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A Hybrid of Multi-Objective Optimization and System Dynamics Simulation for Straw-to-Electricity Supply Chain Management under the Belt and Road Initiatives

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Abstract: The Belt and Road Initiative (BRI) provides immense opportunities for agro-waste utilization among countries situated along the routes. However, there is a lack of design of motivational mechanisms to put it into managerial practice. This study uses agro-straw as the typical agro-waste to structure a hybrid of multi-objective optimization and system dynamics simulation for optimizing the structure of straw-to-electricity supply chain and designing motivational mechanisms to enhance its sustainability. Since existing studies on the design of motivation mechanisms mainly stressed static motivation, two different dynamic subsidy mechanisms are devised in this study to facilitate the stable collaboration among stakeholders involved in the supply chain. A case study is provided to demonstrate the hybrid method. Discussion about the limitations of the study lays the foundation for further improvement.

Keywords: agro-waste; Belt and Road Initiative; supply chain management; multi-objective optimization; system dynamics

1. Introduction

The Belt and Road Initiative (BRI) is a proposition of China for regional economic cooperation under the development of economic globalization [1]. It aims at reinforcing efficient policy coordination to construct an open, encompassing and shared economic mode [2]. Agriculture is the dominating industry of the national economy for countries along BRI routes. Agricultural development inevitably produces a substantial amount of agro-wastes, of which agro-straw is a major portion that accounts for 80.5% of the total [3–5]. Due to the biomass abundance in agro-straws, proper energy recovery could be a win–win strategy for both the economy and the environment.

The BRI also places special emphasis on transitioning the industry chain to a new energy and low carbon design [6,7]. Nevertheless, straw biomass use has yet to reveal a large-scale industrial pattern which is mainly due to the sparse distribution of straw and the high external cost of its reuse [8–10]. In addition, the existing motivational mechanisms for farmers and biomass power plants have inadequate effectiveness resulting in straw shortage and insufficient social investment in the industry [11,12]. From this perspective, the following study conducts structural optimization of the supply chain of straw biomass for energy utilization to lower the overall cost and carbon emissions in the supply chain for promoting its sustainable development. Consequently, this study designs motivational mechanisms that finely adjust the level of supply chain engagement by different stakeholders to steer supply chain operations towards stability.

The remaining parts of the study are structured as follows: Section 2 gives a literature review regarding supply chain management of straw biomass utilization. Section 3 presents the optimization and system dynamics model. Section 4 addresses the case background and data source. Results and discussions are given in Section 5. Lastly, conclusions and research limitations are expressed in Section 6.

2. Literature Review

Currently, studies on the supply chain management of straw biomass utilization focus on two aspects: supply chain network optimization and design of motivational mechanisms for supply chain stakeholders [13]. Mobini et al. [14] used discrete event simulations and integrated factors, such as the equilibrium moisture content and carbon emissions, to optimize the logistic routes of the straw biomass supply chain. Meanwhile, Yu et al. [15] computed and decomposed straw collection costs and incorporated the GIS model for planning the allocation of biomass power plants. Zhao and Li [16] conducted a similar study, where costs of logistics and associated carbon emissions were used as the objective functions to construct a 0–1 bi-objective integer programming model for determining the allocation of biomass power plants. The GIS model was also employed by Chiueh et al. [17] who analyzed the impacts of straw drying pre-treatment on the supply chain cost and carbon emissions to optimize the transportation routes. Then, Delivand et al. [18] adopted GIS and multi-objective decision-making to optimize the logistic network for southern Italy's straw-to-electricity supply chain based on the logistic cost minimization. Roni et al. [19] built a hub-and-spoke supply chain network and undertook supply chain structure optimization by using biomass co-firing as the energy source. Turki et al. [20] further transformed the hub-and-spoke supply chain into a closed-loop supply chain, and proposed optimization model to enhance its sustainability. Vance et al. [21] used P-graph Framework with minimizing cost, ecological footprint, and energy input to design a reverse supply chain based on agro-waste electricity generation. Examining the costs of minimal biomass electricity generation was also an objective for Singh [22]. He also used factors such as average fuel distribution or straw collection as the constraints for determining the optimum capacity of biomass power plants and the straw collection radius.

In terms of the motivational mechanism design for supply chain stakeholders, Yan et al. [23] devised a subsidy scheme for biomass power plants based on the principal-agent theory while considering the impacts of straw collection and storage costs on the plants. The agent-based approach was also employed by Luo et al. [24] to combine with game theory for analyzing the villagers' willingness of providing straw feedstocks for the biomass-based power supply chain. Xue and Wang [25] built a dynamic model based on the game theory to redesign the motivation mechanisms. Furthermore, they discussed the balance among government subsidies for farmers, brokers and biomass power plants. Game theory was also applied to a dynamic model developed in the study by Wen et al. [26] which focused on analyzing the impacts of straw power plants on the straw acquisition. Using two-person game theory, i.e., two supply chain stakeholders, brokers and villagers' committee, Zhang et al. [27] designed a synergistic mechanism for both parties to undertake straw collection together.

These above mentioned studies, while quite useful in informing our approach, do not address issues raised in management implementation of the optimized supply chain, i.e., there is a lack of design of motivational mechanisms to put it into managerial practice. In such case, this study articulated external policy incentives with the supply chain optimization. Additionally, existing studies on the design of motivation mechanisms mainly stressed on static motivation, rarely considered the influences of dynamic incentives on the stakeholders involve in supply chain. This study adopts a hybrid of multi-objective optimization and system dynamics to investigate possible influences of different incentives (subsidies) on the supply chain. The integration of these two methods guide the transition to low-carbon supply chains and design the optimal supply chain structure of straw biomass utilization, thus to enhancing the sustainability of the supply chain. Accompanied with proper dynamic subsidy schemes that facilitate supply chain management practices, it aims at providing a theoretical basis for countries under the Belt and Road Initiative to construct a reverse supply chain of agro-wastes.

3. Model Construction

3.1. Model Assumptions

The stakeholders of the supply chain in this study mainly consists of the farmers, centralized collection center, bio-energy plants and residents as shown in Figure 1. The centralized collection center determines the straw collection radius based on straw demand and its purchase from the farmers at a specific price before pre-treating and storing the straw altogether. Afterwards, the straw is transported to bio-energy plants for power generation, which is then connected to the regional power grid.

Figure 1. The proposed straw-to-electricity supply chain network.

Given this context, the following assumptions are proposed regarding the supply chain design, which are by analogy to Garg [28] and Zhao et al. [29]:

(1) The straw inventory is fixed.
(2) The straw wastes are homogeneous where differences among crops are neglected and evenly distributed across the collection regions.
(3) The locations of all potential straw collection regions, centralized collection and transportation sites as well as the logistic routes are given in advance.

The parameter notations and definitions are given in Table 1:

Table 1. Notation for sets, input parameters and decision variables.

