

Development of a decision support tool for optimizing the short-term logistics of forest-based biomass

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HIGHLIGHTS

- Transshipment and routing models are developed for short-term biomass logistics.
- The models include biomass storage, pre-processing, and truck routing decisions.
- Models are applied to a large forest-based biomass logistics company.
- Average reduction of 12% in cost and fuel consumption is observed using the models.
- An Excel-based decision support tool is developed for the company.

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ABSTRACT

High cost of logistics is one of the barriers of using forest-based biomass for energy and fuel production. Biomass logistics is complex and includes interdependent decisions related to storage, pre-processing and transportation. While these decisions have been considered in numerous medium-term planning models, those for short-term planning are limited. The existing models focused only on optimal truck routing without considering intermediate storage facilities which are essential to match biomass supply and demand. In this study, a decomposition-based approach is used and optimization models are developed for the short-term planning of a large biomass logistics company located in the Lower Mainland region of British Columbia, Canada. The company deals with collection, storage, pre-processing and transportation of biomass. Several operational constraints related to truck-location compatibilities and truck-biomass compatibilities arising from heterogeneity of trucks and biomass types which further complicate the logistics planning are incorporated in the models. First, a transshipment model is developed and solved using a mixed integer formulation to determine comminution schedules and the number of truckloads of each biomass type to be transported each day using each type of truck. Then, a routing model, which uses the results of the transshipment model, is developed to determine the optimal routing for the available trucks. A decision support tool to optimize the company's weekly transportation and comminution operations is also developed for the company. Experiments were conducted on real data from the company over a span of four weeks. The results indicate 12% reduction in the total average cost and a similar reduction in fuel consumption compared to the actual routes implemented by the company. It is suggested that savings could be obtained by using larger trucks for longer distance transportation and smaller trucks for shorter distances. Direct delivery of biomass from suppliers to customers, bypassing the yard, could result in cost savings.

1. Introduction

There has been a growing interest in using alternative energy and fuel sources for sustainable development. Among alternative energy

sources, forest-based biomass has received attention due to its advantages. It is a versatile source of energy that can be used to generate heat, electricity, biofuels or a combination of them [1]. It can be stored and used as per demand [2]. Its local availability in many regions could

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facilitate fuel security and could reduce carbon dioxide emissions as the carbon dioxide that releases during combustion is captured by trees during the photosynthesis process [3]. These advantages have encouraged the development of efficient technologies for converting it to energy and fuels.

Despite the potential advantages of using biomass for energy and fuel generation, the economic performance of a bioenergy project depends on the logistics cost [4,5]. Logistics, which involves collection, storage, pre-processing and transportation of biomass, could contribute to as much as 90% of the total feedstock cost in some cases [6]. Collection of biomass deals with picking up biomass from supplier locations, and can be demand-driven or supply-driven. In demand-driven collection, biomass is picked up from suppliers to meet the demand at conversion facilities. Supply-driven collection, similar to industrial waste collection, deals with the pickup of the entire quantity of biomass available at the supply points, irrespective of the demand. Storage of biomass deals with decisions related to the location and quantity of biomass to be stored. Biomass can be stored at supply points, conversion facilities, and/or at intermediate storage facilities. Pre-processing includes activities such as comminution and drying of biomass to meet the size and quality requirements for the conversion process. Transportation relates to the movement of biomass between different locations of the network. Similar to other forest products, biomass is transported by trucks, trains and ships, while trucking is the main mode of transportation in many regions [7].

Logistics operations can be expensive and challenging due to the complexities involved at the operational level. Collecting residues from industrial sites is particularly challenging due to limited storage space, which necessitates timely pickup of residues irrespective of the demand for biomass. When biomass supply and demand do not match, storage of biomass becomes imperative at some intermediate facilities. Moreover, these residues can be of different types, and some of them may require additional pre-processing such as comminution before they can be used in the conversion facilities. Depending on equipment availability, comminution can take place at supply points, conversion facilities and/or intermediate facilities which necessitates an integration of transportation, storage planning and pre-processing scheduling. In addition, restrictions related to requirement of specific truck types to carry each type of biomass often exist due to differences in size and properties of biomass types. Moreover, not all truck types can visit all locations of the supply chain due to limitations on truck size and space available at each location. This results in a transportation network with multiple products, multiple supply and demand points, and heterogeneous fleet of trucks with restrictions related to truck type-product type compatibilities and truck type-location compatibilities leading to a complex planning problem. In the presence of an intermediate storage yard, additional decisions regarding whether biomass picked up from each supplier should be delivered to the storage yard or directly to a customer, and whether to meet the demand of a customer by delivering biomass from the yard or from a supplier complicate the decision making process. Storage and pre-processing decisions must be taken along with the transportation decisions. Furthermore, daily truck routes must be determined to minimize the total transportation costs.

Previous research on biomass supply chain logistics optimization mostly focused on long-term and medium-term planning [4]. Optimization models dealing with short-term planning are limited in number. Previous short-term logistics optimization models focused on daily truck routing decisions in networks with multiple suppliers and customers [8], or multiple suppliers and a single customer [9], without considering storage at intermediate sites. These studies considered either a single type of truck [9] or multiple types of trucks [8]. The study by Han and Murphy [8] which considered multiple types of trucks assumed that the transportation quantities of biomass were pre-determined and dealt only with routing trucks to satisfy the transportation orders. Zamar et al. [9] included decisions related to the quantity of biomass to be picked up from suppliers using identical trucks making

the transportation decisions relatively simple. Short-term biomass logistics optimization models which consider the entire network including biomass suppliers, storage facilities and customers, along with decisions related to storage and comminution of biomass, and daily transportation using multiple truck types were not developed in the literature.

