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Optimisation of Logistic Model Using Geographic Information Systems: A Case Study of Biomass-based Combined Heat & Power Generation in China

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ABSTRACT

Biofuel large-scale application was constrained due to cost control. In order to reduce biofuel production cost and increase profitability, long-term strategy (strategic) and medium-term strategy (tactical) combined logistic model were assessed in this study. Geographic information system has been integrated into logistic model to minimize the effect of uncertainty on logistic modelling accuracy, with aims of transferring uncertainty problem to be certain. Combined heat and power generation plant as a case study present in logistic model, which provide a method in plant location and capacity selection criteria; logistic model design; and interaction between logistic model and local conditions. The logistic plan with compression as a pre-treatment technology has the optimal profitability performance, their properties affect the selection of the transport route, especially optimal for a lower availability of agricultural residues. With increased availability, torrefaction turns to more efficiency biomass pre-treatment technology due to storage cost significant reduction. With geographic information system transportation route assistance, logistic model transportation cost and CO_2 emission has a 0.02% and 0.01% reduction.

1. Introduction

At present, diesel and gasoline represented fossil fuel has been widely applied in transportation, agricultural and industrial sector for energy supply. To balance the increase of fuel demand and the sustainable development, biofuel was seen as a sought solution. Biofuel refers biomass produces primary fuels, including liquid, gaseous and solid fuels, such as ethanol, biogas and biochar [1]. In spite of biofuel is a renewable and biodegradable fuel that has potential to replace fossil fuel, its production has been very limited. One of the biggest considerations is the cost control. According to Ekşioğlu's estimation [2], the cost of biomass supply accounts for approximately 20-40% of the total cost of biofuel production. To further reduce the biofuel production cost, it is imperative in designing low-cost and high-efficiency supply chain coordination and management mechanisms. To develop cost-effective supply chain models, decision making strategies and levels are indispensable, which involve long-term strategy at a strategic decision making level, medium-term strategy at a tactical decision making level, and short-term decision-making strategy at an operational level [3]. Fig. 1 describes the decision making at each level of biomass supply chain and its main objective.

Tactical decision-making level plays a crucial role in connecting long-term and short-term decision-making strategy. Furthermore, tactical decision-making related biomass logistics cost shares the largest part of supply cost, about 90% [2]. It is therefore important to develop a highly efficient biomass logistic model. The structure of biomass supply chain varies depending on biomass type, conversion technologies and bioproducts characterization. The generic supply chain of biomass from fields to biorefinery plant contribute by numbers of entities which encompass field, processing depot and biorefinery plant [4]. These entities contribute to six main sub-process of biomass supply chain, which includes harvesting, collection, transportation, pre-treatment, storage

Abbreviations: GIS, Geographical Information Systems; PI, Profitability Index; NPV, Net Present Value; LP, Linear Programming; MILP, Mixed-Integer Linear Programming; NLP, Non-Linear Programming; MINLP, Mixed Integer Non-Linear Programming; CHP, Food And Agriculture Organization Statistical Database; TGA, Thermogravimetric Analyser; CHN analyser, Carbon Hydrogen and Nitrogen Analyser.

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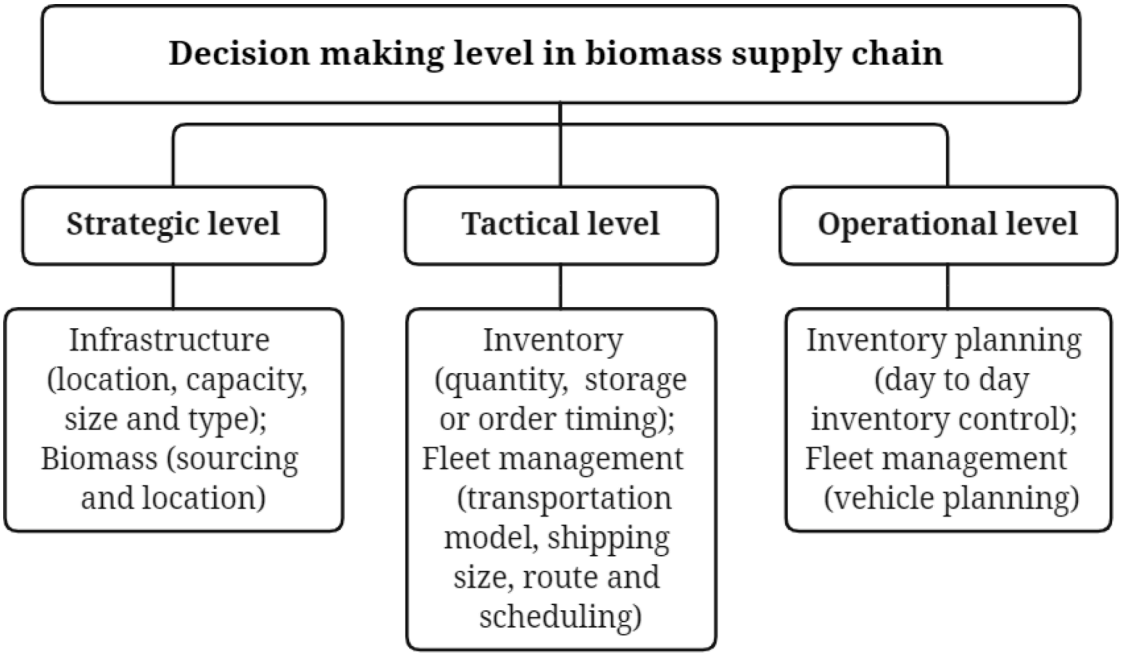

Fig. 1. Decision making level of biomass supply chain.

and handling.

In general, biomass harvesting and collection appear to consistently be moving toward high input, high yield processes that are heavily mechanized [5]. In biomass harvesting, machine collection rate should be taken account to biomass quantity estimation. It was suggested 10-20% biomass residues loss is expected in mechanism harvesting [6]. Biomass transportation is a significant component in biomass supply chain cost, energy use and CO_2 emission. Bussemaker et at. [7] simulated the lignocellulosic biomass supply chain process, they found that the transportation cost could account up to 20% of overall supply chain cost. Depending on feedstocks origins, transportation distance and local conditions (i.e., infrastructure construction and terrain restrictions), transportation modes (e.g., rail or truck) are different. While truck has been often considered as the primary mode in transportation for financial consideration as biorefinery operators often set a 50-mile biomass collection radius [8] [9].

Forms of pre-treatment may vary depending on biomass types and its application. For instance, in biomass power generation, in order to reduce transportation cost and increase supply chain efficiency, biomass feedstock is often required to increase its bulk density and reduce moisture [8]. The main objective of pre-treatment is to process low density and unstable biomass to be adequate for its transport and utilizations [10]. Various pre-treatment methods are available for deification such as pelletizing, briquetting, or cubing. In general, increasing higher bulk density needs a higher energy consumption and more complex operation process. Reasonable density can save not only the cost in energy consumption and transportation but also depot storage space.

Due to seasonal variations, biomass require storage for biorefinery plant all year around operation. Therefore, maintaining high quality and low dry matter losses are main task for biomass storage. Rentizelas et cl. [4] mentioned that high moisture is a crucial factor for maintaining biomass quality, and they pointed that the moisture content between 40% and 50% when biomass collected, while the safely storage moisture

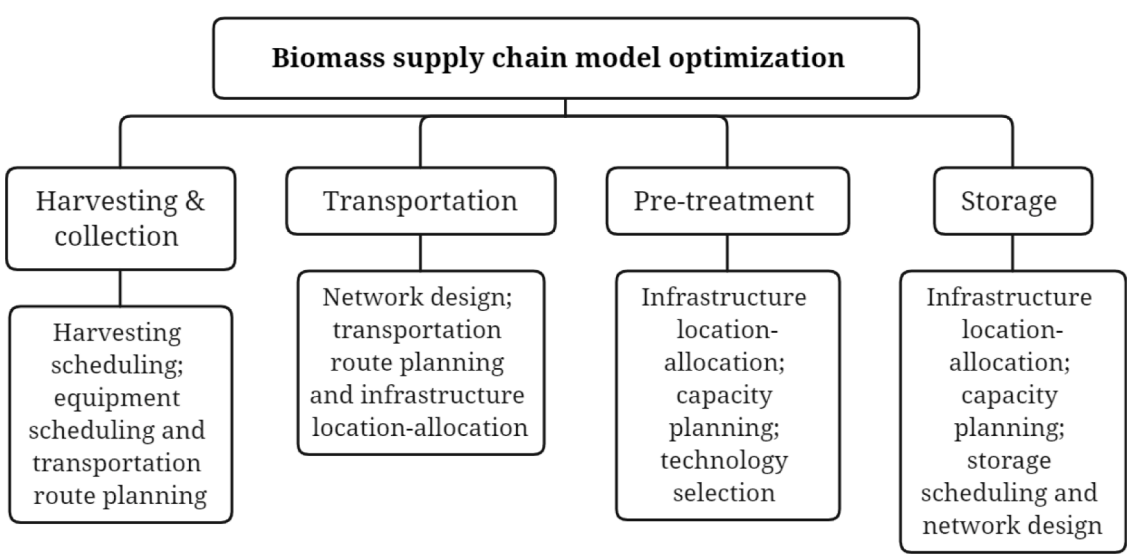

Fig. 2. Biomass supply chain model optimization research fields.