Nomenclature	
sets	
i	Sets of potential straw collecting site
k	Key bio-energy plant
j	Sets of operated incinerators
Input parameters	
Cc_i	Collecting cost per tonne straw in collecting site i
C_{ik}	Unit transportation cost from collecting site i to bio-energy plant
L_{ik}	distance between collecting site i to bio-energy plant
Cs_i	Storage cost of collecting site i
Ec	Electricity generation cost of per tonne straw
Cm_j	maintenance cost when the number of operated incinerator is j
EM_i	Emission factor of straw collection, per tonne straw in collecting site i
EM_{ik}	Emission factor of transportation from i to k
$EMco$	Emission factor per tonne straw combustion for electricity generation
EMs_i	Emission factor of ith straw storage
EM_j	Emission factor of incinerators operation when amount of incinerators j are operated
EMd	Emission factor of straw direct burning
$Cap^s{}_{min}$, $Cap^s{}_{max}$	The maximum and lower limited operational capacity of the bio-energy plant
$Cac^i{}_{max}$	The maximum straw production amount
a_j	The needed amount of straw collecting sites when amount of incinerators j are operated
b	The amount of incinerators operated simultaneously
Decision variable	
x_{ik}	Amount of straw transported from collecting site i to bio-energy plant
x_i	Binary variable when the potential collecting site i is selected
z_j	Binary variable when amount of incinerators j are operated

3.2. Bi-Objective Optimization Model

The optimization model is complied with two objectives: (1) minimization of total economic cost; and (2) minimization of carbon emissions of the supply chain network.

The economic cost indicates the costs of straw collection, transportation, storage, and power plant operations and maintenance. Its objective function is given as follows:

$$OBJ_1 = C_c + C_t + C_s + C_e + C_m \tag{1}$$

where

$$C_c = \sum_i Cc_i \cdot x_{ik}^{3/2} \tag{2}$$

$$T_c = \sum_i x_{ik} \cdot c_{ik} \cdot L_{ik} \tag{3}$$

$$S_c = \sum_i Cs_i \cdot x_i \tag{4}$$

$$E_c = \sum_i Ec \cdot x_{ik} \tag{5}$$

$$M_c = \sum_j Cm_j \cdot z_j \tag{6}$$

In the above formulae, C_c denotes the straw collection cost, which is proportional to the straw collection volume to the 1.5th power [30]; T_c is the transportation cost; S_c is the storage cost; E_c represents the cost of electricity generation, which consists of the operation costs of incinerators and generator sets as well as the cost of exhaust gas processing; and M_c denotes the operation and maintenance cost, which is related to the capacity of the installed incinerators.

In this study, carbon emission concerns are the direct emissions during events such as straw collection, pre-treatment, transportation and incineration. The objective function is given as follows:

$$OBJ_2 = CE_c + CE_t + CE_{co} + CE_s + CE_o - CE_{avoided} \tag{7}$$

where

$$CEc = \sum_i EM_i \cdot x_{ik} \tag{8}$$

$$CE_t = \sum_i x_{ik} \cdot EM_{ik} \cdot L_{ik} \tag{9}$$

$$CE_{co} = \sum_i x_{ik} \cdot EM_{co} \tag{10}$$

$$CE_s = \sum_i x_i \cdot EMs_i \tag{11}$$

$$CE_o = \sum_i z_j \cdot EM_j \tag{12}$$

$$CE_{avoided} = \sum_i EM_d \cdot x_{ik} \tag{13}$$

In the above formulae, CEc denotes the direct carbon emissions during straw collection. It includes carbon emissions due to energy consumption during pre-treatment procedures such as cutting, briquetting and packing in the loading trucks. CE_t is the transportation emissions, CE_{co} is the emissions during straw burning, CE_s denotes the carbon emissions during warehouse storage, CE_o refers to the carbon emissions during the operation of the generator sets caused by the electricity consumption of the generators per se, and $CE_{avoided}$ stands for the carbon emissions during the unorganized burning of straw of the same mass as well as for the direct emissions avoidable by incineration.

3.3. Constraints

Some generic constraints are given in the optimization model based on the decision variables including capacity limit constraint, operations limit and the constraints of decision variables.

(1) Capacity limit constraint:

$$\sum_s Cap_{min}^s \le \sum_i xik \le \sum_s Cap_{max}^s \tag{14}$$

$$x_{ik} \leq Cac^{i}_{mas} \tag{15}$$

Formula (14) suggests that the total volume of straw biomass utilization must range between the minimum volume stipulated by biomass power plants and the current maximum capacity. Formula (15) proposes that the amount of straw that can be gathered by each collecting site must not exceed the local production amount.

(2) Operations limits:

$$\sum\nolimits_{i} x_i = \sum\nolimits_{j} a_j \cdot z_j \tag{16}$$

$$\sum\nolimits_{j} z_j = b \tag{17}$$

According to Formula (16), power plants determine the maximum production capacity of straw biomass based on the number of operated biomass boilers, thus ascertaining the number of straw collecting sites. Formula (17) means that the confirmed number of operated boilers in the biomass power plants is fixed.

(3) Constraints of decision variables:

$$x_{ik} \geq 0 \tag{18}$$

$$x_i,\ z_j \in \{0, 1\} \tag{19}$$

Formula (18) determines that the decision variable x_{ik} is a positive value, while Formula (19) defines $x_i,\ z_j$ as binary integer variables.

3.4. Solution of the Optimization Model

The study employs "Normalized Normal Constraint Method" (NNC) to obtain the Pareto frontier, which was proposed by Messac et al. This method is advantageous because it can obtain a well-distributed set of Pareto solutions with high stability and effectiveness [31]. As a result, a Pareto solution can be selected as a relatively satisfactory solution of the optimization model according to the decision-makers' preference. The solution is given as follows:

Let the solution of OBJ1 and OBJ2 be μ_1 and μ_2. For the single-objective solutions of OBJ1 and OBJ2, the optimal objective functions are $\overline{\mu}^{1*}$ and $\overline{\mu}^{2*}$, respectively, and the optimal solutions are x^{1*} and x^{2*}, respectively. The normalization design metrics are obtained through objective normalization using the following formula:

$$\overline{\mu} = \left\{ \frac{\mu_1(x) - \mu_1(x^{1*})}{\mu_1(x^{2*}) - \mu_1(x^{1*})}, \frac{\mu_2(x) - \mu_2(x^{2*})}{\mu_2(x^{1*}) - \mu_2(x^{2*})} \right\} \tag{20}$$

The Utopia line is defined based on Formula (21), which shows the direction for obtaining the Pareto frontier, as shown in Figure 2:

$$N = \overline{\mu}^{2*} - \overline{\mu}^{1*} = [1, 0] - [0, 1] = [1, -1] \tag{21}$$

Based on the number of required Pareto solutions, m, the increment along the Utopia line is $\delta = 1/(m-1)$; the weight coefficients, α_{1j}, α_{2j}, are as follows:

$$0 \leq \alpha_{1j}, \alpha_{2j} \leq 1;\ \alpha_{1j} + \alpha_{2j} = 1 \tag{22}$$

