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Biomass supply chain coordination for remote communities: A game-theoretic modeling and analysis approach

Zahra Vazifeh [a], Fereshteh Mafakheri [a,*], Chunjiang An [b]

[a] Concordia Institute for Information Systems Engineering, Concordia University, Montreal, H3G 1M8, Canada
[b] Department of Building, Civil, and Environmental Engineering, Concordia University, Montreal, H3G 1M8, Canada

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ABSTRACT

Biomass, as one of the most available renewable energies, could reduce dependency on fossil fuels and the consequent environmental impacts. There is a need for biomass supply chain management, which is managing bioenergy production from harvesting feedstock to energy conversion facilities. In case of remote communities, bioenergy adoption requires dealing with dispersed geographies of suppliers and places of consumption with small scales of energy demand. As such, coordination plays a key role in increasing the efficiency of the biomass supply chain network through bundling of demand and thus improving the economy of scale. This paper employs a game-theoretic approach to formulate a coordinated biomass supply chain with three echelons including suppliers, hubs, and energy convertors. To investigate the strategic interactions of participants, three decision making structure scenarios have been considered under Stackelberg game providing insights into the impact of power distribution, the role of side payments in enforcing the flow of decisions, and the resulting efficiency and performance improvements. In doing so, a case study bioenergy supply chain for three northern Canadian communities is explored to demonstrate the application of the proposed formulation, solution methods, and the practicality and significance of the adopted approach and outcomes for remote communities.

1. Introduction

The use of renewable energy sources as a solution to decrease the world dependency on fossil fuel and to alleviate climate change has been increasingly studied in past decades. Among all types of renewable energies, biomass is one of the highly used sources, which includes plant and animal materials, forestry and agricultural residues, crops, seaweed, and some organic substances originating from living organisms (Mafakheri & Nasiri, 2014). Biomass has been the main source of energy in rural areas for centuries. However, there are several issues impacting the efficiency of bioenergy sector including low energy density of biomass materials, their seasonal availability, and as such, high variability of the investment and operational costs (Mafakheri & Nasiri, 2014). Beside these barriers, uncertainties involved in the biomass sourcing, transportation, logistics, production, operation, demand and price have further hindered the performance of biomass supply chains (Awudu & Zhang, 2012).

To overcome these barriers and challenges, coordination of biomass supply chain could play a key role (Awudu & Zhang, 2012). Supply chain coordination (or channel coordination) aims at improving supply chain performance by aligning the plans and the objectives of individual enterprises (Chan & Chan, 2010). It is a means of optimizing the entire benefit of supply chain by facilitating the information flow and/or providing incentives for key players to cooperate in the network. Although many articles have studied coordination among the players of traditional supply chains, studies that focus on channel coordination in biomass supply chains and its benefits to participating parties are very limited (Mafakheri, Adebanjo, & Genus, 2020).

A typical biomass supply chain is comprised of a three echelon channel representing one or multiple biomass suppliers (and first level) that collect and wholesale biomass to hubs (that coordinate the supply and demand sides). The hubs sell biomass to energy conversion facilities (at the third echelon of the chain) where biomass is converted to heat and energy for end users. This hierarchical structure of decisions resembles a (non-cooperative) Stackelberg leader-follower game (Zhang & Liu, 2013). The situation at which any individual member of the supply chain tries to maximize its own profit can be described as a non-cooperative game. Stackelberg games are a category of non-cooperative games in which the member with a dominant power (as a leader in the game) governs the other members who will follow the

* Corresponding author.
E-mail address: f.mafakheri@concordia.ca (F. Mafakheri).

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leader's actions. This creates a strategic advantage (power) for the leader in anticipating and controlling the actions of the follower members, which is critical in elaborating the interactions among different supply chain members (Zhang & Liu, 2013).

Literature indicates that three main types of (leader-follower) Stackelberg games have been mainly adapted; first, single-leader-single-follower games (Yue & You, 2017) (namely referred to as standard Stackelberg games), in which the leader takes actions first and then the follower reacts to the leader's decisions in a rational manner. The second category includes the single-leader-multiple-follower games (Bai, Ouyang, & Pang, 2012; Yue & You, 2014, 2017). In this case, the leader takes actions first and then the followers react to the leader's decisions simultaneously and might compete for a common resource/incentive. The third group accounts for multiple-leader-multiple-follower games (DeMiguel & Xu, 2009; Hori & Fukushima, 2019; Sinha, Malo, Frantsev, & Deb, 2014) in which a group of channel members take action primarily and the followers optimize their objectives in reflection of decisions made by the leading members.

In leader-follower games, the leadership management and the resulting assumption of the players' roles is a challenge. Although, traditionally, in manufacturing-oriented supply chains, a manufacturer acts as the leader, in recent years, the cases of the leading power being assumed by other players have been investigated (Shi, Zhang, & Ru, 2013) In this sense, many authors have studied the impact of power structure scenarios in manufacturer–retailer coordination problems (Li, Xu, Deng, & Liang, 2018; Sadigh, Mozafari, & Karimi, 2012; SeyedEsfahani, Biazaran, & Gharakhani, 2011; Shi et al., 2013). Sadigh et al. (2012) investigated non-cooperative games for a multi-product manufacturer and retailer under two different power structures including manufacturer as Stackelberg leader and retailer as Stackelberg leader. They demonstrated that each channel member gains more benefit when playing the Stackelberg leader at the expense of the follower. Shi et al. (2013) examined the impact of power structure and demand uncertainty on performance of supply chain members. Their work showed that benefit gained from a leadership position in the game is influenced by the expected demand. Liu, Wang, and Zhu (2015) explored the impacts of control power on the profits of manufacturer, retailer, and the overall supply chain under four modes of decision making, including a decentralized decision-making dominated by the manufacturer, a decentralized decision-making dominated by the retailer, a centralized decision-making, and a Nash equilibrium (negotiation) decision-making. They concluded that the profit of the whole supply chain with a centralized decision-making is higher than those of the other three modes. They also showed that the order quantity will increase and the wholesale price will decrease when control power is transferred from manufacturer to retailer.