This study addresses the above-mentioned gaps by developing optimization models for the short-term planning of biomass logistics using the case of a large biomass logistics company located in the Lower Mainland, British Columbia, Canada. The company deals with collecting biomass from several industrial sites and delivering feedstock to customers. Biomass types collected from suppliers include sawdust, shavings, clean wood and unclean wood. While sawdust and shavings are delivered to customers without pre-processing, clean and unclean wood are comminuted into chips and hog fuel, respectively, before they are delivered to customers. The company owns a central yard where biomass collected from suppliers can be stored, and clean and unclean wood can be comminuted using chippers and grinders. Each supplier can supply multiple types of biomass and each customer can demand multiple types of feedstock. Transportation of biomass is carried out using a heterogeneous fleet of trucks, and restrictions related to truck-location compatibilities and truck-product compatibilities further complicate the problem. Each supplier and customer could be visited by more than one truck type depending on the truck-location compatibilities, and each truck type can carry more than one biomass type. Each week, the company receives information about supply and demand quantities from each supplier and each customer for the following week. Depending on the information received, the company makes decisions related to comminution and transportation of biomass. Comminution decisions prescribe the quantity of each type of biomass to be comminuted at the yard each day. Transportation decisions include the quantities of biomass to be transported to the yard, to be sent directly from suppliers to customers, and quantities of feedstock to be sent from the yard to customers. Transportation decisions also include the truck type to be sent to each location and the resultant routes to be taken by each truck. Currently, transportation and comminution decisions are made by the logistics managers of the company. The overall goal of this paper is to develop optimization models to optimize the company's weekly logistics planning and provide a decision support tool to the company. Fig. 1 shows a schematic of the logistics operations of the company.

2. Literature review

Numerous optimization models were developed in the literature to minimize biomass logistics cost. They can be divided into two groups based on the decision planning level: tactical and operational. Most of the models encountered in the literature focused on tactical level planning with medium-term planning horizons. A group of these models focused on agriculture-based biomass (e.g., [10,11]) and few of them considered forest-based biomass (e.g., [12,13]). Studies on agriculture-based biomass logistics, such as those by Ekşioğlu et al. [10] and Memişoğlu and Uster [11], included decisions related to the locations of the conversion facilities along with other logistics decisions in their models. On the contrary, facility location decisions were not included in forest-based biomass logistics optimization models as these decisions are generally incorporated in long-term strategic planning models (e.g., [14]).

Biomass logistics models for medium-term planning considered one-year planning horizon with either weekly (e.g., [15]) or monthly decisions (e.g., [16,17]). In these studies, transportation decisions were included in the mathematical models as product flow values between different locations of the network during each period of the planning horizon. A few of these studies, such as those by Akhtari et al. [13] and De Meyer et al. [18], included decisions related to the storage of biomass at intermediate facilities to account for biomass seasonality. Other

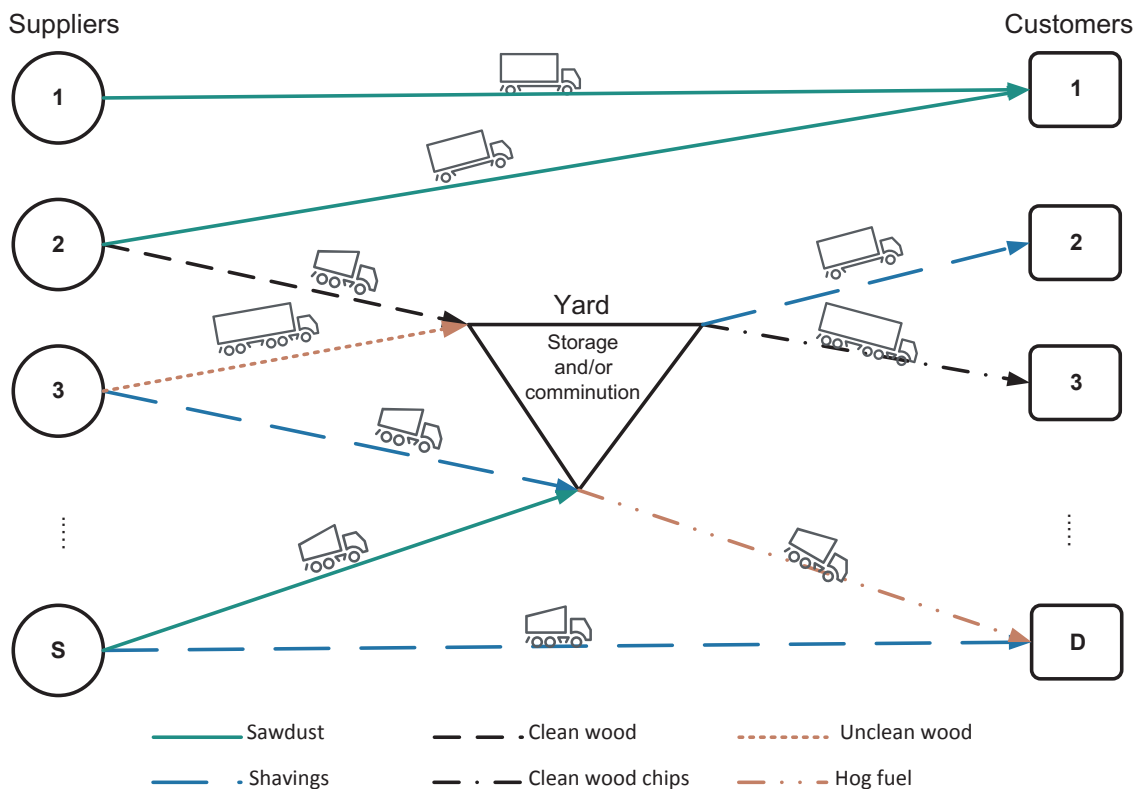


Fig. 1. Schematic representation of the logistics operations of the case study.

studies including Shabani and Sowlati [12] and Memişoğlu and Uster [11] considered direct delivery of biomass from supply points to demand points without including an option to store biomass at intermediate facilities. Decisions related to comminution of biomass were included in some studies (e.g., [13,19]), while other studies that did not include these decisions either considered the supply of biomass in its comminuted form (e.g., [12]) or assumed comminution to happen at the conversion facilities (e.g., [11,20]).

Several recent studies considered the transportation of biomass over long distances using multiple modes of transportation such as rail/barge and trucks. These studies assumed that trucks were used to transport biomass from supply areas to multi-modal facilities, which had access to rail or barge. Biomass was transported over long distances using rail or barge because of their larger capacity compared to trucks. Along with the transportation of biomass, Xie et al. [21] included the transportation of biofuels from conversion facilities to final customers using multiple modes of transportation. Marufuzzman and Ekşioğlu [22] incorporated the effect of natural disturbances such as hurricanes and drought seasons in their models, which dynamically selected transportation modes and the transportation hubs through which biomass should be transported. Along with minimizing total logistics costs, Roni et al. [23] included environmental objective of minimizing total carbon dioxide emissions and social objective of maximizing total jobs in their model, which considered transportation of biomass using trucks, single railcar and a train. Pellet transportation using trucks and barge was studied by Andersen et al. [24] who considered transportation of pellets from a pellet plant to a port using barge, and from the port to demand points using truck.