A set of evenly distributed points on the Utopia line is then obtained:

$$\overline{X}_j = \alpha_{1j}\overline{\mu}^{1*} + \alpha_{2j}\overline{\mu}^{2*} \tag{23}$$

Through solving the following optimization model, the Pareto solutions are obtained:

$$\min_{x} \overline{\mu}_2 \tag{24}$$

$$s.t\overline{N}\left(\overline{\mu}-\overline{X}_j\right)^T \leq 0;\ \overline{\mu}=\left[\overline{\mu}_1(x),\overline{\mu}_2(x)\right]^T \quad (25)$$

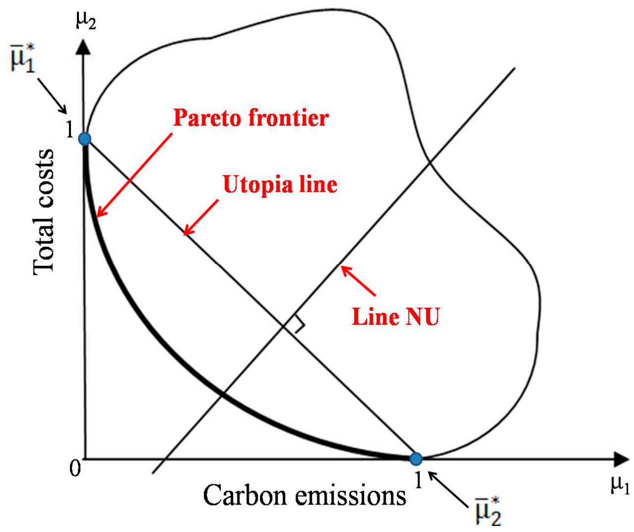


Figure 2. The Pareto frontier between total cost and carbon emission.

3.5. Systems Dynamics Model Construction

After obtaining the optimal supply chain structure by using the multi-objective programming model, this study designed external motivational mechanisms to facilitate its effective operation with the aid of system dynamics. It is a method for simulating the time-varying behavior and feedback mechanisms in complex systems using system modeling and dynamic simulation [32]. The straw biomass supply chain in this study can be deemed as a complex dynamic system. Upon the introduction of government motivation measures, complex interaction among the interests of main supply chain stakeholders, including the power plants, farmers, and residents, influences the operation of the supply chain. Therefore, this study attempts to divide the supply chain under the influence of government subsidy into three sub-systems: (1) those of residents' electricity consumption; (2) farmers' straw supply; and (3) electricity production. The key relationships involved in the three sub-systems are based upon common consensus, and mainly derived from the existing studies. For example, increase of installed capacity may give rise to a growth of revenue of power plants [33]. This study further restructures these relationships to formulate the specific causal loop diagrams as follows:

Figure 3a shows the residents' electricity consumption sub-system, which includes a balancing loop and a reinforcing loop. To explain, a balancing loop occurs by subsidizing the biomass power plants, and the government lowers the market price of electricity and stimulates the residents' demand for straw bio-electricity. As a result, the revenue of the power plants increases and then expands the capacity of their installed incinerators. With a reinforcing loop, increase in the installed capacity raises the revenue of the power plants which leads to their expansion.

Figure 3b illustrates the farmers' sub-system. It mainly consists of a reinforcing loop because, by subsidizing the farmers, the government increases the farmers' revenue and then their straw supply. In turn, this lowers the acquisition price of straw and reduces the operations costs of the biomass power plants, which results in boosting their profit. This expands their installed capacity and eventually the demand for straw.

Figure 3c shows the electricity production sub-system. It mainly contains a balancing loop where the increase in installed capacity narrows the gap between the real capacity and the expected capacity. As a result, the former gradually approaches the default level of the latter.

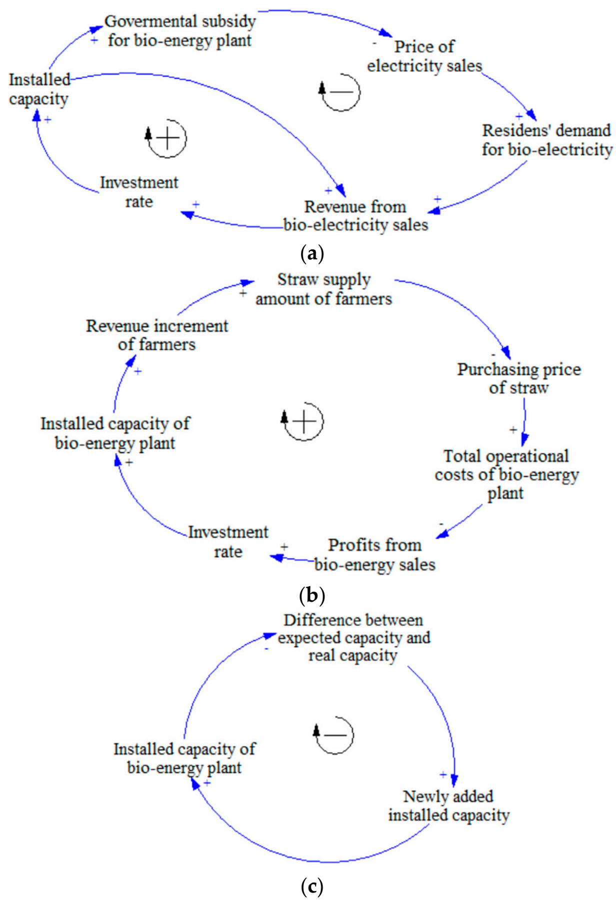


Figure 3. Causal loop diagram of straw to bio-electricity supply chain: (**a**) residents' electricity consumption sub-system; (**b**) straw supply sub-system of farmers; and (**c**) electricity production sub-system of bio-energy Plant.

As shown in Figure 4, according to the causal loop diagram, the STELLA software package is adopted to build a stock–flow diagram for quantifying the interrelations among main variables. The SD model constructed uses the carbon emissions of the supply chain as the main observation indicator. The variables involved in the model are divided into the three groups of stock, flow and auxiliary variable. The details are shown in Table 2, and the corresponding equations are listed in the Appendix A.

Table 2. Key variables of the SD model.