For model formulation, most of the researches in the literature have focused on the maximization of net revenues of individual members. In this setting, the net revenue of the supply chain's leader is maximized according to the other members' optimal decisions (Bai et al., 2012). Early works on modelling the interactions of supply chain's members as Stackelberg games focused on bi-level Linear programming (LP) and Quadratic Programming (QP) problems (Ortiz-Gutierrez, Giarola, Shah, & Bezzo, 2015). Later, more complex problems, considering continuous or categorized quantity discounts, were formulated through Non-Linear Programming (NLP) and Mixed Integer Non-Linear Programming (MINLP), respectively (Bai et al., 2012; Ortiz-Gutierrez et al., 2015; Wang, Wang, Wan, & Lv, 2007).

In the light of the above literature review, this paper investigates the performance of biomass supply chain coordination, for remote communities, under three power structure (leader-follower combination) scenarios as listed in Table 1. The aim is to investigate the effects of each power structure scenario on coordinating the decisions of biomass channel members and on overall efficiency and performance of the biomass supply chains. This is of particular importance as the economy of scale is the main barrier to implement biomass supply chains for

Table 1
Summary of possible/potential leadership scenarios.

	Suppliers	Hubs	Energy convertors
Scenario 1	Leader	Follower	Follower
Scenario 2	Follower	Leader	Follower
Scenario 3	Follower	Follower	Leader

remote communities (Mafakheri et al., 2020). This comparison provides the basis to analyze the effect of a number of supply chain coordination strategies (incentives), including quantity discounts and side payments, in directing a dominant equilibrium solution across these alternative power structures. The results reveal the importance of having communities to strategically assume a leading role in biomass supply chains in order to ensure an equilibrium solution with highest cost-efficiency, in contrary to conventional supply chains where suppliers lead the game (Mafakheri & Nasiri, 2013).

Discount quantities in supply chains (Shin & Benton, 2007) are adopted by supplying entities (suppliers or hubs) to encourage larger purchases which in turn serve as a motivation for bundling of orders. Side payments are provided by the leading entity to follower parties in a Stackelberg game to guarantee stability of an equilibrium solution and prevent follower parties to deviate and seek a leadership role in the game (Jackson & Wilkie, 2005; Zeng, Li, Cai, Tan, & Dai, 2019). Assuming and maintaining a leadership role provides the leader with the strategic advantage in driving the other players' choices. Obviously, the party that is better leveraged to provide side payments will be better positioned to assume and maintain the leadership role.

In this paper, the quantity discount policy is formulated such that to adopt both purchasing (discount from suppliers) and ordering (discount from hubs) prices as functions of biomass quantity. This double-discount is to guarantee an increase in bundling of purchases as well as order quantities, such that the associated prices decrease with increase of the scale, presenting an improved economy of scale. The net revenues of suppliers and hubs are maximized and the cost for energy convertors is minimized following the order of the leadership. In addition, the problem is formulated as a multi-period problem, reflecting the realities of biomass supply chains in terms of the need to continuity and reliability over time (Sinha et al., 2014). This results in a multi-period model where the optimization problem of a follower serving as constraints for the preceding leader creating a joint decision space for players. The solution approach to such a complex (multi-level) decision making problem will be further discussed in the subsequent sections.

While, the coordination of biomass supply chain players has been investigated at the city (for district heating systems) (Akgül & Seçkiner, 2019) or building scales (Nasiri, Mafakheri, Adebanjo, & Haghighat, 2016), a focus on coordination of small and dispersed communities is emerging in the literature (Mafakheri et al., 2020). This study presents a first attempt at examining the impact of alternative power structures in coordination of biomass supply chains in case of remote communities (with dispersed small scales of demand). The coordination of biomass supply chain through means of demand bundling (encouraged by quantity discounts) and side payments is examined to seek the best strategy for improving the economy of scale and making the biomass a viable choice. A schedule of decisions including wholesale price, purchasing quantity, ordering quantity, and amount of produced bioenergy are examined in relation to the resulting performance of supply chain members.

A rational player can dominate the flow of information and assume a first mover advantage by offering a side payment to other (rational) players persuading them to remain a follower. This argument is based on the assumption that the players are rational and that the decisions are made according to players' objective functions with no involvement of negotiations/politics. In this regard, this study investigates the various leaders-follower scenarios in biomass supply chains, in case of remote communities, in order to identify the power structure that requires a lower side payment giving the leader a strategic first mover advantage to dictating the direction of information flow.

The remaining of the paper is organized as follows. Section 2 describes the background, assumptions, objectives, decision variables, constraints and parameters of the biomass supply chain channel problem. In the Section 3, formulation of the proposed models is presented under the three power structure scenarios. Section 4 investigates the solution procedure as well as its implementation in the context of biomass supply for three remote communities in northern Canada. Section 5 is devoted to discussing the results of the case study, and finally the section 6 presents concluding remarks and a summary of avenues for future research.

2. Methodology

2.1. Problem description

A three-echelon biomass supply chain includes suppliers, for collecting and harvesting the biomass, hubs, for coordinating the ordering and transport of biomass, and energy conversion facilities as users of biomass (Fig. 1). Each party, as a rational player, is a profit maximizer. The suppliers intend to maximize their profit by deciding on selling price of biomass. In the second echelon, hubs are coordinating (and matching) the supply and demand sides of the supply chain. Since the existence of hubs must be economically feasible, they strive to maximize their own profit. The decision variables of hubs are the quantities to order from suppliers as well as the selling price of biomass to the energy conversion facilities. In the third echelon, biomass is converted to energy and transmitted to the consumers. The energy conversion facilities aim at minimizing the cost of energy production (their revenue is assumed independent of the source of energy) by deciding on the quantity of biomass to purchase and the amount of energy to generate from biomass. The interaction across this hierarchy of players resembles as a leader–follower Stackelberg game (Yue & You, 2017). In this setting, the leader is the party that uses a first mover advantage in making a decision such that to align the other parties as a follower.