While significant work has been done in optimizing medium-term biomass logistics planning, its short-term planning (operational level) has received limited attention. Biomass logistics optimization at operational level includes decisions related to collection, transportation, storage and pre-processing of biomass over a short-term planning horizon such as a week or a day. Operational level plans are crucial for efficient implementation of logistics decisions [25]. To the best of our

knowledge, there are only two studies [8,9] that focused on short-term biomass logistics optimization, and both of them dealt with mill residues. Overall, the focus of these two studies was to optimize truck routes for a single day planning horizon. The considered biomass was in the form of chips, therefore there was no need for comminution. No intermediate storage facility was included in the supply chain, and there were no decisions related to storage of biomass in the models.

The study by Han and Murphy [8] considered that the number of truckloads of each product to be picked up from each supply point and be delivered to each demand point as pre-determined values. Therefore, the mathematical model in their study focused on routing of trucks such that the pre-determined transportation orders were satisfied. On the contrary, instead of assuming pre-determined transportation orders, Zamar et al. [9] included decisions related to the quantity of biomass to be collected from each supplier under biomass quality uncertainty. However, their study considered delivery to a single demand point using a homogeneous fleet of trucks making the transportation decisions less complex. Furthermore, their model was demand-driven implying that some biomass could be left uncollected at supply points. However, collection of biomass from industrial sites is often considered similar to the industrial waste collection problem, where waste has to be completely collected from all the supply points, irrespective of the demand [26]. Therefore, collection of biomass from industrial sites dictates a supply-driven system, while delivering the feedstock to conversion facilities requires a demand-driven system. To the best of our knowledge, biomass logistics optimization models for short-term planning including supply points, intermediate storage facilities and demand points, with supply-driven pickup and demand-driven delivery, along with decisions related to biomass storage, comminution and transportation using heterogeneous trucks are not developed in the literature yet.

Inclusion of storage decisions at a central yard makes our problem a variation of the well-studied Transshipment Problem. However, most of the transshipment models reported in the literature only consider one type of product that must always transit through intermediate storage

facilities. Indeed multi-product transshipment models for hybrid networks, where products could bypass the intermediate facilities, with multiple suppliers and customers are relatively less explored in the literature [27].

Due to large volumes of biomass supply and demand, transportation of biomass typically happens in full-truckloads [7]. Guastaroba et al. [27] observed that transshipment models which consider product flow in number of truckloads were less explored in the literature. Two of the previous studies that included product flow as number of truckloads were by Ma et al. [28] and Ali and O'Connor [29]. Ma et al. [28] considered the distribution of a single product using a homogeneous fleet of trucks, while Ali and O'Connor [29] considered transportation using a heterogeneous fleet of trucks, where one type of truck was used for transportation between a warehouse and distribution centers and the other type of truck was used for transportation from distribution centers to demand points. Transshipment models with product flow in number of truckloads using heterogeneous fleet of trucks, where different trucks can be used in all tiers of the network, are not studied in the literature to the best of our knowledge.

3. Mathematical models

In this section, the mathematical models developed for the optimization of short-term logistics of forest-based biomass are presented. The logistics problem is solved using a decomposition-based approach, where the problem is divided into two sub-problems. Two optimization models, one for each sub-problem, are developed. The first sub-problem is the transshipment problem used to determine the truckloads of biomass to be transported using different truck types along with the storage and comminution decisions at the storage yard. The results of transshipment model are used as inputs of the truck routing problem. The routing model is used to determine the daily routes for each truck. Similar decomposition-based approach has been used in previous studies for solving transportation and routing problems (e.g., [30,31]). In these studies, the problem was decomposed into a transportation problem to determine product flow quantities, and a Vehicle Routing Problem which used the results of the transportation problem to determine the daily truck routes. However, these studies considered networks involving only suppliers and customers, and did not include the option of storage and pre-processing of products at intermediate

facilities. A schematic of the solution framework is shown in Fig. 2.

3.1. Transshipment model

A transshipment model is developed to determine the number of truckloads of each biomass type to be sent from each source to each destination using each truck type. Other decisions in the transshipment model include the quantity of biomass to be comminuted and stored at the yard during each period of the planning horizon. Constraints of the model include those related to supply, demand, storage and comminution of biomass on a daily basis. Constraints related to maximum operating hours per truck and the number of trucks available for each truck type are also included in the transshipment model to prevent infeasibility in the routing model. This requires an estimation of the total operation time per truck type which can be used in the objective function and constraints of the transshipment model.

The notations used in the transshipment model are shown in Table 1.

3.1.1. Objective function

The objective function of the model is to minimize the sum of transportation, loading, unloading and comminution costs as shown in Expression (1).

$$\begin{aligned} \text{Minimize } & \sum_{i \in S'} \sum_{p \in P} \sum_{c \in C} \sum_{t \in T} n_{i0pct} * TC_c * TT_{i0c} + \sum_{k \in D'} \sum_{p \in P} \sum_{c \in C} \sum_{t \in T} n_{0kpct} * TC_c * TT_{0kc} \\ & + \sum_{i \in S'} \sum_{k \in D'} \sum_{p \in P} \sum_{c \in C} \sum_{t \in T} n_{ikpct} * TC_c * TT_{ikc} + \sum_{t \in T} \sum_{p \in P_{bc}} CC_p * c_{pt} / \delta_p \end{aligned} \quad (1)$$

The transportation cost is obtained by multiplying the estimated total transportation time with the unit transportation cost for each type of truck, where the total transportation time includes the full and empty travels of the truck, as well as its loading and unloading time. The first, second and third terms in the objective function represent the transportation, loading and unloading costs of truckloads from suppliers to yard, yard to customers, and suppliers to customers, respectively. The final term of the objective function represents the total comminution cost.

3.1.2. Constraints

Constraints related to the supply and demand of biomass are shown in Expressions (2) and (3).