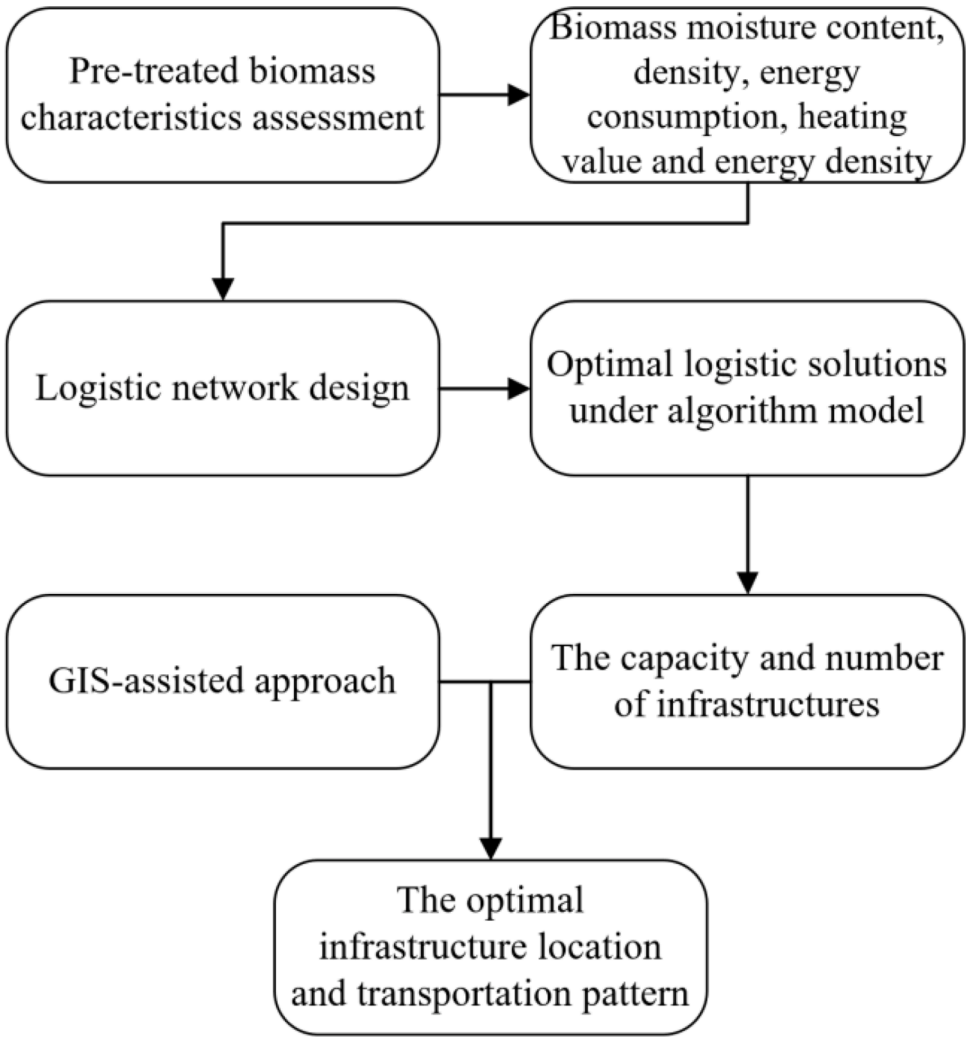

Fig. 3. The flow diagram of logistic network optimization.

content should maintain at 15% to 20%. A higher moisture content may result in quality degradation and microbes dangerous related human health crisis. Whilst biomass handling occurs at the process of biomass transferring from farm to vehicle, loading and unloading, where highly intensive labour and loading equipment may require.

The classic biomass supply chain optimization models can be summarized as network design optimization (applied in transportation process), scheduling optimization (applied in harvesting and collection, storage, and transportation), infrastructure location-allocation optimization (applied in pre-treatment and storage), transportation routing planning optimization (applied in harvesting and collection, and transportation) and technology selection optimization (applied in pre-treatment process) (shown in Fig. 2). Due to symbiosis between each process in supply chain, for instance, transportation optimization programming designing strategy can be extended to field in like location of storage and biomass collection strategy [11]. Various of studies optimize biomass supply chain from different viewpoints such as operational, tactical and strategic field which can be categorised as: mathematical optimization approach, heuristic approach, and IT-driven approach [12], among which mathematical programming plays domination status in supply chain model improvement [13].

Mathematical programming is the most common optimization approach in transportation planning, which including algorithms like linear programming (LP), mixed-integer linear programming (MILP), mixed integer non-linear programming (MINLP) and non-linear programming (NLP). Depending on objective functions, supply chain optimization can be classified to economic (e.g., maximize profit, minimize cost and maximize net present value), environmental (e.g., minimize CO_2 emission and minimize energy consumption) and social object (e.g., job opportunity and social impact) [14]. In general, biomass supply chain mathematical optimization could gain an exact optimal solution depending on objective function. However, with model algorithms complexity raise, the computational time increases exponentially [14]. Thus, a tread-off approach between optimal solution and computing time proposed. Heuristic algorithm related approaches have capable of computing complex problems in near optimum result in short time. Due to local condition restrictions, mathematical approach represented traditional algorithm optimization cannot reflect real solutions in decision making such as transportation issue. IT-driven approach is integrating various data and supporting application software to coordinate process in supply chain management [15, 16]. This approach significant increase the visibility throughout the supply chain. IT-driven approach representing by Geographical information system (GIS) has been widely applied in road network and biorefinery infrastructure location related problems, which enhance reliability of supply chain model and visibility of local conditions, such as road network, water flows, and administrative boundary.

At the present, most of optimization efforts were concentrated on the biomass economic performance as the objective function. To design a sustainable biomass supply chain, multiple objectives need to be considered. Svanberg et al. [17] analysed torrefaction (a biomass pre-treatment process) cost distribution under biomass logistic model.

They determined the optimal torrefaction configuration by minimize total cost. Roni et al. [18] optimized biomass logistic model assisting by GIS, which enhance 177.4% supply volume without increase feedstock delivery cost. Zahraee et al [19] developed a biomass dynamic simulation model to analyse the effect of transportation model on delivery cost and greenhouse gas emissions. Results showed that truck has lowest greenhouse gas emissions but highest delivery cost comparing with train. Salleh et al [20] improved biomass logistic model by GIS, which optimised biomass supply point, biomass processing facility and biomass demand centre. In spite of each biomass supply chain process has been detailed studied, research of integrating interconnected processes into a generic framework is rare. The optimum solution in one process might not the best option in another, which may cause further negative impact for others process. Thus, it is important to improve biomass supply chain efficiency by considering processes as a whole system for optimization. This work aims to reduce supply chain cost by long-term (strategic level) and medium-term (tactical level) decision making, which optimize biomass supply chain model (medium-term) and infrastructure location (long-term). To do that three step approaches included, firstly, a supply chain model (mathematical programming) is developed to assess the effect of pre-treatment technologies (shredding, compression and torrefaction) on supply chain cost (environmental sustainability and financial cost); secondly, a long-term decision making assisted by GIS is applied for determining infrastructure location; lastly, CHP production as a case study will be conducted towards building more efficiency and low cost industry, connecting both the long-term and the medium-term decision makings.

2. Methodology

The research of biomass logistic model optimization in this paper can be divided into three interconnected submodules, which involved in biomass characteristics assessment, logistic model establishment and GIS assisting optimization.

Biomass feedstocks (i.e., rice straw and corn stalk) characteristics were assessed experimentally, which are characterized with high moisture content and low buck density. In order to increase transportation efficiency and reduce total logistic cost, pre-treatment methods application in biomass logistics need to assessed, including feedstocks density, energy consumption, heating value, and CO_2 emission. Therefore, the effect of most common pre-treatment methods (shredding, compression and torrefaction) on biomass supply chain model will be investigated. To simulate logistic model as close to reality as possible, multiple factors need to conclude in logistic model. Depending on statistical data, GIS could plan the optimal biorefinery plant and storage depot capacity, location and distance, which constrains logistic model optimization range. Lastly, a case study of biomass CHP will be analysed. The flow diagram of biomass logistic model network design present in Fig. 3, where the methodologies of biomass feedstocks pre-treatment characteristics assessment present in section 2.1, logistic network design show in section 2.2, while, GIS-assisted approach display in section 2.3.

2.1. Assessment of pre-treated biomass characteristics

To design an efficiency supply chain network, cost-effective pre-treatment technology is desired. Gaining optimal pre-treatment technology applying in biorefinery industry, pre-treated biomass characteristics investigation needs to assess.

2.1.1. Biomass feedstock moisture content assessment

This experiment will be only tested with corn stalk and rice straw due to limitation of accessible material. The selected rice straw and corn stalk were harvested in north of China. To make sure uniformity of materials, this experiment chose to cut selected materials in length of 5cm. And then, for sample preparation, materials were weighted and replaced into oven dried to constant weight. The oven was calibrated to 105°C with a precision of ±2°C . All samples will be tested and recorded three times to make sure uniformity, only errors with ±2% can be determined as qualified data. Applying the average value of these results, the sample moisture content was determined.

2.1.1.1. Torrefied and raw material properties assessment. In order to obtain the optimal torrefied feedstock conditions (competitive low energy consumption and high energy density), the aim of this section is to investigate heating value, energy density and energy consumption of torrefied feedstocks and raw feedstocks.

The torrefaction system consist of nitrogen cylinder, rotameter, voltmeter, tube furnace, boat crucible and product gas treatment unit. The nitrogen flow was controlled by rotameter, and a voltmeter was used to measure the energy consumption during torrefaction tests. The tube furnace is equipped with a quartz tube and a temperature controller. Experimental samples were carried by a boat crucible, which is replaced in the middle of quartz tube. Three thermocouples were mounted in the inlet, the middle and outlet of the quartz tube to monitor the temperature changes. With assistance of a conical flask used as the waste gas treatment unit. Tars and exhaust gas that generated from torrefaction were eliminated and purified. To make sure result reliability, nitrogen leakage was tested before the experiments. Samples undergoing the same torrefaction conditions were repeated three times, and relative error of results between each run was less than 5%.

It was known that the final temperature, heating rate and residence time are significant factors in torrefaction tests. Thus, the effect of temperature to torrefaction products have been investigated at five different torrefaction temperature ranged from 220°C to 300°C with a fixed residence time of 30 mins, a heating rate of 20°C/min, and a nitrogen flow rate of 100 mL/min. Sample weight was recorded before and after each test. Each experiment was repeated three times to make sure the reliability of the test results.

The contents of carbon, hydrogen, sulphur and nitrogen were measured using a CHN Analyser, and the oxygen content was calculated by difference [142]. All experiments were run two times and averaged to compensate experimental reproducibility. The higher heating value was obtained from Eq. 1:

$$HHV = 0.3491X_C + 1.1783X_H + 0.1005X_S - 0.0151X_N - 0.1034X_O - 0.0211X_{ASH} \left[\frac{MJ}{kg}\right] \quad (1)$$

Where, X_i is the content of carbon (C), hydrogen (H), sulphur (S), nitrogen (N), oxygen (O) and ash in wt%.

2.2. Logistic network design

The objective of this model is to maximize profitability index (PI) value during whole supply chain period by maximize revenue and minimize cost, which includes the cost in collection, pre-treatment, transportation, storage and the revenue of profit. PI is applied in capital budgeting to measure the profitability of a project. The PI value can be indicate the paying back for every dollar invested [21]. Therefore, the PI value above 1 means a profitable case. At the meanwhile, CO_2 emissions during in the process of pre-treatment, transportation, feed handing and biorefinery will take account into supply chain model environmental assessment. depending on objective function (financial and environmental consideration), supply chain model will provide corresponding solution. By input biomass parameters (characteristics and distribution), the number and size of collection facilities and biorefinery plant can be identified.