Stackelberg games are closely associated with bi-level optimization problems (Colson, Marcotte, & Savard, 2007; Sinha et al., 2014), which are characterized by two levels of optimization problems where the constraint region of the upper level problem is implicitly determined by the lower level optimization problem. In this paper, the interactions between the supply chain members are formulated through a bi-level programming. The model will serve as a basis to investigate the various scenarios of the leadership (power structures) among the players in a biomass supply chain. These alternative scenarios are Suppliers-Stackelberg (suppliers act as the leader), Hubs-Stackelberg (hubs act as the leader), and Energy convertors-Stackelberg (Energy convertors act as the leader).

2.2. Model assumptions

The main modeling assumptions are itemized as follows:

- The cost of biomass transportation from a supplier to a hub is covered by the supplier.
- The cost of biomass transportation from a hub to an energy conversion facility is covered by the hub.
- In case of biomass supply to remote communities with small scale of supply and demand, it is to the best interest of members in each echelon, as rational parties, to form collations and act collectively to benefit from improving the economy of scale (through higher quantity discounts resulting in higher orders). Under this rational assumption, we consider a collective objective function of them in each echelon. Further to the improvement of the economy of scale, such collations provide the opportunity for using collective capacities in harvesting, storage, transportation, and conversion, considering the geographical distribution of the biomass, which further contributes to improving the efficiency of the supply chains.
- Supply chain members, as rational players, optimize their own objective function but will not share information with members in other echelons, due to anticipated conflicting interests (objectives).
- The initial (capital) costs (to create the generation capacities) are assumed to be compensated through the investments from the government and thus are not included in the proposed supply chain model.

2.3. Model formulation

Below, the optimization problems of players in the biomass supply chain game are first formulated (i.e. suppliers' problem, hubs' problem, and the energy convertor's problem). Then, in each power structure scenario, one of the players assumes the leadership role forming the upper level problem, and the two other players form the lower level (follower) problems. Thus, this joint (hierarchical) decision process is formulated as a bi-level non-linear program (BNLP) problem (Colson et al., 2007; Nasiri & Zaccour, 2009). The non-linearity originates from the incorporation of quantity discount policies (to encourage bundling of biomass quantities across communities), which promotes a decrease in prices when quantities increase. This will be followed by exploring the solution approach for each of the power structure scenarios.

The descriptions of acronyms, parameters and variables used in the model formulations are provided in the Appendix 1.

2.3.1. Formulation of the suppliers' problem

The objective function of suppliers' problem (Obj_{sup}) reflects maximization of the total (annual) payoff, presented by Eq. (1). The first term in this equation represents the revenue obtained from the sale of biomass to hubs, which is calculated as the product of the biomass price at time 't' (P^t_{ik}) and the total quantity sold to hubs ($\sum_k X^t_{ik}$). Other

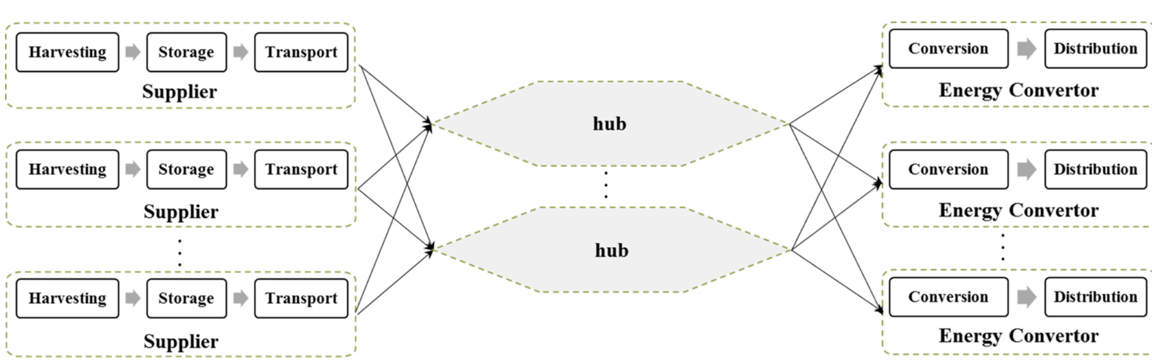


Fig. 1. The three-echelon biomass supply chain network.

components of the suppliers' objective function incorporate harvesting/processing, holding, and transportation costs.

$$Max\ Obj_{sup} = \sum_i \left\{ \sum_t \left[\left(\sum_k X_{ik}^t\ P_{ik}^t \right) - hs_i\ S_i^t - H_i\ IS_i^t - \sum_k X_{ik}^t\ T_{ik} \right] \right\} \quad (1)$$

where biomass price at time 't' (P_{ik}^t) is considered as a function of sale quantity and capacity of the supplier (reflecting a quantity discount policy). This relationship is given by Eq. (2)

$$P_{ik}^t = P_i^u - \left(P_i^u - P_i^l \right) \frac{X_{ik}^t}{S_i^t} \quad (2)$$

Inventory level for supplier 'i' at time 't' is calculated considering the inventory level at time 't − 1', available (harvested/processed) biomass (i.e. supplier's capacity) at time 't', and the amount of biomass deliveries to hubs at time 't':

$$IS_i^t = IS_i^{t-1} + S_i^t - \sum_k X_{ik}^t\ , \quad IS_i^0 = 0 \quad (3)$$

There are also a number of technical constraints. First, the amount of biomass dispatched for delivery to hubs from each supplier shall not exceed its capacity:

$$\sum_k X_{ik}^t \leq S_i^t \quad (4)$$

In addition, each supplier's inventory cannot exceed its capacity:

$$0 \leq IS_i^t \leq S_i^t \quad (5)$$

With the nonnegative decision variables of:

$$X_{ik}^t \geq 0 \quad (6)$$

2.3.2. Formulation of the hubs' problem

The optimization problem of hubs is formulated as Eq. (7). The first term denotes the revenue of hubs, which is calculated as the product of total quantity sold to energy convertor facilities ($\sum_j y_{kj}^t$) and hubs' biomass price at time 't' (B_{kj}^t). The costs include biomass purchasing (from suppliers) and holding cost.

