storage cost excessively.

(2) Changes in the profit of the acquisition station

When the upper and lower layers correspond to scenario B and scenario A respectively, the profit difference between the adjustment of single biomass supply and the adjustment of both biomass supply changes with the period, as shown in Fig. 11.

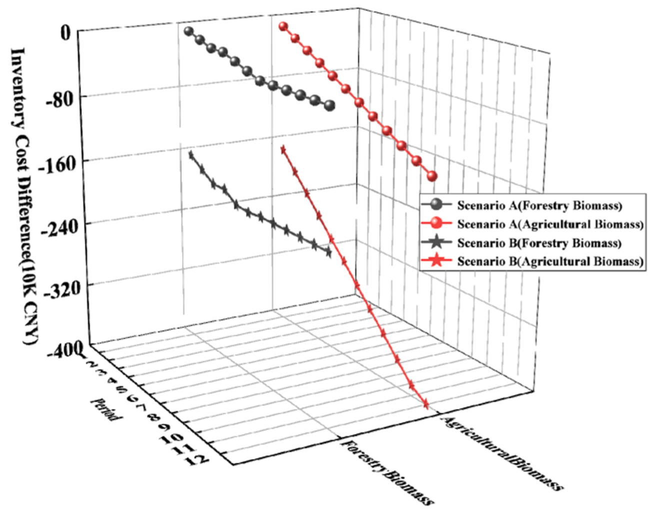

Fig. 10. The change of inventory cost difference in each period of acquisition station.

In Fig. 11, under different scenarios, the profit margin of each period brought by increasing the supply of agricultural biomass is large. In Scenario A, increasing the supply of agricultural biomass increases profits by 26 % to 322 % more than increasing the supply of forestry biomass. In scenario B, the profit is even as high as 533 %. Agricultural biomass is more adapted to the demand fluctuation of the supply chain, and the corresponding profit is more profitable. By reasonably adjusting the supply structure of agricultural and forestry biomass, the cost can be controlled and the income can be increased, and the inventory optimization of the supply chain can be realized.

6. Discussion

The existing research rarely considers the inventory replenishment problem in the biomass power generation industry. This paper innovatively combines the characteristics of agricultural and forestry biomass and adjusts the biomass supply structure to study the inventory optimization of the supply chain. Different from the previous research on single biomass or fixed inventory parameters, this paper comprehensively considers the coordinated supply of agricultural and forestry biomass and the dynamic changes of multi-period inventory, which

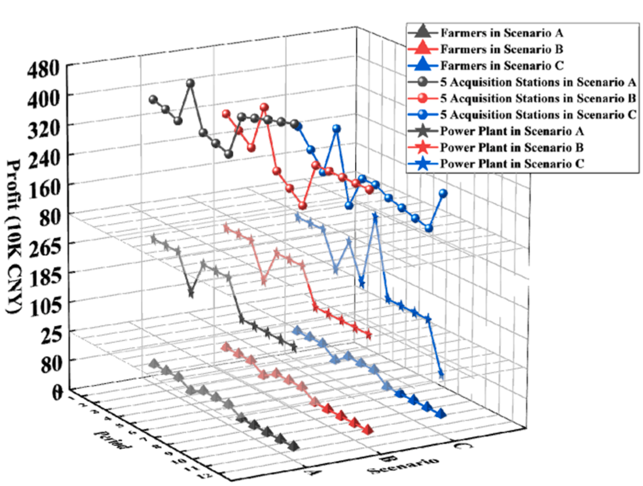

Fig. 9. Profit changes when supply changes.

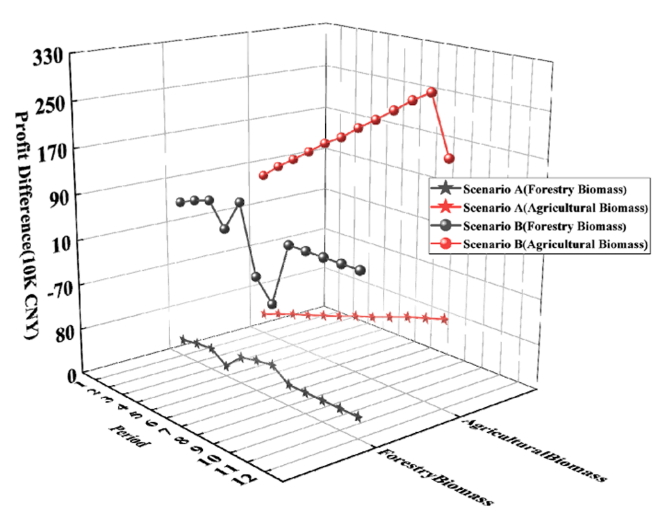

Fig. 11. The change of profit difference in each period of acquisition station.

broadens the scope and depth of application of inventory optimization research. By introducing the mixed integer programming (MILP) model, the optimization model of biomass power supply chain is successfully constructed, which accurately captures the dynamic inventory characteristics of multi-period and multi-node supply chain, and significantly improves the warehouse area and operation cost.

After optimization, the warehouse area is reduced by 75.99 %, the operating cost decreased by 9.77 %, and the average annual saving was about 850,000 *CNY* These results not only verify the efficiency and practical value of the model, but also provide accurate decision-making basis for power generation enterprises to cope with seasonal demand fluctuations. Sensitivity analysis further shows that reasonable reduction of warehouse area and increase of supply can effectively optimize inventory management strategy. In particular, the space utilization rate of agricultural biomass is low and the mobility is strong. By reducing idle space and optimizing supply allocation, the inventory cost can be effectively reduced. Forestry biomass has more spatial advantages and requires careful management and coordination of supply.

This study extends the research on inventory optimization of cooperative supply of agricultural and forestry biomass and makes up for the gap in the existing literature on supply structure adjustment. MILP model captures dynamic inventory characteristics and provides a new idea for complex supply chain optimization. The research results not only provide theoretical support for power generation enterprises to formulate more refined inventory management strategies, but also help enterprises to realize rational resource allocation in the face of seasonal demand fluctuations.

7. Conclusion

Due to the single supply of biomass, power plants often suffer from fuel shortage and loss. This paper considers the coordinated supply of agricultural and forestry biomass to alleviate the shortage problem. Taking the three-stage biomass supply chain consisting of farmers, brokers and power plants as the research object, the dynamic changes of inventory in acquisition stations and power plants were analyzed according to the seasonal characteristics of biomass. Based on mixed integer linear programming, the multi-cycle inventory optimization model of agricultural and forestry biomass power supply chain was constructed. Taking a 30MW power plant as an example, the results show that the broker-led model is conducive to the long-term stable development of the supply chain. After optimization, the warehouse of the power plant covers an area of 0.83 hm^2, and the five acquisition stations cover a total area of 4.81 hm^2 Compared with the non-optimized state, the operating cost is saved by 9.77 %, saving about 850,000 *CNY* per year. Sensitivity analysis shows that appropriately reducing the warehouse area and increasing the biomass supply can reduce the inventory cost and increase the profit of the acquisition station. By adjusting the supply structure and optimizing the multi-period dynamic inventory, this study achieves the dual goals of income maximization and inventory optimization, and provides a theoretical basis for other countries to formulate cooperative supply and resource allocation optimization policies. However, this paper only starts from economic benefits, and social benefits and environmental benefits should be further considered into the optimization model in the future.

CRediT authorship contribution statement

Zhenfeng Wang: Writing – review & editing, Writing – original draft, Resources, Methodology, Funding acquisition. **Yanru You:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Zhanwu Wang:** Writing – review & editing, Formal analysis. **Heng Wang:** Writing – review & editing, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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