Two variables contribute decision criteria of present supply chain model, which includes PI value and CO_2 emissions during supply chain processes. To evaluate project financial sustainability, net present value (NPV) and PI value are traditional evaluation factor that direct reflect

the profitability of business. The amount of CO_2 emission is evaluated supply chain whether sustainable project.

2.2.1. Supply chain mathematical model

The objective function of supply chain model is maximized profit by evaluate NPV and PI value , which shown in Eq. 2 and Eq. 3. Where,

$$NPV = \left(R_p - C_c - C_{mi} - C_{emi} - C_{fuli} - C_t - C_{s1} - C_{s3} - C_{ash} - C_{pm} - C_{ps}\right)D_f - \left(C_{pi} + S_s C_c + \frac{Q}{h\beta_i}C_{ei}\right) \tag{2}$$

$$PI = \frac{\left(R_p - C_c - C_{mi} - C_{emi} - C_{fui} - C_t - C_{si} - C_{s3} - C_{ash} - C_{pm} - C_{ps}\right)D_f}{C_{pi} + S_s C_c + \frac{Q}{h\beta}C_{ei}} \tag{3}$$

Where R_p is power plant revenue; C_c is biomass purchasing cost; C_{mi} is pre-treatment maintain cost; C_{emi} is pre-treatment employee's cost; C_{fuli} is pre-treatment fuel cost; C_t is transportation cost; C_{s1} is storage fixed cost; C_{s3} is storage flexible cost; C_{ash} is ash disposal cost; C_{pm} is power plant maintain cost; C_{ps} is salary and welfare cost; D_f is discounting coefficient; C_{pi} is power plant capital cost; S_s is storage area; C_c is storage construction cost; Q is the total amount of biomass for power generation; h is pre-treatment equipment working time; β_i is pre-treatment equipment working capability; C_{ei} is pre-treatment equipment capital cost.

2.2.2. Constraints

The mass balance must be satisfied at each process in supply chain model, which the total required biomass Q should equal to the following Eq. 4:

$$Q = n\pi r^2 \rho \tag{4}$$

Where, r is radius collection radius from field to depot; ρ is biomass distribution density; n is the number of depots.

According to Zhuang *et al* [22] residues collection radius should not 50km thus, therfore, the collection radius shown in Eq. 5. Where,

$$R = r + L2 \leq 50km \tag{5}$$

Where L2 is distance between depot and power plant.

For biomass availability consideration, the amount of total biomass in the selected area should not less than the amount of biorefinery plant minimal requirement. Therefore, the biomass refinery plant capacity constraints are expressed by Eq. 6. Where,

$$\frac{3.6 \times 10^3 P_n h}{\eta LHV_i} \leq \pi R^2 \rho \partial \tag{6}$$

Where P_n is power plant capacity; LHV_i is biomass lower heating value; η is power plant efficiency. ∂ is agriculture residues available collection index.

Biomass demand for operation is displayed in Eq. 7. Where,

$$Q_0 = \frac{3.6 \times 10^3 P_n h}{\eta LHV} = \pi R^2 \rho \partial \tag{7}$$

Due to biomass will loss during transportation and storage, the amount of actual requirement should higher than ideal demand. The total amount of required biomass is expressed in Eq. 8. Where,

$$Q = Q_0 1 + \mu(1 + M) = \pi R^2 \rho \partial \tag{8}$$

Where, μ is losses index; M is the moisture content of received residues.

2.2.3. Total cost for power generation

The total cost for power generation was contributed by biomass purchasing cost, pre-treatment cost, transportation cost, storage cost, ash cost and production cost. Shown in Eq. 9:

$$C_{total} = C_c + C_{pt} + C_t + C_s + C_{ash} + C_p \tag{9}$$

The cost of *pre-treatment* is present in Eq. 10. Where,

$$C_{pti} = C_{di} + C_{mi} + C_{emi} + C_{fuli} \tag{10}$$

Where C_{di} is pre-treatment Equipment cost.

Pre-treatment equipment cost is shown in Eq. 11. Where,

$$C_{di} = \frac{Q}{h_i \beta} C_{ei} \frac{(1 - RV_i)}{n_i} \tag{11}$$

Pre-treatment maintain cost is displayed in Eq. 12. Where,

$$C_{mi} = C_{omi} \frac{Q}{h\beta_i} C_{ei} h \tag{12}$$

Pre-treatment employees' cost in Eq. 13. Where,

$$C_{em1} = N_i \frac{Q}{h * \beta_i} C_{sal} \tag{13}$$

Pre-treatment fuel cost is shown in Eq. 14. Where,

$$C_{fuli} = O_{coni} \frac{Q}{\beta_i} C_{ful} \tag{14}$$

Transportation cost (Eq. 15) includes the cost from filed to collection point, the cost from collection point to power station and handing cost.

$$C_t = C_{t1} + C_{t2} + C_{t3} \tag{15}$$

Transportation cost from filed to depot is shown in Eq. 16. Where,

$$C_{t1} = \sum_{i=1}^{n} \iint^{\frac{\rho \partial \pi r^2}{\rho_1 V_v}} * P_t dr d\theta \tag{16}$$

Transportation cost from depot to power station is present in Eq. 17. Where,

$$C_{t2} = n \frac{\pi r^2 \rho}{\rho_i V_v} f L_2 P_t \tag{17}$$

Loading and unloading cost is displayed in Eq. 18.Where,

$$C_{t3} = 4 P_L Q \tag{18}$$

Storage cost involved fixed cost, facility capital cost and variable cost show in Eq. 19, where,

$$C_s = C_{s1} + C_{s2} + C_{s3} \tag{19}$$

which shows in the following:

Storage Fixed Cost is exhibited in Eq. 20. Where,

$$C_{s1} = \frac{Q}{\rho_i H} C_{sm} \tag{20}$$

Storage Facility Capital Cost is shown in Eq. 21. Where,

$$C_{s2} = S_s C_c \frac{(1 - RV_4)}{n_4} \tag{21}$$

Storage Variable Cost display in Eq. 22. Where,

$$C_{s3} = P_{os} Q \tag{22}$$

Ash disposal cost present in Eq. 23. Where,

$$C_{ash} = P_{ash} M_{ash} Q_0 \tag{23}$$

Power station cost includes investment capital cost, maintain cost, salary and welfare cost, shown in Eq. 24. Where,

$$C_p = C_{pai} + C_{pm} + C_{ps} \tag{24}$$

Power plant capital investment cost present in Eq. 25. Where,

Table 1
Properties of raw, torrefied corn stalk, and rice straw.

	Ultimate analysis (wt%,db)				Ash (%)	Energy density	HHV (MJ/kg)	Energy consumption(MJ/kg)
	C	H	O	N				
Rice straw								
Raw	38.78	5.76	45.47	0.69	9.30	1.00	15.42	-
220°C	41.05	5.39	39.70	0.84	13.02	1.06	16.29	15.80
240°C	43.03	5.22	37.76	0.64	13.35	1.10	16.98	15.32
260°C	46.78	5.09	33.53	0.66	13.45	1.20	18.52	15.86
280°C	48.53	4.95	30.63	0.94	14.95	1.25	19.28	18.61
300°C	54.71	4.39	17.87	1.10	21.94	1.42	21.95	20.05
Corn stalk								
Raw	42.51	6.00	43.92	0.33	7.24	1.00	17.21	-
220°C	45.50	5.79	43.43	0.53	4.75	1.05	18.11	14.85
240°C	45.95	5.75	38.97	0.69	8.64	1.08	18.56	15.32
260°C	48.52	5.59	36.21	0.51	9.17	1.14	19.58	15.86
280°C	51.03	5.37	32.95	0.49	10.16	1.19	20.51	17.79
300°C	60.87	4.70	18.14	0.78	15.51	1.43	24.57	20.05

$$C_{pai} = C_{pi}\frac{(1 - RV_i)}{n_i} \tag{25}$$

Power plant maintain cost show in Eq. 26. Where,

$$C_{pm} = \gamma C_{pai} \tag{26}$$

Salary and welfare cost display in Eq. 27. Where,

$$C_{ps} = \lambda C_{pai} \tag{27}$$

Biomass grinding energy consumption is calculated using Eq 28:

$$C_{bg} = E_{bg}\frac{1000}{36000}Q_0 C_{ele} \tag{28}$$

Where, E_{bg} is electricity consumption for grinding 720 kJ/kg, while E_{bg-t} torrefied product grinding electricity consumption 36-217 kJ/kg

2.2.3.1. Power plant revenue. Power plant revenue includes power generation revenue and heating selling cost, shown in Eq. 29. Where,

$$R_p = R_{pg} + R_h \tag{29}$$

Power plant power generation revenue is pesented in Eq. 30. Where,

$$R_{pg} = 1000\ (P_{ele} + P_s)P_n h \tag{30}$$

Power station heating sealing revenue can be summarized in Eq. 31. Where,

$$R_h = P_h Q_0 H_{LHV} E_h \tag{31}$$

Power plant net profit is shown in Eq. 32. Where,

$$R_{net} = \left(R_p - C_{total}\right)(1 - income\ tax\ rate) \tag{32}$$

2.2.3.2. CO_2 emission. CO_2 emission for logistic model includes CO_2 emission during transportation, pre-treatment, and storage, present in Eq. 33. Which,

$$E = E_t + E_{pt} + E_s \tag{33}$$

Transportation emission from field to depot is displayed in Eq. 34. Where,

$$E_{t1} = \sum_{i=1}^{n}\iint^{\frac{\rho d f r^2}{\rho_1 V_v}} E_{diesel}\left(Q_{c_{full}} + Q_{c_{emp}}\right) dr d\theta \tag{34}$$

Transportation emission from depot to power plant shown in Eq. 35. Where,

$$E_{t2} = nfL\left(Q_{p_{full}} + Q_{p_{emp}}\right)E_{diesel}Q\Big/\rho_i V_v \tag{35}$$

Transportation emission in loading and unloading is present in Eq. 36. Where,

$$E_{t3} = \frac{Q}{\beta_i}O_{coni}E_{diesel} \tag{36}$$

pre-treatment emission can be be calculated in Eq. 37. Where,

$$E_{pt} = E_{ele}O_{coni}\frac{Q}{\beta i} \tag{37}$$

storage emission shown in Eq. 38. Where,

$$E_s = \frac{Q}{\beta_i}P_{stack} + \frac{Q}{\beta_i}P_{unstack} \tag{38}$$

Diesel emission can be present in Eq. 39. Where,

$$E_{diesel} = 1 \times 10^{-3} Q_{carbon}\varphi_{carbon}\delta_{carbon}LHV_{carbon} \tag{39}$$

The logistic model variables input values, symbols and references can be found in the supplementary document.