$$Max\ obj_{hub} = \sum_k \left\{ \sum_t \left[\left(\sum_j y_{kj}^t\ B_{kj}^t \right) - \sum_i X_{ik}^t\ P_{ik}^t - Hc_k\ h_k^t \right] \right\} \quad (7)$$

Hubs' biomass price offered to energy convertors at time 't' (B_{kj}^t) is considered as a function of selling quantity and capacity of the hub (reflecting hubs' discount policy):

$$B_{kj}^t = B_{kj}^u - \left(B_{kj}^u - B_{kj}^l \right) \frac{y_{kj}^{t-rp}}{h_k} \quad (8)$$

Inventory level at hub 'k' at time 't' is presented as:

$$h_k^t = h_k^{t-1} + \sum_i X_{ik}^{t-rs} - \sum_j y_{kj}^t\ , \quad h_k^0 = 0 \quad (9)$$

This inventory cannot exceed the hub's capacity:

$$h_k^t \leq hk(k) \quad (10)$$

With the nonnegative decision variables of:

$$y_{kj}^t \geq 0 \quad (11)$$

2.3.3. Formulation of the energy convertors' problem

The optimization problem of energy convertors is formulated as Eq. (12). The costs include biomass acquisition cost paid to hubs, biomass holding cost, biomass to electricity conversion cost, and electricity generation cost from an alternative (competing or backup) source:

$$Min\ Obj_{cf} = \sum_j \left\{ \sum_t \left[\left(\sum_j y_{kj}^t\ B_{kj}^t \right) + (I_j^t\ a_j) + (LB_j\ z_j^t) + (LD_j\ (D_j^t - z_j^t)) \right\} \right. \quad (12)$$

The consideration of an alternative source is a reflection of the need to have a reliable production of energy in case of biomass supply fluctuations from the perspectives of quantity and/or price. Also, in many remote (off-grid) communities, diesel is used as the main source for generation of electricity (NEB, 2014). In this sense, the energy convertor facility decides about the least cost mix of energy sources between the conventional/existing source (such as diesel) and biomass. In doing so, minimization objective function presented in Eq. (12) could result in having biomass as part of the energy mix only if biomass is a viable option in comparison with the alternative source(s) as the last component of the equation (capturing the cost associated with alternative source) is in tradeoff with the remaining components of the equation (representing the costs associated with biomass).

Inventory levels of each conversion facility 'j' at time 't' is presented as:

$$I_j^t = I_j^{t-1} + \sum_k y_{kj}^{t-rp} - \frac{z_j^t}{fc_j},\ I_j^0 = 0 \quad (13)$$

There are a number of technical constraints. First, bioenergy production at each conversion facility is bounded by (the minimum of) associated energy demand and energy production capacity of the facility. This relationship could be represented by Eq. (14) for any given month (720 h):

$$z_j^t \leq \min\left(D_j^t,\ Lf_j * Z_j * 720 \right) \quad (14)$$

Also, inventory levels of biomass conversion facility 'j' at time 't' cannot exceed its storage capacity:

$$I_j^t \leq Ib_j \quad (15)$$

With nonnegative decision variables of:

$$z_j^t \geq 0 \quad (16)$$

2.3.4. Formulation of BNLP problem

In the scenario 1, the suppliers' Stackelberg problem includes the objective function (1) and constraints (2)–(16). In the scenario 2, the hubs' Stackelberg problem includes the objective function (7) and constraints (1)–(6) and (8)–(16). In the scenario 3, the energy convertors' Stackelberg problem includes the objective function (12) and constraints (1)–(11) and (13)–(16).

2.4. Solution approach

This section presents the solution strategy for the Stackelberg single-leader-multi-follower game formulated as a multi-period BNLP problem. In BNLP problems, the outcome of any solution or decision taken by the upper level authority (leader) to optimize their goals is affected by the response of lower level entities (follower), which also tend to optimize their own outcomes (Nasiri & Zaccour, 2009). When the lower-level problem is convex, the conventional solving approach to the BNLP problems is to transform the original two-level problems into a single level one by replacing the lower level optimization problem with the set of equations that define its Karush–Kuhn–Tucker (KKT) conditions (Jiang, Li, Huang, & Wu, 2013). Using the KKT conditions, Kim and Ferris (2019) introduced an extended mathematical programming (EMP) to reformulate the bi-level problem to its equivalent Mathematical Program with Equilibrium Constraints (MPEC) framework solved with an MPEC solver in General Algebraic Modelling System (GAMS) (GAMS, 2020). They showed that their approach resulting less error compared to the traditional complementarity based models that require the derivative computation of the Lagrangian by hand. In this study, EMP tool in GAMS is adopted to transform the hierarchical problem into its MPEC equivalent problem. The transformed problem is then solved by using the non-linear program with equilibrium constraints (NLPEC) solver in GAMS.

3. Case study

A case study of northern Quebec communities is considered for adoption of biomass as an alternative source for electricity generation. This is in recognition of the energy security (and resilience) concerns for this region as these isolated communities are entirely dependent on diesel fuel for electricity generation (NEB, 2014). This single-source situation could result in high operating costs, low efficiency, high environmental risks and total dependence on a fossil fuel with elevated carbon dioxide emissions. The case study considers three Quebec northern communities of Kangigsujuaq (KA), Salluit (SA), and Ivujivik (IV). Despite the fact that Canada has access to a great amount of biomass resources from various sources, there is strictly no possibility of relying upon a local biomass supply in this region, because of the unsuitable vegetation texture of the region not supporting any reliable sources of biomass. Therefore, biomass must be imported from other places. In this situation, pellets are considered as the preferred type of biomass due to their higher level of standardization and higher energy density, making them a suitable candidate for delivery and storage. In this study, six suppliers from both Canada and US have been considered to provide biomass for energy production in these communities. A schematic superstructure of the investigated biomass supply chain is presented in Fig. 2.