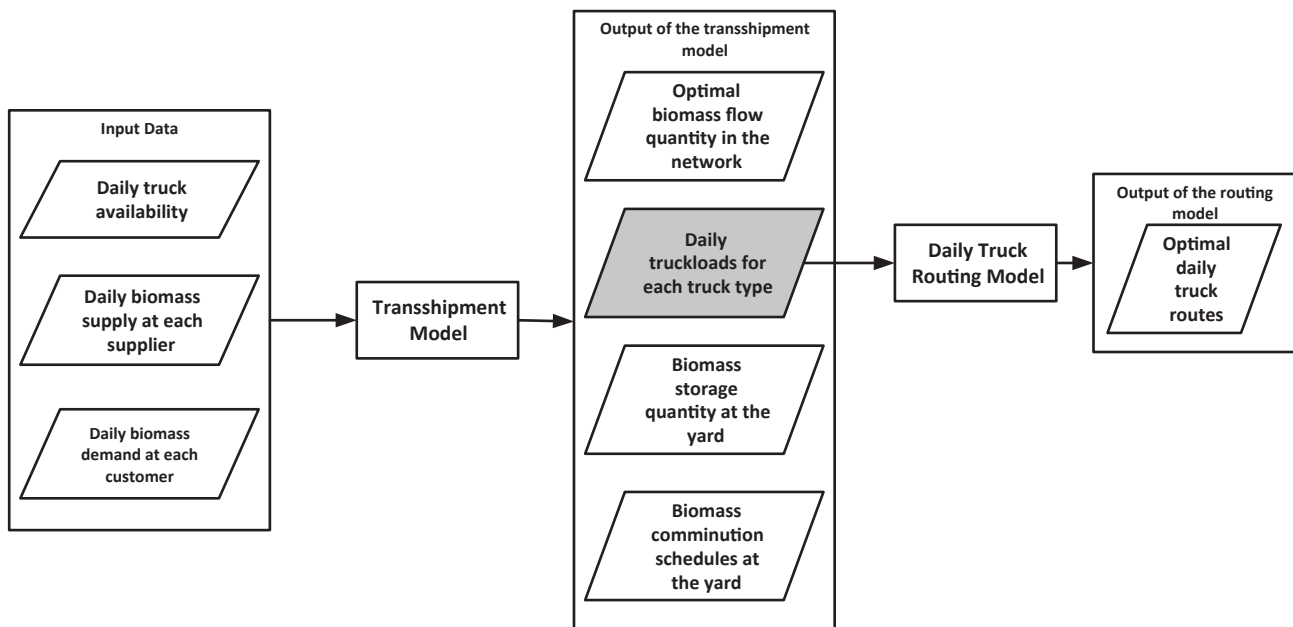


Fig. 2. Decomposition-based solution approach to solve the short-term biomass logistics problem.

Table 1
Notations used in the transshipment model.

Sets	Definition
P	Set of all biomass types $p \in \{0,1,\dots,P\}$ including biomass before and after comminution
P_{nc}	Subset of biomass that do not need comminution, $P_{nc} \subset P$
P_{bc}	Subset of biomass that need comminution, before comminution, $P_{bc} \subset P$
P_{ac}	Subset of biomass that need comminution, after comminution, $P_{ac} \subset P$
S	Set of all suppliers, $i \in \{0,1,\dots,S\}$ where $\{0\}$ is the yard and $S' = S \setminus \{0\}$ are the other suppliers
D	Set of all customers $k \in \{0,1,\dots,D\}$ where $\{0\}$ is the yard and $D' = D \setminus \{0\}$ are the other customers
T	Set of all time periods $t \in \{1,\dots,T\}$ in the planning horizon
C	Set of vehicle types $c \in \{1,\dots,C\}$
V_c	Set of vehicles $v \in \{1,\dots,V_c\}$ of type $c \in C$
Decision variables	Definition
q_{ikpt}	Volume of biomass $p \in P$ to be transported from supplier $i \in S$ to customer $k \in D$ using vehicle type $c \in C$ at period $t \in T$
n_{ikpt}	Number of truckloads of biomass $p \in P$ from supplier $i \in S$ to customer $k \in D$ using vehicle type $c \in C$ at period $t \in T$
I_{pt}	Inventory of biomass $p \in P$ to be stored during period $t \in T$
c_{pt}	Volume of biomass $p \in P_{bc}$ to be comminuted at period $t \in T$
Parameters	Definition
s_{ipt}	Volume of biomass type $p \in P$ available from supplier $i \in S'$ at period $t \in T$
d_{kpt}	Volume of biomass type $p \in P$ required by customer $k \in D'$ at period $t \in T$
$I_{p,0}$	Initial inventory of biomass type $p \in P$ at the yard
β_{ic}	Binary parameter equal to 1 if vehicle type $c \in C$ can pick up/deliver biomass at location $i \in S \cup D$
β_{pc}	Binary parameter equal to 1 if truck type $c \in C$ can pick up/deliver biomass type $p \in P$
δ_p	Quantity of biomass type $p \in P_{bc}$ that can be comminuted per minute at the central yard
γ_p	Maximum quantity of comminuted biomass type $p \in P_{ac}$ that can be produced during each day
λ_p	Conversion factor for comminuting biomass type $p \in P_{bc}$ (volume of comminuted biomass obtained from unit volume of uncomminuted biomass)
Q_c	Capacities of vehicle type $c \in C$
TT_{ike}	Total estimated travel time to transport a truckload from supply point $i \in S$ to delivery point $k \in D$ using truck type $c \in C$ (includes back-and-forth travel of trucks from supply point i to delivery point k , and truck loading and unloading times)
TT_{max}	Maximum time of travel permitted per truck per day
TC_c	Transportation cost per minute for vehicle type $c \in C$
CC_p	Cost per minute for comminuting biomass type $p \in P_{bc}$
LC	Cost of loading per minute
ϵ	Factor to limit the empty truck volume in each truckload

$$\sum_{k \in D} \sum_{c \in C} q_{ikpt} = s_{ipt} \quad \forall i \in S', p \in P, t \in T \quad (2)$$

$$\sum_{i \in S} \sum_{c \in C} q_{ikpt} = d_{kpt} \quad \forall k \in D', p \in P, t \in T \quad (3)$$

Constraint set (2) implies that the whole quantity of biomass supplied at each supplier is picked up daily. In these constraints, the daily quantity of biomass transported from a supplier to the yard and to all customers is equal to the biomass supply quantity. Similarly, constraint set (3) makes sure that the demand is met on a daily basis for each customer. In these constraints, the total biomass received by a customer from the yard and from all suppliers is equal to its biomass demand.