2.3. IT-driven approach (GIS) as an assisting tool

A visualized decision supports system could significantly reduce cost in logistic management by identifying potential risk in the aspect of infrastructure planning. In order to further reduce supply chain cost, in the present section, GIS as main technical approaching for supply chain model in terms of agricultural residues potential investigation, transportation route planning, storage location allocation and biorefinery plant location determination.

To operate biofuel refinery plant, long-term decision strategy applied for overview consideration. In previous research [23], biomass potential was assessed in order to evaluate biorefinery plant probability and capacity in a region. Since a potential region has been determined, biofuel refinery plant location need to be figured. four step approaches are applied in this study. Firstly, cooperating with statistical data (existing biorefinery plants and biomass density), the existed biorefinery plants collection radius and available collection area for new biofuel plant can be analysed by GIS. Once biofuel plant collection area confirmed, GIS could analyse the optimal collection radius, biorefinery plant location and capacity for logistic model for further analysis. Secondly, in logistic model, the optimal pre-treatment method, the number of optimal depots for pre-treatment and storage can be exam. Flowed by, logistical model results will be as input variables in GIS for biomass transportation and collection route calculation. In the end, route information will return to logistical model to output final medium-term decision strategy.

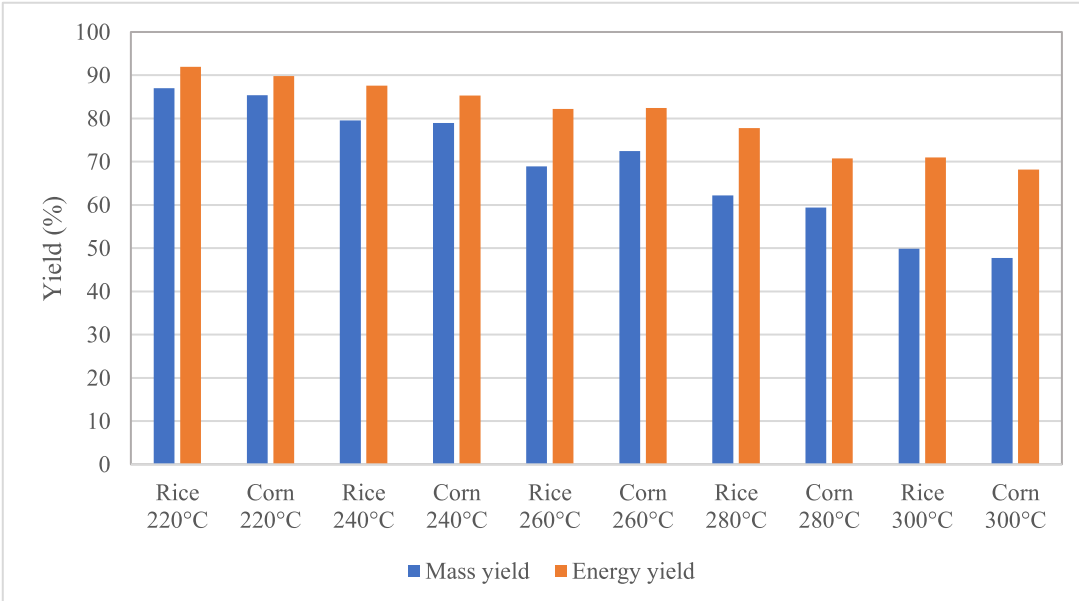

Fig. 4. Mass yield and energy yield of rice straw and corn stalk at different torrefaction temperature.

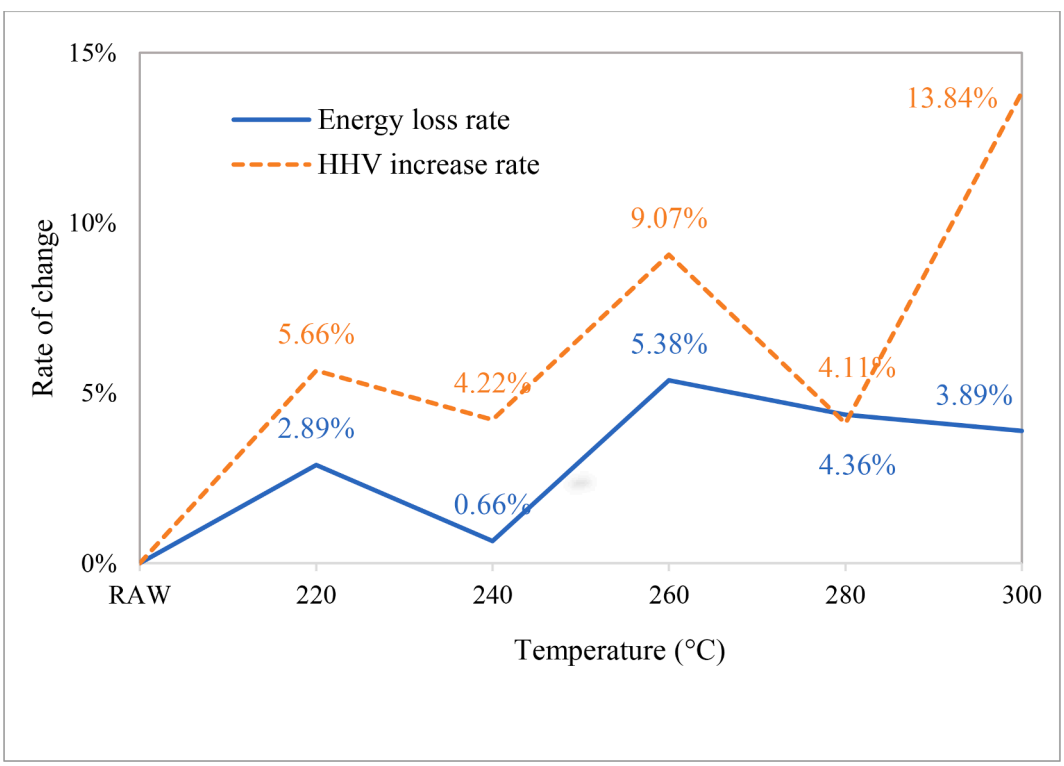

Figure 5. Rice straw HHV increase rate and energy loss rate under various torrefaction temperature.

3. Results and discussion

3.1. Analysis of biomass pre-treatment method characteristics

The experiment result shows that the moisture of received rice straw and corn stalk are 3.45% and 20% respectively. The changes in the element component of material under various torrefaction conditions are present in Table 1. Samples under higher torrefaction conditions witnessed significant mass reduction, which is due to hemicellulose decomposition and the start of cellulose decomposition. As volatile matter (includes carbon dioxide, carbon monoxide, large amount of acetic acid and other heavier products of organic molecules [24]) released in decomposition process, which encouraged oxygenated and hydrogenated compounds to escape and torrefied products concentrate in fixed carbon. Therefore, it can be seen that the carbon ratio in biomass component increases along with higher torrefaction temperature. On the contrary, oxygen and hydrogen content were corresponding decrease, which results in nitrogen has relative increase.

In the change of heating value and energy density for each sample under various torrefaction conditions, as ratio of carbon content

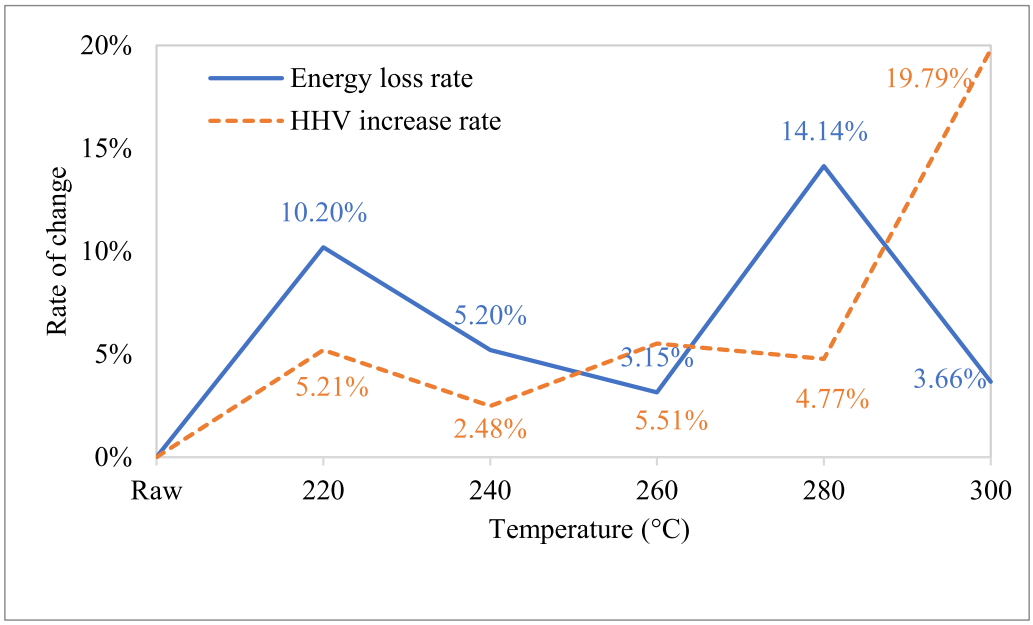

Figure 6. Corn stalk HHV increase rate and energy loss rate under various torrefaction temperature.

increase in the sample, the HHV and energy density have corresponding improve. On the other hand, torrefied biomass is competitive than raw biomass in logistic transportation, due to higher energy density means higher energy to carry. The higher torrefaction temperature results in volatile matter decomposition, which affect mass yield and energy yield decrease in samples.