Hubs contribute to increasing the economy of scale and coordination of supply and demand in biomass supply chains. Two hubs are considered in the biomass supply chain. This is the minimum number of hubs needed to ensure a diversification of supply-demand matching channels. One hub is located in the west of Quebec (QC) province and the other one in the northeast of New Brunswick (NB) province, in line with the main alternative transportation pathways to northern Quebec via Hudson Bay or Labrador Sea, respectively. The parameters of the models associated with the case study are described and presented in Table 2 (Mafakheri et al., 2020).

The solution of the BNLP model associated with the case study was obtained using an Intel (R) Core (TM) i5-4210U CPU 1.70 GHz computer equipped with General Algebraic Modelling System (GAMS) software. The bi-level problem is reformulated as a Mathematical Program with Equilibrium Constraints (MPEC) and is passed to a NLPEC solver. The computational time to solve the above BNLP models was 5.7 s. The solutions obtained are presented in the Tables 2–5.

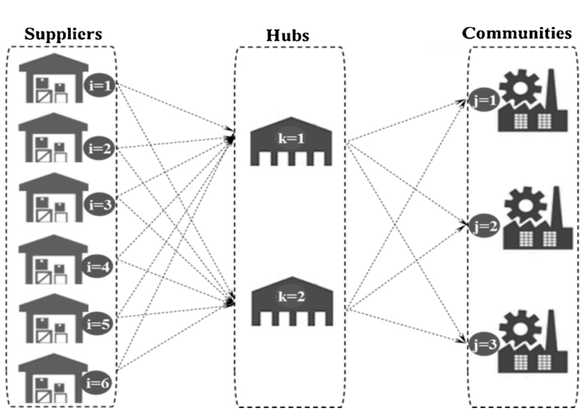


Fig. 2. Superstructure of the case study supply chain.

Table 2
Parameters of the model and their values used in the case study.

Definitions	Symbols and Units	Value
Transportation cost from supplier ‘i’ to hub ‘k’	T_{ik}($/kg)	Shown in Appendix 2
Capacity (biomass availability) of supplier ‘i’ at time t	S_i^t (kg)	Shown in Appendix 3
Biomass price of supplier ‘i’ without discount	P_i^u($/kg)	Shown in Appendix 3
Biomass price of supplier ‘i’ with discount	P_i^l($/kg)	Shown in Appendix 3
Biomass harvesting cost for supplier ‘i’	hs_i ($/kg)	0.04
Holding cost for supplier ‘i’	Hi_i($/kg)	Shown in Appendix 3
Capacity of hub ‘k’	h_{kk} (kg)	350,000, 400,000
Holding cost at hub ‘k’	Hc_k($/kg)	0.0020, 0.0015
Biomass ordering cost from hub ‘k’ without discount	B_{kj}^u($/kg)	Shown in Appendix 4
Biomass ordering cost from hub ‘k’ ‘j’ with discount	B_{kj}^l($/kg)	Shown in Appendix 4
Capacity of biomass inventory at energy convertor ‘j’	Ib_j(kg)	200,000, 200,000, 1,500,000
Holding cost at energy convertor ‘j’	a_j($/kg)	0.004, 0.003, 0.003
Conversion rate of biomass to electricity at convertor ‘j’	fc_j(kWh/kg)	4.7, 4.8, 4.6
Loading factor of energy convertor ‘j’	Lf_j (%)	80, 85, 80
Electricity generation cost from biomass	LB_j($/kWh)	0.046, 0.044, 0.048
Electricity generation cost from diesel	LD_j($/kWh)	0.208, 0.215, 0.207
Demand in energy convertor ‘j’ at time t	D_j^t (kWh)	Shown in Appendix 5
Capacity of electricity generation	Z_j (kW)	500, 500, 500
Delivery time between supplier ‘i’ and hub ‘k’	rs (Month)	1
Delivery time between hub ‘k’ and convertor ‘j’	rp (Month)	1

Table 3
Players’ objective function values based on alternative leadership scenarios.

Players	Objective	Scenario 1	Scenario 2	Scenario 3
Suppliers	Max (Revenue)	**$393,600**	$323,000	$322,900
Hubs	Max (Revenue)	$265,000	**$563,090**	$-60,773
Communities	Min (Cost)	$-1,577,400	$-1,889,956	**$-1,008,500**

4. Results and discussions

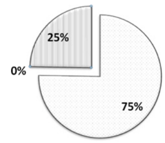
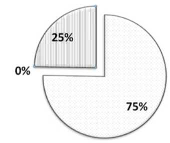
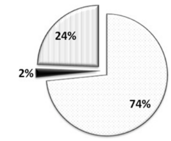
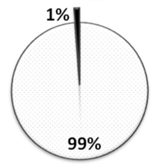
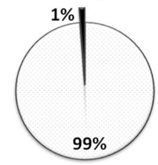
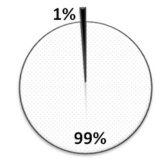
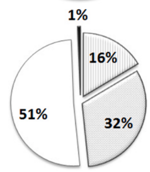
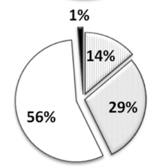
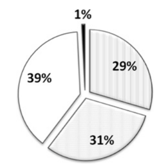
In this section, the results obtained based on three power structure scenarios will be discussed and compared. The values of the objective functions obtained for players in each scenario are presented in Table 3. The results show that the suppliers generate $393,600 revenues when they act as the leader, which is approximately 20 % higher comparing to their gains in other scenarios. If scenario 2 is employed, hubs assume the leadership with higher benefits achieved in comparison with the other scenarios. By choosing scenario 3, the communities would gain the most savings while the hubs will lose at the highest level of $60,773.

As the price of biomass and ordering costs offered by each supplier to each hub changes over time, to establish a pricing indicator for each scenario, the weighted average prices, for suppliers (i.e. biomass price) and hubs (i.e. ordering cost), are calculated according to Eqs. (17) and (18) and reported as presented in Fig. 3:

$$\overline{P} = \frac{\sum_{i,k,t} X_{ik}^t \; P_{ik}^t}{\sum_{i,k,t} X_{ik}^t} \tag{17}$$

$$\overline{B} = \frac{\sum_{k,j,t} y_{kj}^t \; B_{kj}^t}{\sum_{k,j,t} y_{kj}^t} \tag{18}$$

Table 4
Cost breakdown of biomass supply chain participants.