Certain biomass types must be comminuted at the yard before the corresponding feedstock is delivered to customers. This is ensured by constraint set (4), which prevents the biomass types that require comminution from being sent directly from suppliers to customers without transiting through the yard.

$$\sum_{i \in S'} \sum_{k \in D'} \sum_{c \in C} q_{ikpt} = 0, \quad \forall p \in (P_{bc} \cup P_{ac}), t \in T \quad (4)$$

Trucks that carry biomass from one location to another must be compatible with the biomass type and the pickup and delivery locations. Constraint set (5) ensures the truck compatibility with biomass type, the supplier and customer locations. If the truck type is not compatible with either the biomass type or the pickup or delivery location, this constraint set makes the biomass flow quantity equal to zero.

$$q_{ikpt} \leq M * \beta_{ic} * \beta_{kc} * \beta_{pc} \quad \forall i \in S, k \in D, p \in P, c \in C, t \in T \quad (5)$$

Constraint set (6) imposes that the number of truckloads of a given truck type determined by the model is sufficient to move the given quantity of biomass. For a given quantity of biomass transported between two locations using a particular truck type, these constraints

estimate the number of truckloads required by dividing the biomass quantity with the capacity of the truck.

$$(n_{ikpt}-1)*Q_c \leq q_{ikpt} \leq n_{ikpt}*Q_c, \quad \forall i \in S, k \in D, p \in P, c \in C, t \in T \quad (6)$$

Constraint set (7) is added for practical reasons to prevent the trucks from traveling when the load is less than a certain percentage of the capacity of the vehicle.

$$n_{ikpt} * Q_c - q_{ikpt} \geq \epsilon * Q_c, \quad \forall i \in S, k \in D, p \in P, c \in C, t \in T \quad (7)$$

Constraints (8) and (9) are related to the inventory balance for biomass types that require comminution, and constraint set (10) represents the inventory balance for biomass types that do not require comminution. The inventory balance constraints are included to make sure that the inventory of all biomass types at the yard is maintained from one period to another.

$$I_{pt} = I_{p,t-1} - c_{pt} + \sum_{i \in S'} \sum_{c \in C} q_{i0pt}, \quad \forall p \in P_{bc}, t \in T \quad (8)$$

$$I_{pt} = I_{p,t-1} + \lambda_p * c_{pt} - \sum_{k \in D} \sum_{c \in C} q_{0kpt}, \quad \forall p \in P_{ac}, t \in T \quad (9)$$

$$I_{pt} = I_{p,t-1} + \sum_{i \in S'} \sum_{c \in C} q_{i0pt} - \sum_{k \in D'} \sum_{c \in C} q_{0kpt}, \quad \forall p \in P_{nc}, t \in T \quad (10)$$

Constraint set (11) ensures that the number of trucks available for each type are sufficient considering the maximum shift time per day. In these constraints, the total daily estimated travel time for each truck type is limited by the number of available trucks of that type multiplied by the maximum allowed operation time for each truck. Due to these constraints, the solution obtained from the transshipment model can be used in the routing model without any infeasibilities.

$$\sum_{i \in S'} \sum_{p \in P} n_{i0pct} * TT_{i0c} + \sum_{k \in D'} \sum_{p \in P} n_{0kpct} * TT_{0kc} + \sum_{i \in S'} \sum_{k \in D'} \sum_{p \in P} n_{ikpct} * TT_{ikc} \leq TT_{max} * \left| V_c \right|, \quad \forall c \in C, t \in T \quad (11)$$

Constraint set (12) limits the total volume of each biomass type that is comminuted at the yard on each day to the maximum comminution capacity.

$$\lambda_p * c_{pt} \leq \gamma_p, \quad \forall p \in P_{bc}, t \in T \quad (12)$$

Constraint sets (13)–(16) are used to define the decision variables of the model.

$$n_{ikpct} \in \mathbb{Z}, \quad \forall i \in S, k \in D, p \in P, c \in C, t \in T \quad (13)$$

$$q_{ikpct} \geq 0, \quad \forall i \in S, k \in D, p \in P, c \in C, t \in T \quad (14)$$

$$I_{pt} \geq 0, \quad \forall p \in P, t \in T \quad (15)$$

$$c_{pt} \geq 0, \quad \forall p \in P, t \in T \quad (16)$$

Previous studies on the transshipment problem mostly considered transportation cost to be dependent only on the quantity of product that is transported, and the total transportation cost was calculated using the cost per unit flow of product [27]. However, the actual cost structure could be more complicated and may depend on several distribution attributes such as the number of truckloads required and the duration of empty truck travel. Few studies on the transportation problem considered different cost structures to incorporate empty truck travel cost in their models. For example, Flisberg et al. [30] who studied the transportation of logs from several suppliers to multiple customers assumed trucks always traveled back-and-forth between the log pickup and delivery locations. This way, they incorporated both truck loaded and empty travel costs in their objective function. This cost structure which assumes back-and-forth travel of trucks between pickup and delivery locations could be appropriate when the total supply and demand volumes exceed the volume of one truckload, and multiple truckload pickups and deliveries are required. However, the cost structure used by [30] may not be applicable when the supply and demand quantities are less than a truckload, and trucks visit multiple suppliers and customers during each trip. Cordeau et al. [31], who studied the Inventory Routing Problem for transporting a product from a supplier to multiple customers with less-than-truckload demand, mentioned that assuming back-and-forth travel of trucks between pickup and delivery locations could over-estimate the total cost. Instead, they mentioned that the transportation cost could be approximated by the cost of traveling from the supplier to the customer, without considering the cost of traveling back empty to the supply point. The transportation cost estimation used by Cordeau et al. [31] is a better approximation than the back-and-forth travel assumption when a truck begins its route from the supply point and visits several customers to meet their demand before returning back to the supply point.

Neither of the two cost estimation approaches described above can be used directly in our problem which includes multiple suppliers, multiple customers, a transshipment center which is also the trucks depot, and full truck-loads delivery. The cost of delivering biomass from a supply point to a demand point in our case depends on the type of truckload that is transported. There are three types of truckloads of biomass: (1) truckload from a supplier to the yard, (2) truckload from the yard to a customer, and (3) truckload directly from a supplier to a customer. According to the data we received from the company, most of the truckloads of types 1 and 2 require back-and-forth travel of trucks between the yard and suppliers, and the yard and customers, respectively. Therefore, for each truckload of types 1 and 2, the transportation time coefficients TT_{i0c} and TT_{0kc} include the truck travel time to perform a round trip between the yard and suppliers, and the yard and customers, respectively. On the other hand, trucks that deliver biomass

directly from suppliers to customers (i.e., truckload of type 3) mostly do not go back to the yard until the end of the day. These trucks start at the yard, perform a series of pickups and deliveries between suppliers and customers before returning to the yard. Moreover, the quantities of biomass picked up and delivered are often more than a truckload. This situation is similar to that of Flisberg et al. [30] who considered log transportation between multiple suppliers and customers without including an intermediate storage yard. Following their cost estimation, the transportation time coefficient TT_{ikc} for transporting a truckload of biomass from a supplier $i \in S'$ to a customer $k \in D'$ includes truck loaded travel time from i to k and its empty travel time from k to i . All transportation time coefficients also include the time required for loading and unloading the trucks at pickup and delivery points, respectively.