As expected, mass yield decreased with rising temperature, especially for residues under severe temperature (over 280°C) due to hemicellulose and cellulose decomposition, which result in large increased mass loss (Fig. 4). In other words, thermal decomposition plays a dominating role in high temperature. The mass yield of rice straw decreased dramatically from 86.99% at 220 to 49.85% at 300°C. As well as corn stalk, from 85.36% at 220°C to 47.77% at 300°C on corn stalk. Similar trends can be observed in energy yield. It can be seen that the rice energy yield dropped from 91.91% at 220°C to 70.96% at 300°C. While, pointing to corn stalk, the energy yield decreased from 89.80% at 220°C to 68.20%, where 21.6% energy escaped to torrefied product.

Fig. 5 and 6 presented rice straw and corn stalk heating value increase rate and energy loss rate under various torrefaction conditions. Biomass feedstock has a higher unit heating value after torrefaction treatment, due to the evaporation of its moisture and decomposition of its low molecular volatiles. Energy loss rate and HHV increase rate could indicate the optimal torrefaction conditions, which increase torrefied biomass feedstocks heating value without causing energy waste at the same time. For rice straw, its HHV increase rate is higher than that in energy loss rate before 280°C. The optimal temperature of rice straw is in the range of blow 280°C. Because of minimal energy lose in that temperature range. Fig. 6 shows corn stalk under 260°C to 280°C has a significant mass loss. Therefore, torrefaction of corn stalk over 260°C is inefficient. A temperature of 260°C was chosen as optimum for corn stalk, since less energy is wasted compared with other temperatures.

This study determined moisture content of received rice straw and corn stalk, which tested contain 3.45% and 20% respectively. From biomass torrefaction characteristics assessment, it was found that the heating value for both rice straw and corn stalk increase with torrefaction temperature. Due to biomass component decomposition, energy yield and mass yield decrease with torrefaction temperature increasing. The mass loss in rice straw was observed higher than that in corn stalk. The optimal torrefaction temperature was experimentally determined, which considered by energy loss rate and HHV increase rate. Based on experimental results, optimal torrefaction temperature for rice straw and corn stalk is at the range of 220°C to 280°C and 260°C respectively. Experimental results as input variable will introduce into further logistic model analysis.

Table 2
CHP plant conditions for five scenarios.

Scenario	Raw material	Torrefied material	Loose Density 0.087t/m^3	Compression Density 0.4t/m^3	Density 0.8t/m^3
1	√		√		
2	√			√	
3	√				√
4		√		√	
5		√			√

3.2. *Biomass logistic model based on long-term decision-making strategy assessment: a case study of CHP plant in Heilongjiang*

3.2.1. *Agricultural residues conditions and assessment design*

As results in previous work [23], Heilongjiang province has the largest agricultural residues potential in China. While the number of biorefinery plant and capacity are not match its position. Therefore, it has potential for building more biofuel plant.

Heilongjiang province was estimated over 110 million-ton agricultural residues produced a year under 122940.3 km^2 arable land. For agricultural sustainable consideration, it was expected the residues density 286.42 ton/km^2 (based on agricultural residues sustainable potential analysis on [23]). For agricultural residues characteristics experiment analysis, collected agricultural residues has 15% moisture and 0.087 ton/m^3 bulk density. According [25] research, CHP system has approximate 31.85% electricity efficiency and 49.95% heat efficiency. 30 constructed biomass related biorefinery plants data in Heilongjiang were collected from governmental report and industrial report, which includes plant capacity, biomass consumption and GIS location. The existed biorefinery plant information was summarised in supplementary.

The start point of this study was to identify the location of agricultural residues-based CHP plant, resources available area and infrastructures locations for establishing a cost-effective sustainable

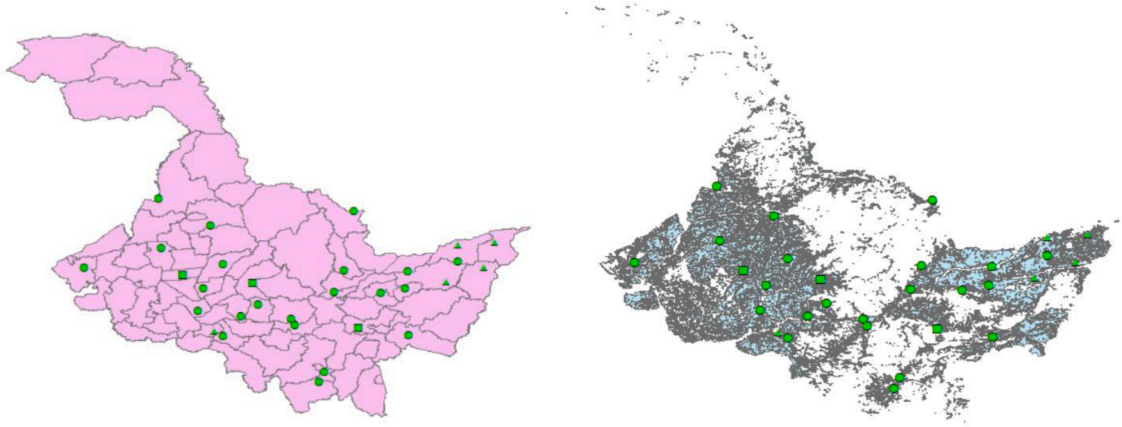

Fig. 7. Left (a) Existing biorefinery plant location in Heilongjiang. Right (b) Arable land distribution in Heilongjiang.

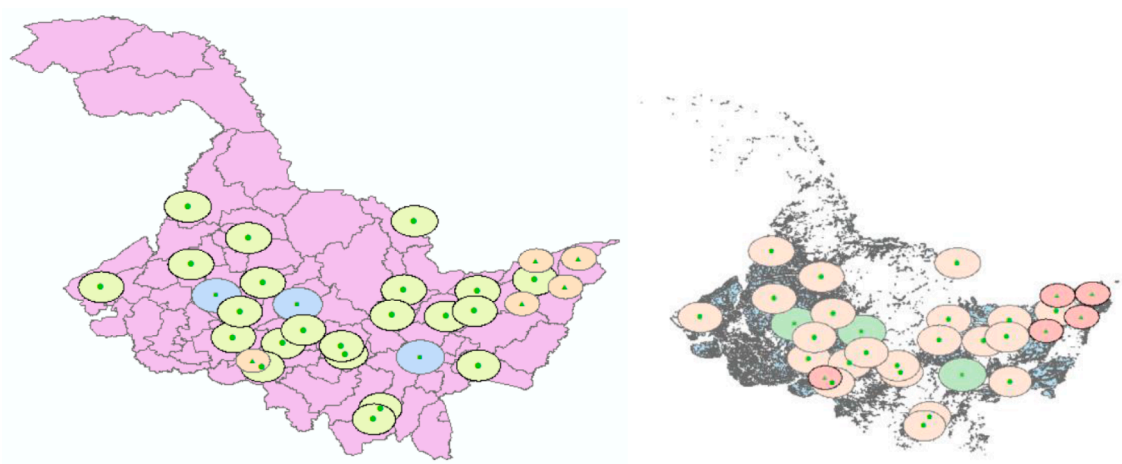

Fig. 8. Left (a) Biomass collection area for existing biorefinery plant. Right (b) Buffer zone in collection area.

logistic model. The effect of pre-treatment method on logistic model was investigate in this research, which includes 5 main scenarios assessment. All scenarios were modelled for collecting demanded agricultural residues and delivering them to final CHP plant for power and heating production. All scenarios are summarized in Table 2.

3.2.2. Determination of candidate CHP plant location

Based on statistical data, the existing biorefinery plant location can be present by GIS in Fig. 7 (a). Among that rectangle, circle and triangle node present biorefinery plant capacity of 40, 30 and 15MW respectively. It observed that biorefinery plant concentrate in southeast and southwest of Heilongjiang. Depending on local arable land distribution (Fig. 7 (b)) and agricultural residues density (results from previous research [23]) and annual biomass consumption, the biomass collection area for each biorefinery plant can be calculated and displayed in Fig. 8 (a). In order to reduce disorderly competition and biorefinery company biomass purchasing cost, a buffer zone (5km longer) introduce into GIS. Fig. 8 (b) present the buffer zone area under arable land. It can be found that under developing arable land in the southwest and east, which this area can be defined as potential biorefinery plant candidate location.

Based on results of existing biorefinery plant collection area, three candidate area present in Fig. 9. Candidate area properties summarized in Table 3. The average residues density gained from previous research [23]. Candidate B has the largest area and arable land, which account 66% of total candidate area and 54% of arable respectively. Biomass potential can be assessed by biomass density, which candidate area A, B and C contain 916691, 2210867 and 949331 tonnes residues. It estimated that the biorefinery plant capacity in area A, B and C are 148, 357 and 153 MW respectively (7600 working hours and 15% moisture applied).

The biorefinery capacity in candidate area can be estimated by LHV (16315 and 19050 kJ/kg for raw and torrefied materials), CHP plant operation time and electricity efficiency, which summarized in Table 4.

This study will analyse candidate area C as a case study of logistic model assessment. Because arable land account approximate 71.8% of total area in candidate C, which concentrated arable land could reduce cost in collection processing. Such as transportation cost and energy consumption. Since candidate biorefinery plant location determined, local conditions can be introduced into logistic model. Due to agricultural residues has others application (e.g., cattle feeding and energy), utilizing residues for biorefinery might not fully employment. Thus, the followed result will analysis the effect of residues available utility on biorefinery pre-treatment selection and logistic model profitability.