Participants	Cost's labels	Scenario 1	Scenario 2	Scenario 3
Suppliers	Harvesting cost Holding cost Transportation cost			
Hubs	Ordering cost Holding cost			
Communities	Biomass to electricity conversion cost Diesel to electricity generation cost Ordering cost Holding cost			

In scenario 1, an average biomass price of $0.21 per kg is achieved, the highest unit price compared among the scenarios. In scenario 2, however, biomass is at its lowest average price; while the ordering cost paid by the communities is at its highest average rate of $0.409 per kg. In scenario 3, biomass ordering cost is of $0.25 per kg is the lowest one among the three scenarios.

The cost breakdown for supply chain members in each scenario is shown in Table 4. Reviewing the results shows that the harvesting cost is a major cost for suppliers, forming around a three quarter of their total costs. The proportion of various costs of suppliers as well as the cost associated with hubs appears to remain the same in all scenarios. However, in case of the communities, the ordering cost appears to be changing amongst scenarios leading to the highest in scenario 2.

Table 5 presents the amount of electricity generated through scenarios in each community and as a fraction of demand. These results indicate that the demand is highly satisfied through scenario 3 to the extent of 92 %, 74 % and 92 % for communities 1, 2, and 3, respectively. The next effective scenario in terms of the biomass electricity power generation would be scenario 1, where the demand is satisfied to the extent of 87 %, 73 % and 86 % for communities 1, 2, and 3, respectively. Amongst all, scenario 2 yields the lowest share.

There are some key findings from the case study:

- The best value of objective function in each echelon is obtained when that echelon acts as a leader. This is due to the strategic (first-mover) advantage given to the leader, to decide while anticipating the response of the follower players. This further confirms the observations made by Shi et al. (2013) reporting on the impact of power structure in the manufacturer–retailer coordination problems.
- If the leadership switches from the suppliers to the hubs, the average biomass price (offered by suppliers to hubs) decreases while the average biomass ordering price (offered by hubs to communities) increases. This power allocation thus has a similar impact, with the hubs acting as leader, and imposing the purchase of biomass at relatively cheaper prices (from suppliers) and the sale of biomass (to the communities) at remarkably higher prices.
- If the leadership switches from the hubs to communities, the average biomass price (offered by suppliers to hubs) increases while the average biomass ordering price (offered by hubs to communities) decreases remarkably. In this case, the communities could use this strategic advantage to acquire biomass at the cheapest possible price to minimizing their cost and thus increasing the share of biomass in their energy mix. In this sense, biomass based electricity generation will be at its highest level when communities assume the leading role. In this scenario, biomass will be at its highest competitive advantage compared to the alternative fuel (diesel).

The findings indicate that the most desired scenario varies across the players meaning that no scenario can be dominating and agreed among all the parties. Each player prefers the scenario that ensures its leadership role. In such circumstances, the player that has the highest leverage to enforce its preferred scenario (leadership) can motivate the other players to remain a follower creating a dominant (stable) scenario that no player will deviate form it. Revisiting objective function values reported in Table 3 could provide insights on the amount of loss each player will incur when accepting a follower role in either of its non-preferred scenarios. These losses provide a basis for calculation of side payments that shall be offered from a leader player to the followers to ensure the dominance of their preferred (leadership) scenario. In doing so, the leader should be able to "match the best outcome of the follower parties" to have them committed to the leader's strategic advantage (Zeng et al., 2019). Otherwise, the other players will deviate from their follower roles in the supply chain.

As the objective function of communities includes both biomass and diesel related costs, the minimization of the objective function automatically generates the best trade-off between biomass and diesel. If the economies of the supply chain results in a competitive cost of biomass for communities, the biomass share increases, otherwise the diesel becomes the dominant one. Table 5 presents the share of biomass in the energy mix ranging from 0 % to 100 % for communities over time.

On that basis, the required side payments to (to ensure dominance of a leader over the followers) are calculated as the difference between the actual outcome of each follower player and its best performance (as a leader). This would be the amount of payment required to motivate a player to remain a follower and accept to have the payment-offering player as the leader. In this sense, Tables 6–8 present the required side payments that communities, suppliers, and hubs have to offer to others in order to maintain a leadership role.

The comparison of the required side payments to guarantee the dominance of each leadership scenarios shows that the scenario with the communities assuming the leadership role (scenario 3 with side payments from communities to suppliers and hubs) is achieved with the least total amount of required side payments ($694,563). Considering the ratio of required side payments to leader's best payoff, the community leadership will be the only scenario that still yields a positive payoff for the leader despite side payments. Moreover, in this scenario

Table 5
Electricity generation, z_j^t (kWh), and share of satisfied demand, $\acute{D}_j$ (%), for communities.