Key Variable	Type	Key Variable	Type
Operational capacity	Stock	Revenue of electricity sales	Auxiliary variable
Capacity increment rate	Flow	Profit increment rate	Flow
Expected capacity	Constant	Economic profit of bio-energy plant	Stock
Gap	Auxiliary variable	Price of agro-straw	Auxiliary variable
Adjusted time	Auxiliary variable	Supply increment from farmers	Auxiliary variable
Investment rate	Auxiliary variable	Low carbon consciousness of farmers	Auxiliary variable
Electricity production	Auxiliary variable	Carbon emission reduction rate	Flow
Subsidy electricity price	Auxiliary variable	Carbon reduction	Stock
Market electricity price	Auxiliary variable	Subsidy for farmers	Auxiliary variable
Demand increment for bio-electricity	Auxiliary variable	Revenue increment rate of farmers	Flow
Revenue of farmers	Stock		

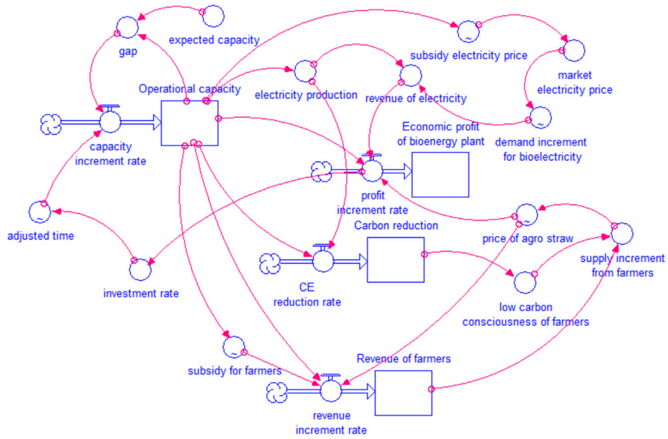


Figure 4. Stock–flow diagram of straw to bio-electricity supply chain.

4. Case Study and Data Source

This case study concerns a straw-to-electricity supply chain in southwest China led by a key bio-energy plant in Cangxi County, Guangyuan City, Sichuan Province. It is under expansion and equipped with two 75 t/h straw boilers. It processes 260,000 tonnes of straw annually, which represents less than 1/5 of the installed capacity. This study decides on four potential straw collection sites labeled as A, B, C, and D while considering other factors such as the straw production volume and traffic in neighboring townships or towns. Their geographic locations are shown in Figure 5. These sites gather straw within a certain radius and transport the pre-treated straws to the bio-energy plant for power generation. Then, the plant is connected to the urban power grid to supply electricity to Cangxi County as well as to neighboring townships and towns. The plant's net price of electricity is set at 0.75 RMB/kwh. The government provides a subsidy of 0.25 RMB/kwh [34].

The input parameters in this study are mainly obtained through field survey and review of related statistics. Among them, the parameters input into the multi-objective programming model are mostly collected by investigating the bio-energy plant in addition to reviewing its environmental impact and energy conservation reports, as shown in Table 3. The input parameters for system dynamics simulation are largely originated from the multi-objective programming model solutions and partially from market survey, as shown in Table 4.

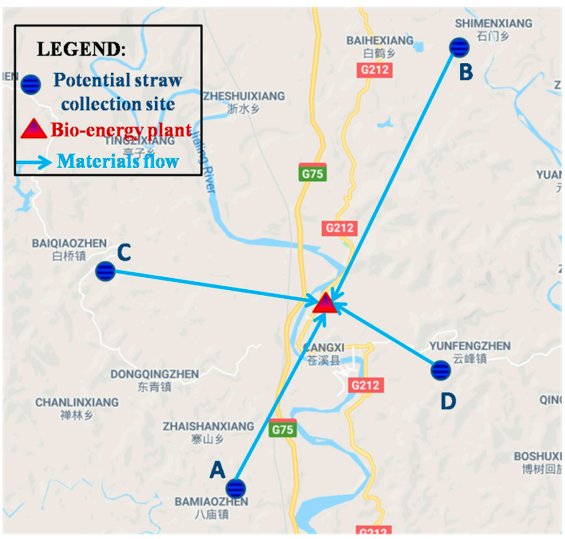


Figure 5. Geographical locations of nodes of the target supply chain.

Table 3. Data for the input parameters of the optimization model.

Input Parameters of the Total Cost								
	Cc_i (Yuan/t)	Cs_i (Yuan)	C_{ik} (Yuan/t·km)	Ec (Yuan/t)	Cm_j (Yuan)	Cap_{smin} (t)	Cap_{smax} (t)	Cac_{omax} (t)
Collecting site A	47	17000	6.21	×	×	×	×	480
Collecting site B	35.3	16800	6.21	×	×	×	×	1080
Collecting site C	44.91	20500	6.21	×	×	×	×	768
Collecting site D	69.3	20000	6.21	×	×	×	×	336
Bio-energy plant	×	×	×	510	14,790 (basic capacity) 22,185 (medium capacity) 29,580 (high capacity)	710 1070 1430	1800 2700 3600	

Input Parameters of the Carbon Emissions						
	Emi ($kgCO_2$/t)	EMik ($kgCO_2$/t·km)	EMco ($kgCO_2$/t)	EMsi ($kgCO_2$)	EMj ($kgCO_2$)	EMd ($kgCO_2$/t)
Collecting site A	1.73	2.73	15.7	1440	×	331.75
Collecting site B	1.05	2.73	15.7	1517	×	331.75
Collecting site C	1.47	2.73	15.7	1405	×	331.75
Collecting site D	1.22	2.73	15.7	1360	×	331.75
Bio-energy plant	×	×	×	×	8568 (basic capacity) 12852 (medium capacity) 17136 (high capacity)	×

Table 4. Measurement of the SD input parameters.

Input Parameter	Value	Measurement
Expected capacity	1.314 Million tonne/year	The capacity of a single incinerator is 75 t/h; the expected capacity is the capacity of three incinerators running at the maximum limit
Initial value of operational capacity	0.669 million tonne/year	From the optimization model
Adjusted time	Lookup function	From the energy conservation assessment report of the plant
Market price of bio-electricity	0.75 RMB/kwh	[34]
Maximum demand increment for bio-electricity	300 million kwh/year	From the market survey
Supply increment of agro-straw	1.3 Million tonne/year	From the market survey

5. Results and Discussion

5.1. Pareto Solutions and the Relatively Optimal Solution

This study uses Lingo 11 software (LINDO Systems, Inc., Chicago, USA) to seek solutions for the integer programming model and obtain the Pareto frontier. Figure 6 clearly demonstrates the tradeoff between cost and carbon emission. For the proposed supply chain, all possible Pareto solutions concerning cost and carbon emissions are given in Table 5.

To pinpoint the relatively optimal solution from a set of Pareto solutions, this study proposes using "Binary Dominant Matrix" to weight the optimization objectives based on their significance. Concerning the Belt and Road Initiative's strategies needs, which are the green and sustainable transitioning of the supply chain, this study assumes that reduction of carbon emissions is more important than that of supply chain cost, as shown in Table 6. Under this condition, the optimal operating parameters of the supply chain are set out in Figure 7.

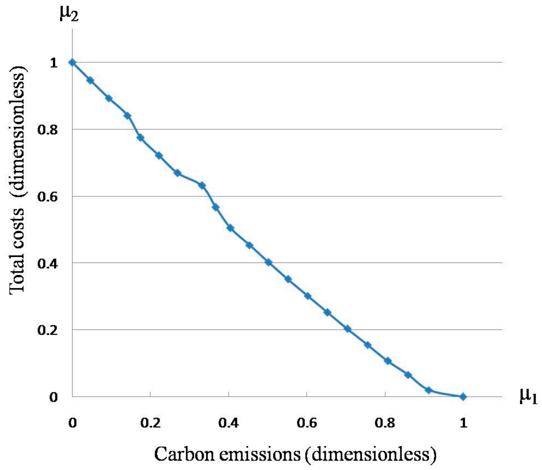


Figure 6. Pareto frontier using NNC approach.