3.2.3. The effect of residues availability on logistic model-based pre-treatment technology selection assessment

3.2.3.1. Financial analysis. Table 5 summarized the PI value of CHP logistic model under five scenarios and agricultural residues availability. It was found that with residues available increase, the minimal refinery plant capacity has corresponding raise. Profitability index is to measure investment attractiveness, which project's PI value above 1 deems a profitable investment. Under a lower availability (20%), the optimal PI value occurs in scenario 2, which indicates compression with bulk

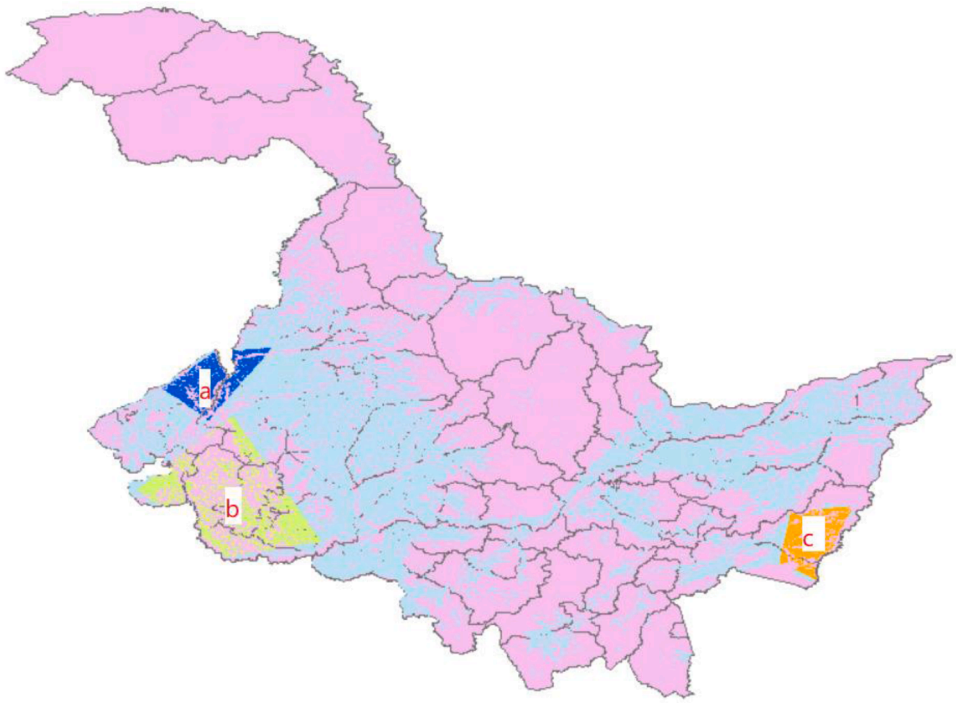

Fig. 9. Candidate biorefinery plant area a, b and c under arable land.

Table 3
Candidate area properties.

Candidate area	Area (km^2)	Collection radius (km^2)	Arable land area (km^2)	Residues density (t/km^2)	Biomass potential (t)
A	4759.37	38.93	3200.50	286.42	916691
B	18194.99	76.12	7718.94		2210867
C	4614.82	38.34	3314.46		949331

Table 4
Biorefinery plant capacity in candidate area. (Unit: MW).

Candidate area	Biorefinery plant capacity (raw material)	Biorefinery plant capacity (torrefied material)
A	148	21
B	357	51
C	153	22

density 0.4 t/m^3 is a cost-effective pre-treatment method for CHP refinery. It changed to torrefaction when residues availability and capacity expanded. The detailed breakdown of financial criteria of each availability are presented in the supplementary.

According to Ministry of Agriculture press office [26], the under-utilized agricultural residues account approximate 20% of total residues production. In this case, 20% resides available utilization will be further detailed analysis.

Table 6. summarized yearly financial criteria CHP plant under five pre-treatment method scenarios. The financial analysis results expose that all pre-treatment method scenarios have positive net present value (NPV), which all projects are profitable. Scenario 1 has the highest NPV value, which pre-treatment cost significantly reduce total expenditure. In pre-treated scenarios, scenario 2 (compression with density 0.4 t/m^3) has the lowest cost and highest income. In spite of scenario 3 (compression with density 0.8 t/m^3) has advantage in storage and transportation, the high expense in pre-treatment equipment and truck maximum loading weight increase expenditure and transportation cost. Torrefaction equipment cost and large amount of biomass for torrefaction drag down torrefaction-based CHP plant NPV value.

From PI value analysis, scenario 2 has the highest PI value. Torrefaction pre-treatment equipment cost restricts its PI performance. Therefore, under mutually exclusive projects, the project with highest value (scenario 2) should be undertaken.

The biomass unit cost for logistic process can be estimated based on total cost, which scenario 5 has the highest unit cost (133.43 €/ton) for transforming biomass from field to CHP plant. While, the lowest unit cost is scenario 1, followed by scenario 2, which estimate 91.05 and 92.52 €/ton respectively. On the other hand, due to torrefied biomass increased grindability and torrefied exhaust gas react into CHP system, which reduce energy consumption in pre-treatment and enhance heating selling income.

In the aspect of logistic cost distribution (Fig. 10), biomass purchasing cost account the largest proportion, which shares over 60% of total logistic cost in all scenarios. In the pre-treated scenarios, pre-treated related employee cost and equipment cost account for a

Table 5
Logistic model PI value under different available utilities and scenarios.

Availability	Capacity (MW)	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
20%	20	4.00	4.02	3.94	2.85	2.98
40%	40	4.91	4.88	4.79	5.30	5.23
60%	65	5.64	5.65	5.55	6.19	6.12
80%	85	6.10	6.12	6.02	6.74	6.66
100%	110	6.08	6.13	6.02	7.29	7.21

Table 6
breakdown of yearly financial criteria for 20 MW CHP scenarios. (Unit: M€).

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Biomass purchasing cost	5.29	5.29	5.29	6.34	6.34
Pre-treatment cost	0.00	0.58	0.78	1.32	1.87
Storage cost	1.08	0.96	0.94	0.65	0.64
Transportation cost	1.26	0.97	1.06	1.18	1.28
Ash disposal cost	0.13	0.13	0.13	0.10	0.10
CHP operation cost	1.82	1.82	1.82	0.09	0.09
Total cost	9.59	9.74	10.01	11.39	12.03
Electricity income	16.71	16.71	16.71	16.72	16.72
Heating income	4.21	4.21	4.21	6.27	6.27
Revenue	20.92	20.92	20.92	22.98	22.98
Total income	11.33	11.18	10.90	11.59	10.59
Net present value	84.17	83.07	80.76	78.13	77.47
Profitability index	4.00	4.02	3.94	2.85	2.98

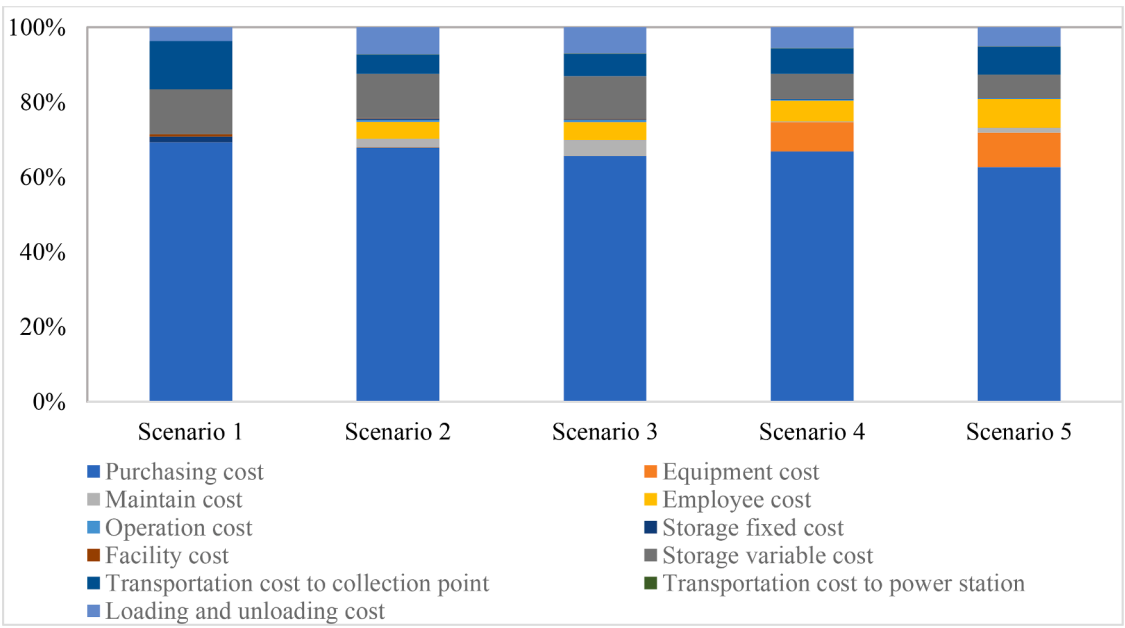

Fig. 10. Biomass logistic model total cost distribution for a year operation.

considerable proportion. In non-pre-treatment and compression scenarios, storage cost is the second largest cost after biomass purchasing cost. Therefore, keeping biomass in low purchasing cost and dry matter loss could enhance project's profitability significantly.

3.2.3.2. Logistic system emission. Biomass based CHP seen as a carbon free system, therefore, the process of transportation, pre-treatment and storage account in CHP supply chain CO_2 emission. In CHP logistic model, the emission of power relayed equipment was exempt, due to electricity source form CHP generation. Fig. 11 summarized CO_2 emission in logistic process, which non-pre-treated biomass has the lowest CO_2 emission (579.80 t). Biomass pre-treatment has advantage in reducing CO_2 emission during in transportation. However, repeated loading and unloading biomass enhance CO_2 emission in biomass logistic system, which biomass need to loading four times for transportation and storage. The higher loading equipment fuel consumption and biomass weight (more raw feedstock for pre-treatment in same CHP capacity) lead to higher CO_2 emission. Thus, biomass loading emission accounts the largest part in these scenarios. On the other hand, pre-treated biomass increased transportation capability, which a significant CO_2 emission reduction can be observed in biomass collection.

It can be seen that transportation in collection emission in scenario 4 higher than scenario 5 under the same conditions. That because of optimal output result difference. In scenario 4, the optimal number of depots under maximum profit as objective function is one, where the depot located in CHP plant. Long collection distance increase CO_2 emission in biomass collection transportation. While, logistic model results shows that distributed depot was the optimum solution for maximum profit in scenario 5. Comparing with centralized depot, multiple distributed depots have advantage in increasing collection efficiency, reducing collection radius and collection cost in financial consideration.

Five different pre-treatment technologies were assessed in logistic model, which non-pre-treated biomass has advantage in CO_2 emission and CHP plant with compression as pre-treatment method has the highest profitability. Due to high expenditure of pre-treatment equipment, torrefaction was not the optimal pre-treatment method for CHP generation. In spite of lower cost in non-pre-treated scenario, with increase transportation distance, the shortage of biomass characteristic (low bulk density) might dramatically increase. Model results reveal that distributed depot has benefit in reduce transportation and CO_2 emission. To achieve both high profitability and low emission might not achieve. Therefore, concession is needed. Since PI value is an indicator that evaluate project attractiveness, Scenario 2 (the highest PI value) will be applied in further GIS analysis and supply logistic model optimization.

3.2.4. GIS-assisted transportation route analysis

The optimal depot of Scenario 2 analysed by logistic model was six.