	First Scenario						Second scenario						Third Scenario					
	j = 1		j = 2		j = 3		j = 1		j = 2		j = 3		j = 1		j = 2		j = 3	
t	z_j^t	$\acute{D}_j$	z_j^t	$\acute{D}_j$	z_j^t	$\acute{D}_j$	z_j^t	$\acute{D}_j$	z_j^t	$\acute{D}_j$	z_j^t	$\acute{D}_j$	z_j^t	$\acute{D}_j$	z_j^t	$\acute{D}_j$	z_j^t	$\acute{D}_j$
1	0	0 %	0	0 %	0	0 %	0	0 %	0	0 %	0	0 %	0	0 %	0	0 %	0	0 %
2	132,028	77 %	173,693	54 %	82,647	89 %	0	0 %	3,582	1 %	92,398	100 %	171,900	100 %	190,168	59 %	92,800	100 %
3	162,688	95 %	290,923	90 %	90,965	99 %	171,000	100 %	48,236	15 %	91,905	100 %	171,000	100 %	306,000	95 %	92,300	100 %
4	179,695	99 %	305,245	89 %	96,393	99 %	155,540	86 %	1192	0 %	97,213	100 %	180,900	100 %	306,000	90 %	97,600	100 %
5	178,503	99 %	305,256	90 %	95,808	99 %	179,700	100 %	272,987	81 %	96,535	100 %	179,700	100 %	306,000	90 %	97,000	100 %
6	167,484	99 %	305,248	96 %	89,907	99 %	168,700	100 %	288,696	91 %	90,490	99 %	168,700	100 %	306,000	96 %	91,100	100 %
7	176,913	99 %	304,962	90 %	95,191	99 %	178,700	100 %	305,668	91 %	92,175	96 %	178,700	100 %	306,000	91 %	96,400	100 %
8	189,845	97 %	305,193	83 %	102,656	98 %	194,800	100 %	2,411	1 %	102,797	98 %	194,800	100 %	306,000	83 %	105,100	100 %
9	211,286	97 %	305,170	75 %	111,650	95 %	216,800	100 %	241,403	59 %	116,643	100 %	216,800	100 %	306,000	75 %	117,000	100 %
10	238,384	97 %	305,141	65 %	123,123	92 %	246,663	100 %	305,819	66 %	132,983	100 %	246,900	100 %	306,000	66 %	133,300	100 %
11	216,779	96 %	305,085	71 %	112,572	92 %	226,243	100 %	305,866	72 %	122,008	100 %	226,500	100 %	306,000	72 %	122,300	100 %
12	186,538	85 %	291,999	70 %	91,268	77 %	213,177	97 %	305,023	74 %	118,187	100 %	219,900	100 %	306,000	74 %	118,700	100 %
Average	**170,012**	87%	**266,493**	**0.73**	**91,015**	**0.86**	**162,610**	**0.82**	**173,407**	**0.46**	**96,111**	**0.91**	**179,650**	**0.92**	**270,847**	**0.74**	**96,967**	**0.92**

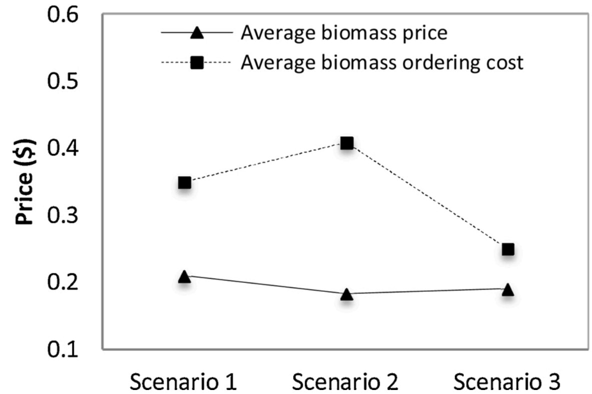


Fig. 3. Average biomass purchasing price and ordering cost in various scenarios.

the expected (average) amount of electricity generated from biomass accounts for 86 % of the electricity mix (14 % share for diesel), which is the highest biomass share compared to other scenarios. As such, this scenario provides enough motivation for the leadership role of communities in the supply chain from both economics and environmental perspectives.

5. Conclusions

This study was a first attempt in examining the impact of alternative power structures in coordination of biomass supply chains in case of remote communities (with dispersed and small scales of demand). In doing so, the interaction of players in a biomass supply chains were formulated as a Stackelberg game. This formulation was used to evaluate the impact of three leadership scenarios of suppliers as leader, hubs as leaders, and communities (energy convertors) as leaders. Each player of the supply chain can assume a leadership role by offering a side payment to other players to persuade them to remain a follower. The key question is to know which player is better leveraged in offering of side payments. In a simple sense, the player who requires a lower side payment has the strategic first mover advantage, by dictating the direction of information flow, and will assume the leadership role.

The problem was uniquely formulated as a multi-period BNLP model with quantity discounts influencing the decisions at each echelon of the biomass supply chain. A case study of a biomass supply chain of three northern Canadian (remote) communities was explored. Although the results indicated that each supply chain member achieves the best payoff when assuming the leadership role, the leverages of leaders to persuade other players to assume follower roles differed remarkably across the scenarios. The concept of side payments, as a coordination incentive, is employed to identify the dominating supply chain coordination (leadership) strategy, with stable leader-follower interactions. The results showed that scenario 3 with communities assuming a leadership position dominated the other scenarios. The communities were better leveraged to provide the required side payments (to suppliers and hubs) preventing their deviation from a follower role. Moreover, it was shown that the share of biomass in electricity generation mix reached its highest under this scenario.

This study could be extended in a number of directions. First, the multi-echelon supply chain formulation can be represented by a network game considering competition among the players at each level. However, for remote communities with small and dispersed scale of demand, such a non-cooperative (competitive) arrangement at each echelon is expected to yield inferior solutions compared to the ones achieved in this study with assumption of cooperation at each echelon. This is due to the fact that the economy of scale for biomass ordering from hubs, and consequently from suppliers, is improved with bundling of orders through cooperation of communities. In addition since the short

Table 6
Required side payments for communities' leadership (scenario 3).

Player	Objective	Best Payoffs ($)	Leader Scenario ($)	Side Payment ($)[a]	Revised lead scenario ($)
Suppliers	Max (Revenue)	393,600	322,900	**70,700**	393,600
Hubs	Max (Revenue)	563,090	−60,773	**623,863**	563,090
Communities	Min (Cost)	−1,008,500	−1,008,500	0	−1,703,063

[a] Total required side payment: $694,563 (as a percentage of leader's best payoff: 68.9 %).

Table 7
Required side payments for hubs' leadership (scenario 2).

Player	Objective	Best Payoffs ($)	Leader Scenario ($)	Side Payment ($)[a]	Revised lead scenario ($)
Suppliers	Max (Revenue)	393,600	323,000	**70,600**	393,600
Hubs	Max (Revenue)	563,090	563,090	0	−388,966
Communities	Min (Cost)	−1,008,500	−1,889,956	**881,456**	−1,008,500

[a] Total required side payment: $952,056 (as a percentage of leader's best payoff: 169.1 %).