3.2. Routing model

The transshipment model described in the previous section provides the details of full-truckloads of biomass to be transported each day. Each truckload is defined by the pickup point, delivery point, biomass type, truck type and the day of transportation. Since the pickup and delivery point of each truckload are known, the time required for transporting each truckload is known. The objective of the routing model is to determine the best route for each truck such that all the truckload deliveries are completed with a minimum cost. A truck route is defined by a sequence of full-truckloads of biomass to be transported by the truck. Since each truckload has a pickup and delivery location, a truck route consists of a sequence of locations to be visited by the truck to pick up and deliver biomass. Truck routes must be determined such that all the truckload deliveries determined in the transshipment model are performed using appropriate truck types and each truck is limited by the maximum number of operation hours per day.

The routing model is developed on an auxiliary graph described as follows. Let L be the set of all truckloads obtained from the transshipment model and let $N = \{0\} \cup N'$ be the set of nodes and A be the set of arcs of the auxiliary graph. $\{0\}$ represents the yard and N' is the set of nodes where each node $j \in N'$ represents a truckload $l \in L$. For every node $j \in N'$, let l_j be the corresponding truckload in L , s_j and d_j be the pickup and delivery locations of the truckload l_j , respectively.

Every pair of nodes in N has an arc in the network. Every arc has an associated time required to travel over it. Let TTA_{ij} be the time required to travel on arcs $(i, j) \in A$ in the auxiliary graph. Since each node $j \in N'$ represents a truckload delivery of biomass, there is a service time STA_j , which includes truck travel, loading and unloading times. The travel times on arcs and the service times of the nodes are defined according to the following steps:

Step 1. For every node $j \in N'$, set the travel time from the yard to the node j equal to the travel time from the yard to the pickup location of truckload l_j . Mathematically, set $TTA_{0j} = TT_{0s_j}$. For a truckload l_j of type 2 which starts at the yard, $TTA_{0j} = 0$.

Step 2. For every node $j \in N'$, set the travel time from j to the yard equal to the travel time from the delivery location of the truckload l_j to the yard. Mathematically, set $TTA_{j0} = TT_{d_j,0}$. For a truckload l_j of type 1 whose destination is the yard, $TTA_{j0} = 0$.

Step 3. For every pair of nodes $\{i, j | i < j\} \in N'$, set the travel time from i to j equal to the travel time between the delivery location of truckload l_i and the pickup location of truckload l_j . Similarly, set the travel time from j to i equal to the travel time between the delivery location of truckload l_j and the pickup location of truckload l_i . Mathematically, set $TTA_{ij} = TT_{d_i, s_j}$ and $TTA_{ji} = TT_{d_j, s_i}$.

Step 4. For each node $j \in N'$, set the service time equal to the sum of travel time between the pickup and delivery locations of the truckload l_j , truck loading time at the pickup location of the truckload l_j and the truck unloading time at the delivery location of the truckload l_j . Mathematically, $STA_j = TT_{s_j, d_j} + LT_c + UT_c$.

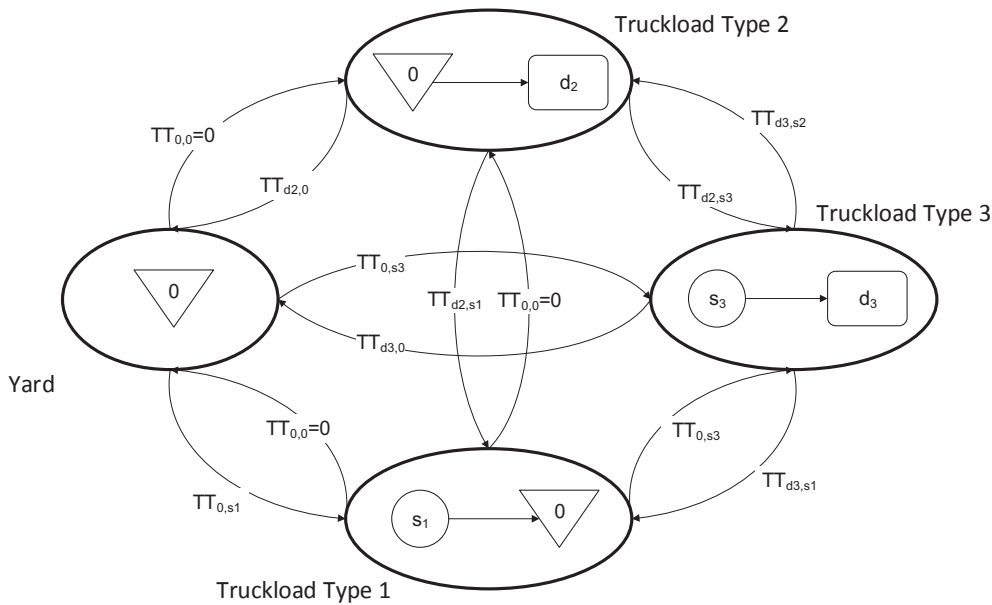


Fig. 3. A sample of an auxiliary graph with 3 nodes showing the 3 types of truckloads in the routing problem.

An example of the auxiliary graph for delivering three truckloads of biomass is shown in Fig. 3. For clarity, each of the three truckloads represent one truckload type. The travel times between each node of the auxiliary network are shown on the arcs connecting them.

The routing problem deals with defining daily routes for each truck located at the yard such that every node $j \in N'$ in the auxiliary graph, which represents one truckload, is visited exactly once. The routing problem is a variant of the Multiple Traveling Salesmen Problem where multiple salesmen located at a central depot are routed such that all the nodes in the network are visited exactly once by the salesmen [32]. Since we deal with routing of a heterogeneous fleet of trucks, the routing problem in biomass logistics is a variant of Multiple Traveling Salesmen Problem with heterogeneous trucks.

Since the truckloads are defined daily, solving the routing model for all the days together is equivalent to solving the routing model for each day separately. Moreover, our experiments suggested that solving the routing model for all days together is computationally intractable using commercial MIP solvers due to the size of the model. Therefore, the routing model is run on the auxiliary network for each day of the week separately.

The notation used in the routing model is shown in Table 2.