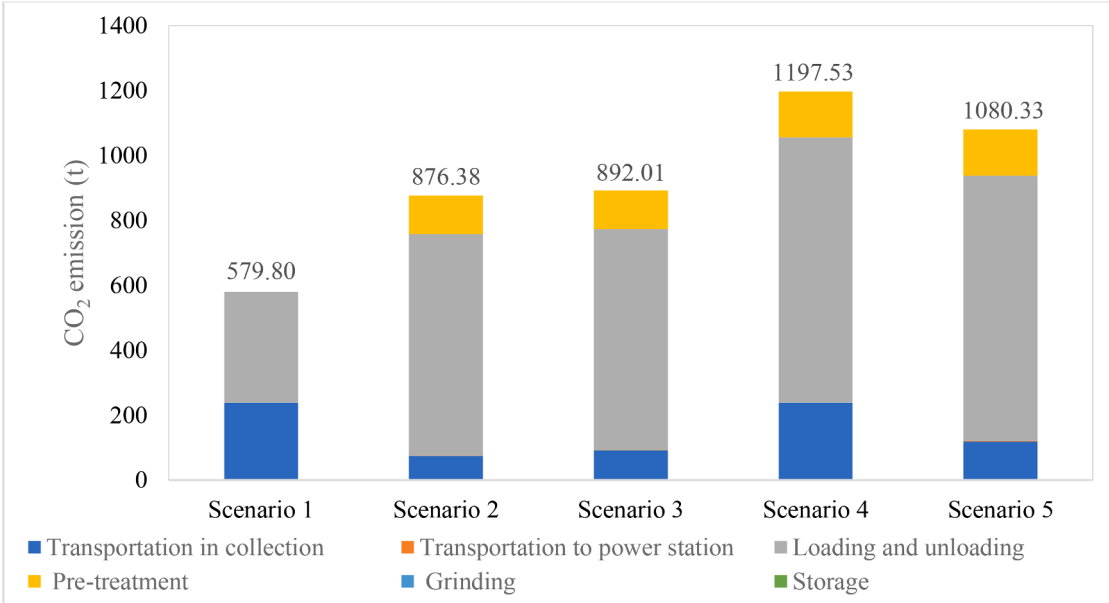

Fig. 11. CO_2 emission distribution in CHP logistic supply chain.

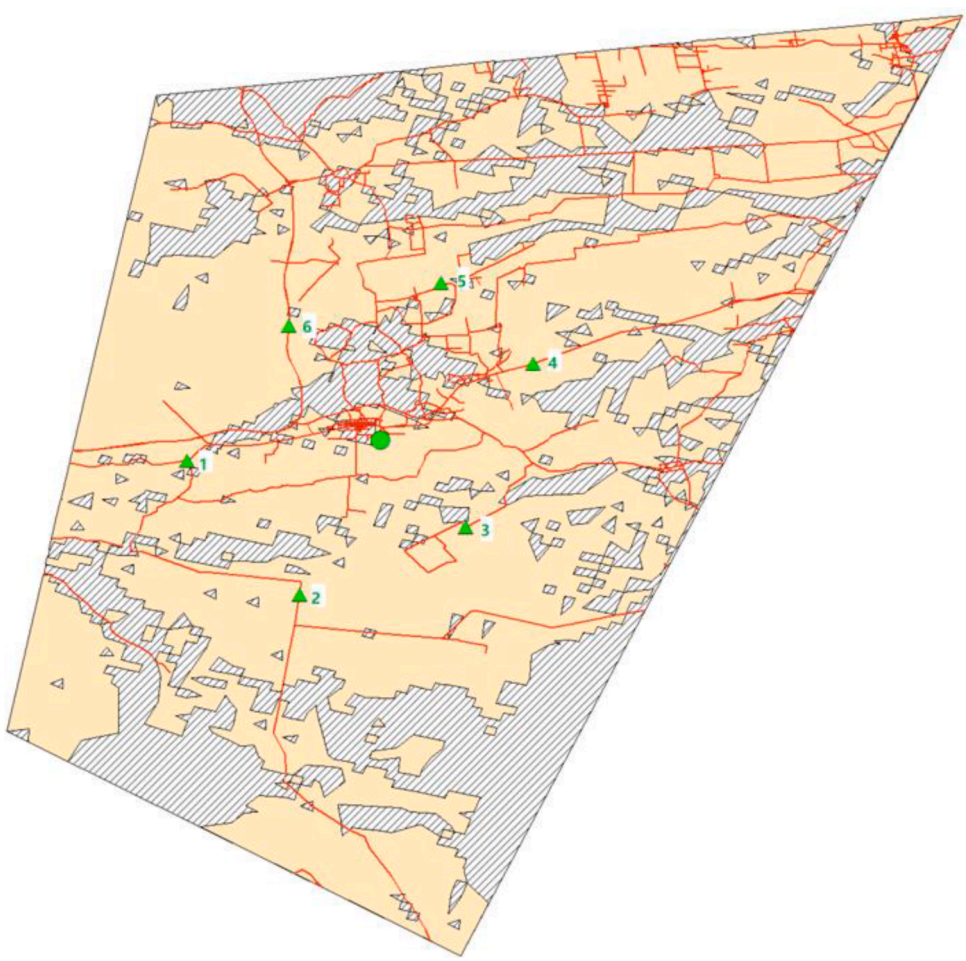

Fig. 12. Optimal location of CHP plant and depots determined by GIS.

Therefore, optimal location of refinery plant and depots determination can be assisted by GIS analysis. Depending on requirements which refinery plant close to city for sufficient labour force and depots close to main road for increasing transportation efficiency, the optimal location for candidate area C illustrated in Fig. 12.

Where, the hatch area represents candidate area C, yellow area

Table 7
Distance between refinery plant and depot.

Depot	Distance (km)
1	18.60
2	24.05
3	25.88
4	18.40
5	23.86
6	21.46
Average distance for GIS analysis	22.04
Average distance for logistic model	22.79

Table 8
CO2 emission and financial analysis under logistic mathematical algorithm model and GIS-assisted model.

	Logistic mathematical algorithm model	Logistic with GIS-assisted model
CO_2 emission (Unit: t).		
Transportation in collection	74.28	74.26
Transportation to power station	1.88	1.81
Loading and unloading	682.30	682.30
Pre-treatment	117.93	117.93
Grinding	0.00	0.00
Storage	0.00	0.00
Total	876.38	876.30
Financial ananlysis (Unit: M€)		
Transportation cost	0.9700	0.9698

represents arable land distribution, red line represents main road, green circle represents optimal CHP biorefinery plant location and green triangle represent depots' location.

The detailed distance between refinery plant and each depot demonstrations in Table 7. GIS results reveal that the average distance between optimal depot and refinery plant is approximate 0.75 km shorter than that in logistic mathematic model, which save 3.4% transportation distance of each depot. Logistic model can provide a general optimal solution to simulate local conditions that minimize effect of uncertainty on solutions as much as possible. While, GIS could provide comprehensive analysis for local conditions. Therefore, to increase logistic model reliability, Logistic model and GIS analysis combination is an optimum solution.

Based on the result of GIS analysed transportation distance by introduce into logistic model, the optimized results observed the transportation cost from €0.9700m reduce to €0.9698m and overall CO_2 emission from 876.38t decline to 876.30t per year, which illustrate a 0.02% and 0.01% reduction respectively. With average 15 years investment lifetime of CHP plant, it could save at least €3000 and 1.2t CO_2 (Table 8).

3.2.5. Logistic model sensitivity analysis based on GIS optimization

The financial analysis illustrated in this work was based on various assumptions, such as biomass purchasing price and equipment's cost, which the stability of parameter value is highly affected by external environment (e.g., supply and demand). Moreover, the value of related to investment (e.g., CAPEX cost and construction cost) parameters can be site-specific, which simulated result was based on the certain situation. Once value of critical parameters is modified, the project profitability might change significantly. For above reason, to minimize the effect of external uncertainty on logistic results stability, it is considered essential to exam sensitivity analysis for logistic model results. Most of parameters adjust in the range of −25% and +25% of their baseline value [25]. The baseline, lower and upper value of parameters for sensitivity analysis are summarized in Table 9. PI value considered as assessment criteria present in Fig. 13.

The sensitivity analysis results show that the most influential parameter is CHP plant capital cost. Capital cost with reduce 25%, the PI value raise from 5.33 to 7.1, which increase over 33.2%. This indicates the criticality of enhancing technology development in order to reduce capital cost. Electricity selling price appears the second influential parameter affecting CHP plant profitability. As power plant most important profit, the effect of electricity price fluctuation on power plant stability is more profound. Discount rate is an unignored parameter for CHP plant investment. It inspired the important of low interest rate funding solutions, in order to reduce investment risk. Biomass purchasing price is an influential cost-related parameter. A 25% decrease in biomass purchasing price results in CHP plant profitability increasing 7% to 5.74.

4. Conclusion

Medium-term decision-making is an important component in connecting others strategy of supply chain, which plays roles in increasing supply chain cost-effective. This paper investigates agricultural residues characteristics under raw material and torrefaction firstly. It was found that torrefied residues have higher energy density and heating value that that in raw material. Decomposition exists in torrefaction, which mass yield and energy yield decrease with increase torrefaction temperature. GIS as a strategic level approach determined three CHP candidate area in Heilongjiang, which estimate residues availability and potential plant capacity. Candidate C as a research case for analysis, because of higher concentred arable land distribution. Residues availability is a critical factor that affect logistic cost and pre-treatment technology selection. The results observed that at lower residues availability(≤20%),

Table 9
Parameters and ranges of sensitivity analysis.