Table 5. Pareto solutions of the optimization model.

(ff1, ff2)	Carbon Emissions (kg)	Total Costs (Yuan)
(1, 0)	−176,847	984,374
(0.95, 0.05)	−198,010	1,127,841
(0.9, 0.1)	−218,751	1,274,682
(0.85, 0.15)	−239,110	1,424,580
(0.8, 0.2)	−264,982	1,530,375
(0.75, 0.25)	−285,715	1,677,288
(0.7, 0.3)	−306,155	1,826,541
(0.65, 0.35)	−320,895	2,021,415
(0.6, 0.40)	−346,223	2,131,542
(0.55, 0.45)	−370,637	2,249,003
(0.5, 0.5)	−390,649	2,401,680
(0.45, 0.55)	−410,621	2,554,673
(0.4, 0.6)	−430,301	2,710,014
(0.35, 0.65)	−449,783	2,866,932
(0.3, 0.7)	−469,075	3,025,364
(0.25, 0.75)	−488,186	3,185,253
(0.2, 0.8)	−507,121	3,346,546
(0.15, 0.85)	−525,887	3,509,192
(0.1, 0.9)	−544,490	3,673,145
(0.05, 0.95)	−562,932	3,838,383

Table 6. Binary dominance matrix for weighting.

	Carbon Emissions	Total Costs	Score	Weight
Carbon emission	×	1	2	0.667
Total costs	0	×	1	0.333

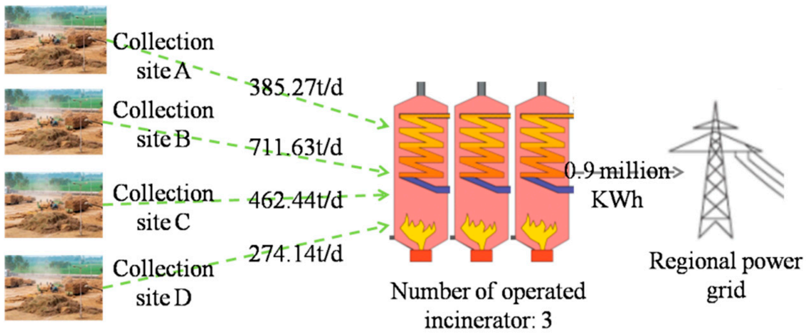


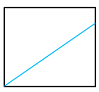
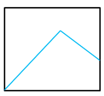
Figure 7. Relatively optimal solution of the programming model.

5.2. Subsidy Performance

The operations cost of the supply chain increases as the scale of straw-based bio-electricity expands. Without the intervention of external motivation, a supply chain can hardly operate independently. This is due to the current lack of subsidies for farmers which has led to straw shortage and increased straw collection costs involved in the supply chain [35,36]. For bio-energy plants, the biomass subsidy in practice is at a uniform level of 0.25 RMB/kwh. Since it is not adjustable to the actual supply chain operations, there is insufficient stimulation for bioenergy utilization. Therefore, this study attempts to introduce dynamic subsidy and observe its impact on the reduction in carbon emissions of the straw biomass supply chain resulting in the optimal subsidy pattern.

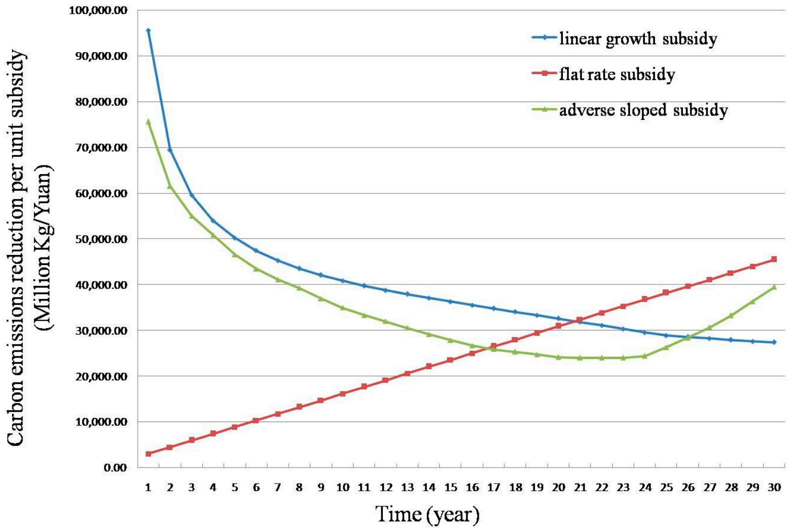
Two subsidy scenarios are proposed for bio-energy plants and farmers respectively, with reference to the subsidy implementation research of Wang et al. [37] and Zhao et al. [38]. Under these scenarios, several sub-scenarios are added. To explain, the two scenarios involve flat rate subsidy, linear growth subsidy and adverse sloped subsidy (Table 7). Flat rate subsidy is set at a constant annual rate with operational capacity. The quota of linear growth subsidy is proportional to the biomass processing capacity of the power plant, whereas the quota of adverse sloped subsidy increases with the volume of electricity generation and decreases when the operational scale reaches a certain level. The objective of these scenarios is to use a subsidy to stimulate supply chain stakeholders to participate in straw-to-electricity production. The subsidies are gradually reduced when the supply chain appears to be relatively stable. The reduction takes place to avoid reliance on subsidies and reduce financial implications of the government.

Table 7. Design of the dynamic subsidies.

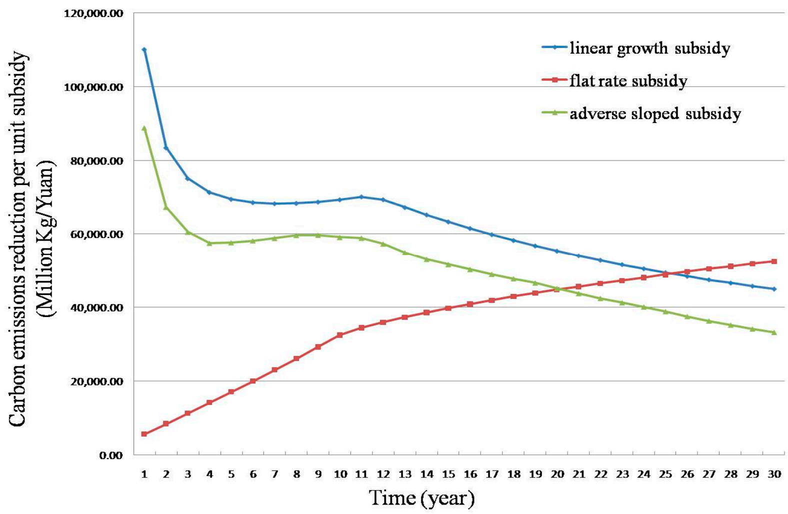
Type	Curves of Subsidies	Equation
Flat rate subsidy		Subsidy for bio-energy plant: Constant = 0.25 Subsidy for farmers: Constant = 50
Linear growth subsidy		Subsidy for bio-energy plant: WITHLOOKUP (Operational capacity, ([(0.669,0)-(1.314,0.7)], (0.669,0), (0.734,0.05), (0.798,0.1), (0.863,0.15), (0.927,0.2), (0.992,0.25), (1.056,0.3), (1.121,0.35), (1.185,0.4), (1.250,0.45), (1.314,0.5))) Subsidy for farmers: WITHLOOKUP (Operational capacity, ([(0.669,0)-(1.314,120)], (0.669,0), (0.734,10), (0.798,20), (0.863,30), (0.927,40), (0.992,50), (1.056,60), (1.121,70), (1.185,80), (1.250,90), (1.314,100)))
Adverse sloped subsidy		Subsidy for bio-energy plant: WITHLOOKUP (Operational capacity, ([(0.669,0)-(1.314,0.5)], (0.669,0), (0.734,0.053), (0.798,0.109), (0.863,0.173), (0.927,0.245), (0.992,0.301), (1.056,0.350), (1.121,0.304), (1.185,0.263), (1.250,0.217), (1.314,0.173))) Subsidy for farmers: WITHLOOKUP (Operational capacity, ([(0.669,0)-(1.314,100)], (0.669,0), (0.734,12.4), (0.798,22.8), (0.863,36.8), (0.927,48.4), (0.992,62.4), (1.056,80), (1.121,65.6), (1.185,54.4), (1.250,44.8), (1.314,33.2)))