3.2.1. Objective function

Expression (17) represents the objective function of minimizing the routing cost of trucks in the auxiliary network. The routing model uses the truckloads resulted from the transshipment model, thus the travel cost of loaded trucks between the locations in the supply chain is a constant in the routing model. Consequently, the model minimizes the empty travel cost of trucks in order to minimize the routing cost.

$$\text{Minimize } \sum_{i \in N} \sum_{j \in N} \sum_{c \in C} \sum_{v \in V_c} x_{ijcv} \times TTA_{ij} \times TC_c \quad (17)$$

3.2.2. Constraints

Constraint set (18) ensures every node in the auxiliary graph is visited once by any vehicle. This means that each truckload of biomass is picked up and delivered exactly once, and no truckloads are left out.

$$\sum_{i \in N} \sum_{c \in C} \sum_{v \in V_c} x_{ijcv} = 1, \quad \forall j \in N' \quad (18)$$

Vehicle flow balance constraints in (19) ensure that each vehicle that visits a node $j \in N'$ also leaves that node. These constraints imply that a

Table 2

Notation used in the routing model.

Sets	Definition
N	Set of all nodes in the auxiliary graph for the routing formulation with $j \in N = \{0, 1, \dots, n\}$, where $\{0\}$ is the yard and $N' = N \setminus \{0\}$, is the subset of all truckloads obtained from the transshipment model
N_c	Set of truckloads for vehicle type $c \in C$ excluding the depot and $N'_c = N_c \setminus \{0\}$
A	Set of all arcs $(i, j) \in \{0, 1, \dots, A \}$ in the auxiliary graph for the routing formulation
Decision variables	Definition
x_{ijcv}	Binary variable equal to 1 if vehicle $v \in V_c$ traverses from $i \in N$ to $j \in N$ and equal to 0 otherwise
y_{icv}	Binary variable equal to 1 if vehicle $v \in V_c$ visits node $i \in N$ and equal to 0 otherwise
w_i	Integer variable representing the node potential of $i \in N'$. These are used to eliminate sub-tours
z_{cv}	Binary variable equal to 1 if vehicle $v \in V_c$ is used and 0 otherwise
Parameters	Definition
TT_{max}	Maximum time of travel permitted per vehicle per day
TTA_{ij}	Travel time between nodes $i, j \in N$ in the auxiliary graph
STA_i	Time required to service node $i \in N'$ in the auxiliary graph
TC_c	Transportation cost per minute for vehicle type $c \in C$
c_i	Truck type of node $i \in N'$

truck would move on to deliver another truckload or go back to the yard at the end of the day after a truckload of biomass is delivered.

$$\sum_{i \in N} x_{ijcv} = \sum_{k \in N} x_{jkcv}, \quad \forall j \in N', c \in C, v \in V_c \quad (19)$$

Constraint set (20) limits the number of vehicles of each type that leave the yard on each day to the number of vehicles available.

$$\sum_{j \in N'} \sum_{v \in V_c} x_{0jcv} \leq |V_c|, \quad \forall c \in C \quad (20)$$

Constraint set (21) is used to define the variables z_{cv} indicating if a vehicle is used or not. The variable z_{cv} is equal to $\sum_{j \in N'} x_{0jcv}$ if a vehicle v of type c travels from the yard to a node $j \in N'$, and 0 if it does not leave the yard.

$$\sum_{j \in N'} x_{0,jvc} - z_{cv} = 0, \quad \forall c \in C, v \in V_c \quad (21)$$

The yard is the trucks depot, this means that the trucks start their trip from the yard and return to the yard at the end of their trip. Constraints that impose that every truck that leaves the yard returns to the yard are shown in Expression (22).

$$\sum_{j \in N'} x_{0,jcv} = \sum_{j \in N'} x_{j,0,cv}, \quad \forall c \in C, v \in V_c \quad (22)$$

Constraint set (23) ensures that if a node is visited by a truck, the truck comes from one of the arcs to that node. It means if $y_{jcv} = 1$, i.e. a node j is traversed by a given vehicle v of class c , then there must be one $x_{ijcv} = 1$, i.e. the same vehicle v of class c , must transit through an arc coming from node i , to reach node j .

$$y_{jcv} = \sum_{i \in N} x_{ijcv}, \quad \forall j \in N', c \in C, v \in V_c \quad (23)$$

Sub-tour elimination is ensured using constraint set (24). A sub-tour is a tour within the set of nodes N' where a vehicle traverses in a cycle. A cycle results when a vehicle visits the node that was visited before. For example, consider nodes $i, j, k, l \in N'$. Assume that the same vehicle visits all the four nodes, and traverses in the following order: $i \rightarrow j \rightarrow k \rightarrow l \rightarrow i$. This is a sub-tour as the vehicle visits the node i twice forming a cycle. On the other hand, if the truck travels to another node m after visiting node l or goes back to the yard, then it would not form a sub-tour. Therefore, sub-tours can be avoided by constraining a vehicle not to visit a node which was previously visited. This can be achieved by defining non-negative numbers, called node potentials, to each node that is visited by each vehicle. For two nodes $i, j \in N'$ which are visited by the same vehicle, node potentials w_i and w_j are defined such that $w_j > w_i$ if the vehicle travels from i to j . Since the node potentials of the nodes visited by a vehicle are always in the ascending order, the vehicle would not re-visit a node which was already visited. For the example explained above, since the vehicle visits node i before node l , then $w_l > w_i$. Now, the vehicle cannot go back to node i from node l as this traversal would contradict the definition of node potentials. Constraint set (24) assigns non-negative node potentials in an ascending order to nodes along the routes traversed by each truck. As a result, sub-tours are eliminated in the optimal routes.

$$w_i - w_j + n \sum_{c \in C} \sum_{v \in V_c} x_{ijcv} \leq n - 1, \quad \forall (i, j) \in A \quad (24)$$

Constraint set (25) limits the maximum travel time per truck per day to the maximum allowable working hours per driver. The travel time of each truck includes the routing time in the auxiliary graph, loaded travel time, and loading and unloading times obtained from the transshipment model.

$$\sum_{i \in N} \sum_{j \in N} (x_{ijcv} \times TTA_{ij}) + \sum_{i \in N'} (y_{icv} \times STA_i) \leq TT_{max}, \quad \forall v \in V_c, c \in C \quad (25)$$

Symmetry-breaking constraints that ensure that a truck $v \in V_c$ is used only after the truck $v-1 \in V_c$ is used are represented by constraint set (26).

$$z_{c,v-1} \geq z_{cv}, \quad \forall c \in C, v \in V_c \quad (26)$$

Each node in the auxiliary graph represents one truckload of a truck type. Therefore, each node in the auxiliary graph is associated with a truck type. Constraint set (27) ensures that a node is visited by a truck type defined by the truckload.