	Baseline Value	Unit	Sensitivity analysis range Lower Parameter Value	Decrease %	Upper Parameter Value	Increase %
Biomass purchasing price	39.7	€/t	29.8	-25%	49.7	25%
Compression equipment price	1986.8	€	1490.1	-25%	2483.4	25%
Mass loss	0.10	-	0.08	-25%	0.13	25%
Oil price	0.9	€/L	0.6	-25%	1.1	25%
Storage management cost	0.5	€/m^2	0.4	-25%	0.6	25%
Storage facility construction cost	2.6	€/m^2	1.9	-25%	3.2	25%
Storage operation cost	6.9	€/t	5.2	-25%	8.6	25%
Transport price	2.6	€/tkm	2.0	-25%	3.3	25%
Loading and unloading cost	0.5	€/t	0.4	-25%	0.7	25%
Ash treatment cost	13.2	€/t	9.9	-25%	16.6	25%
Power plant CAPEX Reference investment cost	36365562.9	M€	27274172.2	-25%	45456953.6	25%
Electricity selling	0.10	€/kWh	0.07	-25%	0.12	25%
Heating selling	5.2	€/GJ	3.9	-25%	6.5	25%
Discount rate	8	%	6%	-25%	10%	25%
Employee salary	29541.1	€	22155.8	-25%	36926.3	25%

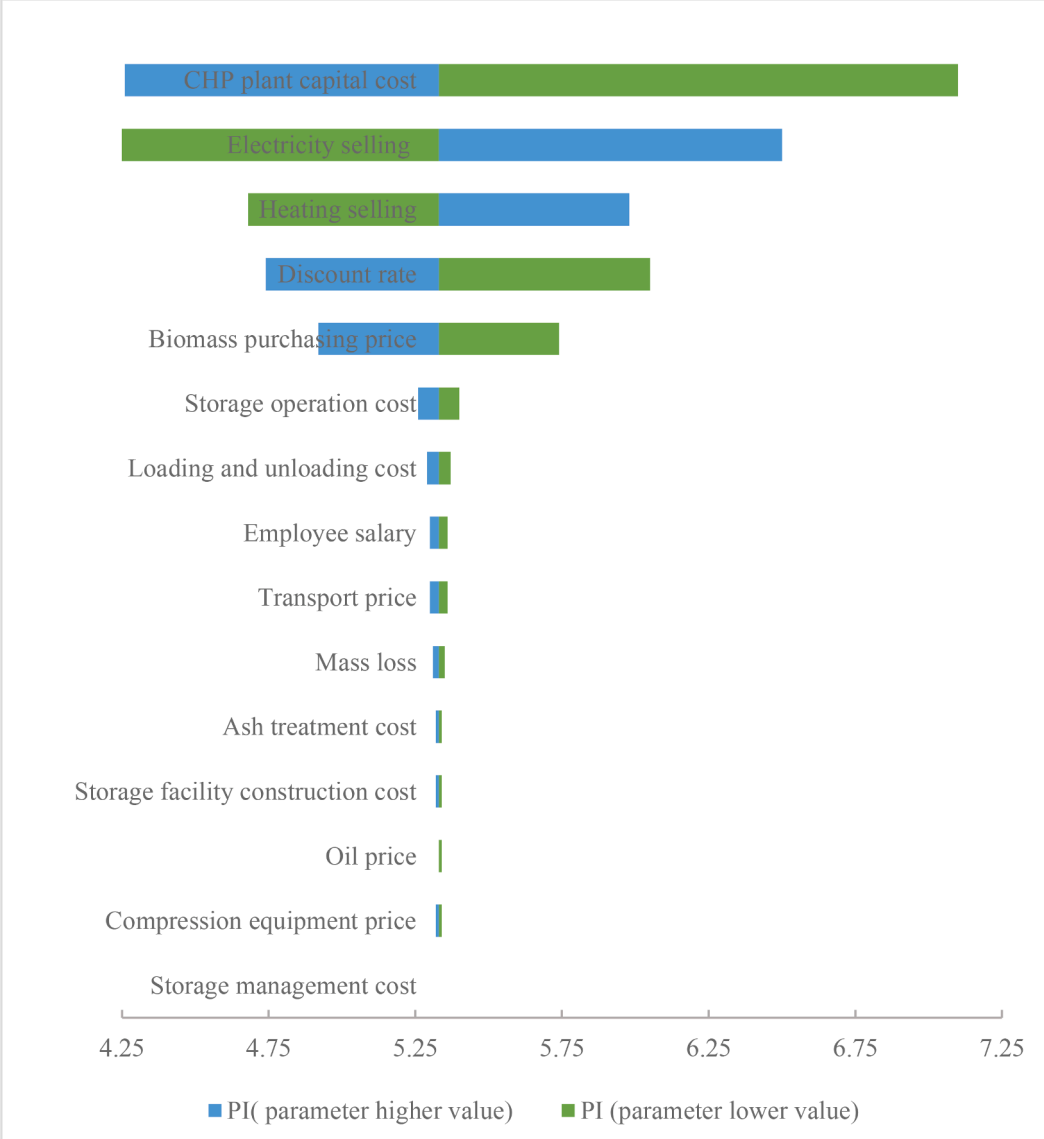

Fig. 13. Sensitivity analysis for biomass compression as pre-treatment scenario.

compression is the optimal pre-treatment technology in CHP project profitability performance. With increase residues availability, CHP plant has torrefaction as residues pre-treatment technology has the optimal profitability performance. Combing GIS and logistic model could further reduce cost and CO_2 emission and increase project profitability. The results shows that GIS-assisted logistic model reduce 0.02% transportation cost and 0.01% CO_2 emission. For the sensitivity analysis, CHP plant capital cost was the most influential parameter for keeping plant profitability stabilization.

GIS-based medium-term decision-making logistic model as a general optimization approach was useful in changing objective function without requiring sophisticated reprogramming, which providing comprehensive analysis and precise solutions. However, repeated utilization between multi-approach for supply chain efficiency improvement increased software complexity and using threshold. Using interactive system optimization will be next research field for reducing using threshold and increasing using efficiency.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jaecs.2022.100060.

References

[1] P. Basu, Biomass gasification, pyrolysis and torrefaction: practical design and theory, Academic press 2018.
[2] Ekşioğlu SD, Acharya A, Leightley LE, Arora S. Analyzing the design and management of biomass-to-biorefinery supply chain. Computers & Industrial Engineering 2009;57(4):1342–52.
[3] Atashbar NZ, Labadie N, Prins C. Modeling and optimization of biomass supply chains: A review and a critical look. IFAC-PapersOnLine 2016;49(12):604–15.
[4] Rentizelas AA, Tolis AJ, Tatsiopoulos IP. Logistics issues of biomass: The storage problem and the multi-biomass supply chain. Renewable and sustainable energy reviews 2009;13(4):887–94.
[5] Abbas D, Handler R, Hartsough B, Dykstra D, Lautala P, Hembroff L. A survey analysis of forest harvesting and transportation operations in Michigan. Croatian Journal of Forest Engineering: Journal for Theory and Application of Forestry Engineering 2014;35(2):179–92.
[6] Mafakheri F, Nasiri F. Modeling of biomass-to-energy supply chain operations: Applications, challenges and research directions. Energy policy 2014;67:116–26.

[7] Bussemaker MJ, Day K, Drage G, Cecelja F. Supply chain optimisation for an ultrasound-organosolv lignocellulosic biorefinery: impact of technology choices, Waste and biomass valorization 2017;8(7):2247–61.
[8] Lautala PT, Hilliard MR, Webb E, Busch I, Hess JR, Roni MS, Hilbert J, Handler RM, Bittencourt R, Valente A. Opportunities and challenges in the design and analysis of biomass supply chains. Environmental management 2015;56(6):1397–415.
[9] Berry MD, Sessions J, Zamora-Cristales R. Subregional comparison for forest-to-product biomass supply chains on the Pacific West Coast, USA. Applied Engineering in Agriculture 2018;34(1):157.
[10] Eranki PL, Bals BD, Dale BE. Advanced regional biomass processing depots: a key to the logistical challenges of the cellulosic biofuel industry. Biofuels, Bioproducts and Biorefining 2011;5(6):621–30.
[11] Nunes L, Causer T, Ciolkosz D. Biomass for energy: A review on supply chain management models. Renewable and Sustainable Energy Reviews 2020;120: 109658.
[12] Bilgen B, Ozkarahan I. Strategic tactical and operational production-distribution models: a review. International Journal of Technology Management 2004;28(2): 151–71.
[13] Zahraee SM, Shiwakoti N, Stasinopoulos P. Biomass supply chain environmental and socio-economic analysis: 40-Years comprehensive review of methods, decision issues, sustainability challenges, and the way forward. Biomass and Bioenergy 2020;142:105777.
[14] Ghaderi H, Pishvaee MS, Moini A. Biomass supply chain network design: an optimization-oriented review and analysis. Industrial crops and products 2016;94: 972–1000.
[15] Min H, Zhou G. Supply chain modeling: past, present and future. Computers & industrial engineering 2002;43(1-2):231–49.
[16] Sharma B, Ingalls RG, Jones CL, Khanchi A. Biomass supply chain design and analysis: Basis, overview, modeling, challenges, and future. Renewable and Sustainable Energy Reviews 2013;24:608–27.
[17] Svanberg M, Olofsson I, Flodén J, Nordin A. Analysing biomass torrefaction supply chain costs. Bioresource technology 2013;142:287–96.
[18] Roni MS, Thompson DN, Hartley DS. Distributed biomass supply chain cost optimization to evaluate multiple feedstocks for a biorefinery. Applied Energy 2019;254:113660.
[19] Zahraee SM, Golroudbary SR, Shiwakoti N, Stasinopoulos P, Kraslawski A. Transportation system analysis of empty fruit bunches biomass supply chain based on delivery cost and greenhouse gas emissions. Procedia Manufacturing 2020;51: 1717–22.
[20] Salleh SF, Gunawan MF, Zulkarnain MFB, Halim A. Modelling and optimization of biomass supply chain for bioenergy production. Journal of Environmental Treatment Techniques 2019;7(4):689–95.
[21] Belyadi H, Fathi E, Belyadi F. Hydraulic fracturing in unconventional reservoirs: theories, operations, and economic analysis. Gulf Professional Publishing; 2019.
[22] Zhuang y, Zhang y, Tian y, Wang g. Research on the Application Mode of Industrialized Collection of Agricultural and Forestry Biomass in China. China engineering sciences 2011;13(2):101–6.
[23] Zhang J, Li J, Dong C, Zhang X, Rentizelas A, Shen D. Comprehensive assessment of sustainable potential of agricultural residues for bioenergy based on geographical information system: A case study of China. Renewable Energy 2021;173:466–78.
[24] Gucho EM, Shahzad K, Bramer EA, Akhtar NA, Brem G. Experimental study on dry torrefaction of beech wood and miscanthus. Energies 2015;8(5):3903–23.
[25] Rentizelas AA, Li J. Techno-economic and carbon emissions analysis of biomass torrefaction downstream in international bioenergy supply chains for co-firing. Energy 2016;114:129–42.
[26] Ministry of Agriculture press office. The comprehensive utilization rate of main crop stalks in China exceeds 80% 2016. http://jiuban.moa.gov.cn/zwllm/zwdt/201605/t20160526_5151375.htm. Accessed 03-17 2018.