For the sake of both the supply chain stakeholders and the government return, this study selected the carbon emissions reduction per unit subsidy as the observation indicator to identify the optimal subsidy mechanism. Figure 8 illustrates the carbon emissions reduction per unit subsidy for the bio-energy plant and farmers. It is evident in Figure 8a,b that the flat rate subsidy is least effective in emissions reduction at the onset of the motivation scheme, but it surpasses the other two gradually around the twentieth year. In contrast, the linear growth and the adverse sloped are more effective in emissions reduction at the onset, but their performances decline after the fourth year. Overall, during the prediction cycle of thirty years, the linear growth subsidy is the most effective in emissions reduction.

Figure 9 shows that when a linear growth subsidy is given to both parties, the carbon emissions reduction per unit subsidy for farmers is evidently more effective than for the bio-energy plant. The simulation results also confirm the research conclusions drawn by Xue and Wang, who have pointed out that subsidies for farmers prevail over those for bio-energy plants [25].



(**a**)



(**b**)

Figure 8. Carbon emissions reduction per unit subsidy in the two scenarios: (**a**) carbon emissions reduction per unit subsidy for bio-energy plant; and (**b**) carbon emissions reduction per unit subsidy for farmers.

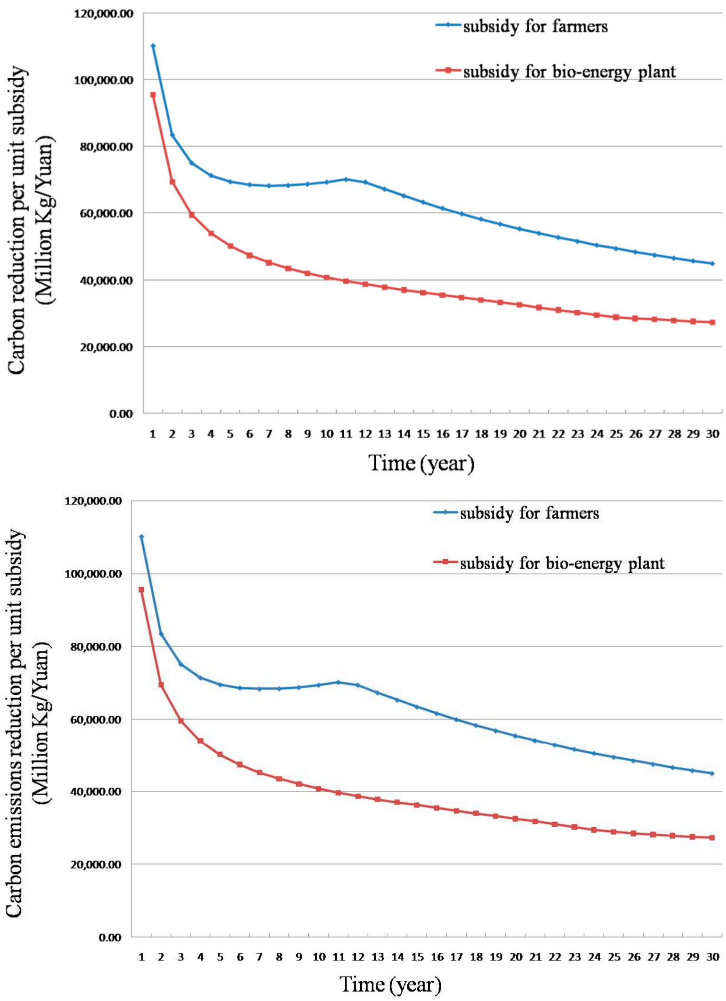


Figure 9. Comparison of the emissions reduction in the two subsidy scenarios.

5.3. Discussion

The case example is employed to demonstrate the application of the hybrid method, which promotes transition to supply chain of waste straws for energy utilization through the structural optimization and motivational mechanism design, thus to enhance sustainability of the supply chain. The results provide insight into construction of a reverse supply chain of agro-wastes for countries under the Belt and Road Initiative, and facilitating the supply chain management practices. Based on the results, even if the farmers are provided with a linear growth subsidy, the government is required to continuously increase the subsidy. Hence, its financial burden cannot be mitigated effectively in the long run. To solve this issue, the government may consider implementing policies that combine taxation and subsidies for the stakeholders of the straw-to-electricity supply chain. Using subsidies would ensure successful operations during the supply chain's early stages. Additionally, collecting taxes from stakeholders when the supply chain operations stabilize would cover the government expense on subsidies.

Moreover, the actual supply chain operations involve the interactive behaviors among stakeholders. For instance, whether the farmers are effectively receiving incentives is related to how their interests coincide with the bio-energy plant. In this study, the subsidy only acts on the stakeholders, such as the bio-energy plant and farmers, separately, instead of taking their interactions into account. Studies have shown that coordination among stakeholders on the supply chain network has great potential of increase of eco-efficiency [39]. Therefore, it is recommended that incentive policies apply to multiple stakeholders at the same time to maximize their synergistic effects and enhance the sustainability of supply chain.

There are also some uncertainties in this study. Firstly, as this is a predictive study, the constructed model may not be verified. Specifically, some changes in parameters are based only on empirical assumptions. Secondly, the system boundaries of the straw-to-electricity supply chain are simplified. Some intermediate stages are left out such as the cultivation of straw crops and the conversion of straw into resources. This has uncertain impacts on the research results and should be discussed in depth by further studies.