Table 8
Required side payments for suppliers' leadership (scenario 1).

Player	Objective	Best Payoffs ($)	Leader Scenario ($)	Side Payment ($)[a]	Revised lead scenario ($)
Suppliers	Max (Revenue)	393,600	393,600	0	−473,390
Hubs	Max (Revenue)	563,090	265,000	298,090	563,090
Communities	Min (Cost)	−1,008,500	−1,577,400	568,900	−1,008,500

[a] Total required side payment: $866,990 (as a percentage of leader's best payoff: 220.2 %).

durability is one of the main disadvantages of biomass fuel, the models can be extended by considering a biomass decay rate (BDR) in each echelon. Also, carbon emission inventories can be incorporated into this supply chain game either as an overall supply chain objective pursued by a social planner (ex. Government) or as a joint target (in form of a constraint) for the communities (Nasiri & Zaccour, 2009). A supplier selection component can also be added as a prerequisite step in order to direct the choice of suppliers based on a select set of criteria before formulating the suppliers' problem (Mafakheri, Breton, & Ghoniem, 2011). Moreover, ordering restrictions can be incorporated into the optimization models of players at each level, including restrictions on schedule or quantity of deliveries as a consequence of the availability or capacity of the means and pathways of transportation. Finally, the BNLP model can be coupled with a simulation model (Nasiri et al., 2016) to incorporate future scenarios for biomass availability and energy demand into problems of suppliers and communities.

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Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix 1 Table of symbols and nomenclatures

Type	Symbol	Description	Units
Sets	I	Set of suppliers	–
	k	Set of hubs	–
	k	Set of energy convertor facilities	–
	t	Time periods	–
Parameters	T_{ik}	Transportation cost from supplier 'i' to hub 'k'	$/kg
	S_i	Capacity of supplier 'i'	kg
	P_i^u	Biomass price of supplier 'i' without discount	$/kg
	P_i^l	Biomass price of supplier 'i' with discount	$/kg
	$\overline{P}$	Weighted average of biomass price	$/kg
	hs_i	Biomass harvesting cost at supplier 'i'	$/kg
	H_i	Holding cost for supplier 'i'	$/kg
	$h_k\mathrm{k}$	Capacity of hub 'k'	kg
	Hc_k	Holding cost at hub 'k'	$/kg
	B_{kj}^u	Biomass ordering cost from hub 'k' to energy convertor 'j' without discount	$/kg
	B_{kj}^l	Biomass ordering cost from hub 'k' to energy convertor 'j' with discount	$/kg
	$\overline{B}$	Weighted average of biomass ordering cost	$/kg
	Ib_j	Capacity of biomass inventory at energy convertor 'j'	kg
	a_j	Holding cost at energy convertor 'j'	$/kg

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Type	Symbol	Description	Units
	fc_j	Conversion rate of biomass to electricity at energy convertor 'j'	kWh/kg
	Lf_j	Loading factor of energy convertor 'j'	%
	LB_j	Electricity generation cost from biomass	$/kWh
	LD_j	Electricity generation cost from diesel	$/kWh
	D_j^t	Demand in energy convertor 'j' at time t	kWh
	$\acute{D}_j$	Share of satisfied demand in community 'j'	%
	Z_j	Capacity of electricity generation	kW
	rs	Delivery time between supplier 'i' and hub 'k'	Month
	rp	Delivery time between hub 'k' and energy convertor 'j'	Month
Decision variables	X_{ik}^t	Quantity of biomass delivered from supplier 'i' to hub 'k' at time 't'	Kg
	y_{kj}^t	Quantity of biomass delivered from hub 'k' to energy convertor 'j' at time 't'	kg
	z_j^t	Electricity generation from biomass in community 'j' at time 't'	kWh
Other variables	IS_i^t	Biomass inventory level at supplier 'i' at time 't'	kg
	h_k^t	Biomass inventory level at hub 'k' at time 't'	kg
	I_j^t	Biomass inventory level at energy convertor 'j' at time 't'	kg
	P_{ik}^t	Biomass price offered by supplier 'i' to hub 'k' at time 't'	$/kg
	B_{kj}^t	Biomass ordering price offered by hub 'k' to energy convertor 'j' at time 't'	$/kg

Appendix 2 Cost of biomass transportation from supplier 'i' to hub 'k'

		Hubs	
		1	2
Suppliers	1	0.012	0.015
	2	0.011	0.016
	3	0.012	0.015
	4	0.014	0.012
	5	0.015	0.011
	6	0.016	0.010

Appendix 3 Holding cost (H_i), Capacity (S_i), and biomass price ranges (P_i^l, P_i^u) of suppliers

Supplier	H_i	S_i	P_i^l	P_i^u
1	0.002	33,300	0.168	0.205
2	0.0015	34,000	0.170	0.210
3	0.002	34,700	0.175	0.200
4	0.002	37,000	0.190	0.215
5	0.0015	35,000	0.190	0.220
6	0.002	34,000	0.185	0.220

Appendix 4 Ordering cost of biomass from hub 'k' for delivery to energy convertor 'j' (B_{kj}^l, B_{kj}^u)

		Communities		
		1	2	3
Hubs	1	(0.235, 0.362)	(0.235, 0.362)	(0.235, 0.362)
	2	(0.266, 0.409)	(0.266, 0.409)	(0.266, 0.409)

Appendix 5 Electricity demand in community 'j' at time 't'

	Community		
Year	1	2	3
1	186,300.000	351,500.000	100,500.000
2	171,900.000	324,400.000	92,800.000
3	171,000.000	322,600.000	92,300.000
4	180,900.000	341,200.000	97,600.000
5	179,700.000	339,100.000	97,000.000
6	168,700.000	318,300.000	91,100.000

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Year	Community 1	2	3
7	178,700.000	337,100.000	96,400.000
8	194,800.000	367,500.000	105,100.000
9	216,800.000	409,000.000	117,000.000
10	246,900.000	465,900.000	133,300.000
11	226,500.000	427,400.000	122,300.000
12	219,900.000	414,900.000	118,700.000

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