6. Conclusions

In conjunction with the Belt and Road Initiative, this study proposes a hybrid method of multi-objective optimization and system dynamics simulation to combine the structural optimization of a straw-to-electricity supply chain with its associated motivation mechanisms design. It obtains optimal operations parameters by using total supply chain cost and carbon emissions minimization as the objectives. Based on the optimal supply chain structure designed in this study, dynamic government subsidy mechanisms are introduced to facilitate the supply chain management and operations. Two scenarios are constructed with bio-energy plant subsidies and also ones for farmers. In these scenarios, the subsidy schemes are further divided into three approaches: flat rate subsidy, linear growth subsidy, and adverse sloped subsidy. Use of the system dynamics simulation reveals that providing the farmers with the linear growth subsidy yields the relatively optimal outcome of carbon emissions reduction. It is expected that the results may provide the evidence to guide the agro-wastes reutilization and enhance the eco-efficiency of the supply chain management of countries along the Belt and Road routes.

However, several limitations in this study can be improved by further studies. In terms of incentive policies, this study merely considers the government subsidy and neglects other motivational measures and combined policy instruments. In addition, the interactive behaviors among stakeholders involving in straw power generation are omitted during modeling. Finally, the model constructed in this study is static and neglects the seasonal characteristics of straw production as well as the consequent changes in stock. Under the motivational mechanism, further studies may incorporate more policy-related scenarios for analysis and adopt the game theory to simulate the interactions among stakeholders. Researchers may also integrate the uncertainty simulation technique for further supply chain optimization.

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Author Contributions: Yiyun Liu proposed the optimization model and implemented the SD simulation. Rui Zhao was involved in conceptualizing the whole study and writing the whole paper. Kuo-Jui Wu implemented the calculation. Tao Huang and Chenyi Cai collected the data. Anthony S. F. Chiu improved the whole structure of the paper.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

operational capacity(t) = operational capacity(t-dt) + (capacity increment rate)dt
capacity increment rate = gap/adjusted time
Gap = expected capacity − operational capacity
adjusted time = GRAPH (investment rate)
(0.00, 40), (0.10, 36.33), (0.20, 33), (0.30, 29.5), (0.40, 26.17), (0.50, 22.67), (0.60, 19.17), (0.70, 15.68), (0.80, 12.18), (0.90, 8.675), (1.0, 5.350)
investment rate = (profit increment rate − min(profit increment rate))/(max(profit increment rate) − min(profit increment rate))
profit increment rate = revenue of electricity − Operational capacity price of agro-straw
economic profit of bio-energy plant(t) = Economic profit of bio-energy plant(t-dt) + (profit increment rate)
electricity production = Operational capacity·500
revenue of electricity= (demand increment for bioelectricity + electricity production)·0.75
marketing electricity price = 0.75 − subsidy electricity price
demand increment for bioelectricity = GRAPH (market electricity price)
(0.45, 298.50), (0.48, 270), (0.51, 240), (0.54, 210), (0.57, 180), (0.60, 150), (0.63, 118.5), (0.66, 90), (0.69, 60), (0.72, 30), (0.75, 1.5)
Price of agro-straw = GRAPH (supply increment from farmers)
(0.80, 299), (0.92, 279), (1.04, 259), (1.16, 239), (1.28, 219), (1.40, 199), (1.52, 179), (1.64, 159), (1.76, 139), (1.88, 119), (2.00, 100)
supply increment from farmers = if Revenue of farmers < 2700 Then low carbon consciousness of farmers (0.9 − 0.086·0.001·Revenue of farmers)
Else low carbon consciousness of farmers·(0.147·10 − 3·Revenue of farmers + 0.272)
low carbon consciousness of farmers = (Carbon reduction − min(Carbon reduction))/(max(Carbon reduction) − min(Carbon reduction))
carbon reduction(t) = Carbon reduction(t-dt) + (carbon reduction rate)dt
carbon reduction rate = 663.49·electricity production − 39.92·Operational capacity
revenue of farmers(t) = Revenue of farmers(t-dt) + (revenue increment rate)dt
revenue increment rate = (price of agro-straws + subsidy for farmers)·Operational capacity

References

1. Huang, Y. Understanding China's Belt & Road Initiative: Motivation, framework and assessment. *China Econ. Rev.* **2016**, *40*, 314–321.
2. Liu, W. Scientific understanding of the Belt and Road Initiative of China and related research themes. *Prog. Geog.* **2015**, *34*, 538–544, (In Chinese with English abstract).
3. Xu, L.J.; Fan, X.C.; Wang, W.Q.; Xu, L.; Duan, Y.L.; Shi, R.J. Renewable and sustainable energy of Xinjiang and development strategy of node areas in the "Silk Road Economic Belt". *Renew. Sustain. Energ. Rev.* **2017**, *79*, 274–285. [CrossRef]
4. Zhao, R.; Liu, Y.; Zhang, Z.; Guo, S.D.; Tseng, M.L.; Wu, K.J. Enhancing Eco-Efficiency of Agro-Products' Closed-Loop Supply Chain under the Belt and Road Initiatives: A System Dynamics Approach. *Sustainability* **2018**, *10*, 668. [CrossRef]
5. Yan, Z.; Song, Z.; Li, D.; Yuan, Y.; Liu, X.; Zheng, T. The effects of initial substrate concentration, C/N ratio, and temperature on solid-state anaerobic digestion from composting rice straw. *Bioresour. Technol.* **2015**, *177*, 266–273. [CrossRef] [PubMed]
6. Zhang, Y.; Tian, Z.; Liu, J.; Chao, F.; Liang, Q. Low Carbon Energy Systems in China: Visioning Regional Cooperation through the Belt and Road. In *Investing on Low-Carbon Energy Systems*; Springer: Singapore, 2016; pp. 31–54.
7. Zhang, N.; Liu, Z.; Zheng, X.; Xue, J. Carbon footprint of China's belt and road. *Science* **2017**, *357*, 1107. [CrossRef] [PubMed]
8. Zhao, X.; Feng, T.; Ma, Y.; Yang, Y.; Pan, X. Analysis on investment strategies in China: The case of biomass direct combustion power generation sector. *Renew. Sustain. Energ. Rev.* **2015**, *42*, 760–772.

9. Sun, Y.; Cai, W.; Chen, B.; Guo, X.; Hu, J.; Jiao, Y. Economic analysis of fuel collection, storage, and transportation in straw power generation in China. *Energy* **2017**, *132*, 194–203. [CrossRef]
10. Wu, Y.; Li, L.; Xu, R.; Chen, K.; Hu, Y.; Lin, X. Risk assessment in straw-based power generation public-private partnership projects in China: A fuzzy synthetic evaluation analysis. *J. Clean. Prod.* **2017**, *161*, 977–990. [CrossRef]
11. Monteleone, M.; Cammerino, A.R.B.; Garofalo, P.; Delivand, M.K. Straw-to-soil or straw-to-energy? An optimal trade off in a long term sustainability perspective. *Appl. Energ.* **2015**, *154*, 891–899. [CrossRef]
12. Bentsen, N.S.; Nilsson, D.; Larsen, S. Agricultural residues for energy-A case study on the influence of resource availability, economy and policy on the use of straw for energy in Denmark and Sweden. *Biomass Bioenerg.* **2018**, *108*, 278–288. [CrossRef]
13. Pan, S.Y.; Du, M.A.; Huang, I.T.; Liu, I.H.; Chang, E.E.; Chiang, P.C. Strategies on implementation of waste-to-energy (WTE) supply chain for circular economy system: A review. *J. Clean. Prod.* **2015**, *108*, 409–421. [CrossRef]
14. Mobini, M.; Sowlati, T.; Sokhansanj, S. Forest biomass supply logistics for a power plant using the discrete-event simulation approach. *Appl. Energ.* **2011**, *88*, 1241–1250. [CrossRef]
15. Yu, H.; Wang, Q.; Ileleji, K.E.; Yu, C.; Luo, Z.; Cen, K.; Gore, J. Design and analysis of geographic distribution of biomass power plant and satellite storages in China. Part 1: Straight-line delivery. *Biomass Bioenerg.* **2012**, *46*, 773–784. [CrossRef]
16. Zhao, X.; Li, A. multi-objective sustainable location model for biomass power plants: Case of China. *Energy* **2016**, *112*, 1184–1193. [CrossRef]
17. Chiueh, P.T.; Lee, K.C.; Syu, F.S.; Lo, S.L. Implications of biomass pretreatment to cost and carbon emissions: Case study of rice straw and Pennisetum in Taiwan. *Bioresour. Technol.* **2012**, *108*, 285–294. [CrossRef] [PubMed]
18. Delivand, M.K.; Cammerino, A.R.B.; Garofalo, P.; Monteleone, M. Optimal locations of bioenergy facilities, biomass spatial availability, logistics costs and GHG (greenhouse gas) emissions: A case study on electricity productions in South Italy. *J. Clean. Prod.* **2015**, *99*, 129–139. [CrossRef]
19. Roni, M.S.; Eksioglu, S.D.; Searcy, E.; Jha, K. A supply chain network design model for biomass co-firing in coal-fired power plants. *Transp. Res. E Log.* **2014**, *61*, 115–134. [CrossRef]
20. Turki, S.; Didukh, S.; Sauvey, C.; Rezg, N. Optimization and Analysis of a Manufacturing-Remanufacturing-Transport-Warehousing System within a Closed-Loop Supply Chain. *Sustainability* **2017**, *9*, 561. [CrossRef]
21. Vance, L.; Heckl, I.; Bertok, B.; Cabezas, H.; Friedler, F. Designing sustainable energy supply chains by the P-graph method for minimal cost, environmental burden, energy resources input. *J. Clean. Prod.* **2015**, *94*, 144–154. [CrossRef]
22. Singh, J. Identifying an economic power production system based on agricultural straw on regional basis in India. *Renew. Sustain. Energ. Rev.* **2016**, *60*, 1140–1155. [CrossRef]
23. Yan, Q.; Qin, Y. A study on electricity price subsidy mechanism of biomass based power generation of China. In Proceedings of the E-Business and E-Government (ICEE), Shanghai, China, 6–8 May 2011; IEEE: Shanghai, China, 2011.
24. Luo, K.; Zhang, X.; Tan, Q. Novel Role of Rural Official Organization in the Biomass-Based Power Supply Chain in China: A Combined Game Theory and Agent-Based Simulation Approach. *Sustainability* **2016**, *8*, 814. [CrossRef]
25. Xue, C.; Wang, X. Study on government subsidy decision-making of straw power generation supply chain. *Procedia Eng.* **2017**, *174*, 211–218. [CrossRef]
26. Wen, W.; Zhang, Q. A design of straw acquisition mode for China's straw power plant based on supply chain coordination. *Renew. Energy* **2015**, *76*, 369–374. [CrossRef]
27. Zhang, X.; Luo, K.; Tan, Q. A game theory analysis of China's agri-biomass-based power generation supply chain: A co-opetition strategy. *Energ. Procedia* **2017**, *105*, 168–173. [CrossRef]
28. Garg, K.; Kannan, D.; Diabat, A.; Jha, P. A multi-criteria optimization approach to manage environmental issues in closed loop supply chain network design. *J. Clean. Prod.* **2015**, *100*, 297–314. [CrossRef]
29. Zhao, R.; Liu, Y.; Zhang, N.; Huang, T. An optimization model for green supply chain management by using a big data analytic approach. *J. Clean. Prod.* **2017**, *142*, 1085–1097. [CrossRef]
30. Liu, H.; Polenske, K.R.; Xi, Y.; Guo, J.E. Comprehensive evaluation of effects of straw-based electricity generation: A Chinese case. *Energ. Policy* **2010**, *38*, 6153–6160. [CrossRef]

31. Messac, A.; Ismail-Yahaya, A.; Mattson, C.A. The normalized normal constraint method for generating the Pareto frontier. *Struct. Multidiscip. Optimiz.* **2003**, *25*, 86–98. [CrossRef]
32. Feng, Y.Y.; Chen, S.Q.; Zhang, L.X. System dynamics modeling for urban energy consumption and CO_2 emissions: A case study of Beijing, China. *Ecol. Model.* **2013**, *252*, 44–52. [CrossRef]
33. Liu, L.; Ye, J.; Zhao, Y.; Zhao, E. The plight of the biomass power generation industry in China–A supply chain risk perspective. *Renew. Sustain. Energ. Rev.* **2015**, *49*, 680–692. [CrossRef]
34. National Development and Reform Commission notice on improving Agriculture and Forestry biomass power generation price policy. Available online: http://www.ndrc.gov.cn/zcfb/zcfbtz/201007/t20100728_363362.html (accessed on 6 November 2017).
35. Glithero, N.J.; Ramsden, S.J.; Wilson, P. Barriers and incentives to the production of bioethanol from cereal straw: A farm business perspective. *Energ. Policy* **2013**, *59*, 161–171. [CrossRef] [PubMed]
36. Giannoccaro, G.; de Gennaro, B.C.; De Meo, E.; Prosperi, M. Assessing farmers' willingness to supply biomass as energy feedstock: Cereal straw in Apulia (Italy). *Energ. Econ.* **2017**, *61*, 179–185. [CrossRef]
37. Wang, Y.; Chang, X.; Chen, Z.; Zhong, Y.; Fan, T. Impact of subsidy policies on recycling and remanufacturing using system dynamics methodology: A case of auto parts in China. *J. Clean. Prod.* **2014**, *74*, 161–171. [CrossRef]
38. Zhao, R.; Zhou, X.; Han, J.; Liu, C. For the sustainable performance of the carbon reduction labeling policies under an evolutionary game simulation. *Technol. Forecast. Soc. Chang.* **2016**, *112*, 262–274. [CrossRef]
39. Zhao, R.; Neighbour, G.; Han, J.; McGuire, M.; Deutz, P. Using game theory to describe strategy selection for environmental risk and carbon emissions reduction in the green supply chain. *J. Loss Prevent. Proc.* **2012**, *25*, 927–936. [CrossRef]