$$y_{icv} = 0, \quad \forall c \neq c_j \quad (27)$$

The decision variables of the model are defined in constraint sets

(28)–(30).

$$x_{ijcv} \in \{0, 1\}, \quad \forall i, j \in N, c \in C, v \in V_c \quad (28)$$

$$y_{icv} \in \{0, 1\}, \quad \forall i, j \in N, c \in C, v \in V_c \quad (29)$$

$$w_i \in \mathbb{Z}, \quad \forall i \in N \quad (30)$$

Solving the model provides the optimal routing on each day for the trucks available considering the given truckloads. The following procedure can be used to obtain the routes from the variables: let N_{cvt} be the set of nodes visited by truck $v \in V_c, c \in C$ on day $t \in T$. For each $i \in N_{cvt}$, the value of w_i can be found from the optimal solution of the model. By the definition of node potentials, $w_j > w_i$ if the truck $v \in V_c, c \in C$ visits node $i \in N_{cvt}$ before visiting $j \in N_{cvt}$. Therefore, by sorting the nodes in N_{cvt} according to their node potentials, we can construct the route for the truck $v \in V_c, c \in C$. The same procedure is to be followed for all trucks.

4. Case study

The developed optimization models are applied to a large biomass logistics company in Lower Mainland, British Columbia, Canada. The company collects biomass from 26 major suppliers and delivers feedstock to 9 major customers, which represents more than 80% of the business. The company is a third-party logistics provider for these suppliers and customers, and has long-term contracts with them. It owns a large yard where biomass can be stored and comminuted. It also owns a fleet of trucks for biomass pickup and delivery operations.

Biomass types collected from suppliers include sawdust, shavings, clean wood, and unclean wood. Each supplier can supply more than one type of biomass. Four types of feedstock are delivered to customers, namely, sawdust, shavings, clean wood chips and hog fuel. Clean wood chips and hog fuel are produced by chipping and grinding clean wood and unclean wood, respectively, at the yard. Each customer can demand more than one type of feedstock.

Depending on whether the biomass requires comminution, biomass can either be delivered directly to customers or be brought to the yard. Clean and unclean wood require comminution, while sawdust and shavings do not. Since comminution happens at the yard, clean and unclean wood are always transported from the suppliers to the yard. After comminution, clean wood chips and hog fuel are delivered to respective customers from the yard. On the other hand, sawdust and shavings can either be sent to the yard for storage or be delivered directly from suppliers to customers, by-passing the yard.

Biomass is comminuted at the yard using a chipper and a grinder owned by the company. The chipper is used to comminute clean wood into clean wood chips. The chipper can produce wood chips of uniform size which is a requirement of the customers. On the other hand, the stationary electric grinder is used to grind unclean wood into hog fuel. The functioning of the grinder is similar to that of a hammer, due to which unclean wood is ground into non-uniform sizes. Both the chipper and grinder incur an operation cost per unit time, and the cost of the grinder is higher than the cost of the chipper. The chipper and the grinder can produce a fixed amount of comminuted biomass per unit time, and the throughput (volume of biomass comminuted per unit time) of the grinder is greater than that of the chipper.

The company maintains inventories of sawdust, shavings, clean wood, unclean wood and clean wood chips at the yard. Capacity for storing these biomass and feedstock types is not a restrictive factor due to the large size of the yard compared to the volume of stored biomass. A minimum inventory of clean wood chips is always maintained at the yard. On the other hand, the company does not maintain inventory of hog fuel, and the quantity of unclean wood ground on a given day is

Table 3
Characteristics of different types of truck.

Truck Type	Number of trucks	Capacity (m ³)	Loading time (minutes)	Unloading time (minutes)	Cost (CDN\$/hour)
Sawdust truck	4	53.56	7	5	90
Long trailer and truck	7	107.57	15	20	125
Roll off truck	2	30.60	10	10	90
End dump truck	5	68.86	10	10	120

equal to the total demand of hog fuel for that day.

Biomass is picked up from suppliers on a daily basis where the total quantity of biomass supplied on a given day must be picked up completely on the same day. Therefore, the company does not have control over inventory of biomass at suppliers. Similarly, feedstock is delivered to customers on a daily basis such that the demand of a customer on a given day is met on the same day. Inventory of feedstock at customer sites is not controlled by the company.

Four different types of trucks are used for pickup and delivery of biomass. They are sawdust truck, long trailer truck, roll off truck, and end dump truck. Table 3 shows different properties of each type of truck. Different types of biomass can be carried using specific types of truck. The origin and destination of truckloads carrying different biomass types and the compatibilities between biomass types and truck types are shown in Table 4. Similar to truck type-biomass type compatibility, trucks also have restrictions related to whether they can visit different suppliers and customers. These restrictions are due to space constraints at the supplier and customer sites. Few suppliers and customers may be visited by multiple types of trucks.

The pickup and delivery of the biomass at supplier and customer sites, respectively, do not require additional loading and unloading equipment. Sawdust and shavings are collected directly from the overhead bins located at supplier sites. Clean and unclean wood are deposited in metal bins or end dump trailers located at supplier sites and are collected using roll off trucks and end dump trucks, respectively. Similarly, unloading of biomass at customer sites does not require additional equipment as all truck types have unloading capability.

In contrast, loading biomass onto trucks at the yard requires loaders. The company rents at least two loaders for the loading operation, and there is a cost associated with loading each truck based on the time it takes to fill the truck. According to the logistics manager of the company, loader's availability is not a bottleneck for their operations. Each truck that is to be loaded at the yard spends ten minutes on average waiting for the loader. The average truck waiting time at the yard, and the associated loader costs for each truckload of biomass from the yard to customers are included in the objective function of the transshipment model and in the constraints related to the maximum operation time of each truck per day.

The trucks are located at the yard, and drivers start and end their routes at the yard each day. Each driver typically drives the same type of truck and visits the same supplier and customer locations as much as possible. Each driver is limited to work no more than 13 h each day.

At the end of each day, drivers fill a report called the “driver cartage report” which contains information concerning the pickup and delivery operations carried out by each driver on that day. Each entry in the

Table 4
Biomass type, origin and destination of trucks, and compatible truck type.

Biomass type	Origin	Destination	Truck type
Sawdust, shavings	Suppliers	Yard, customers	All truck types
	Yard	Customers	All truck types
Clean and unclean wood	Suppliers	Yard	Roll off and end dump trucks
Clean wood chips and hog fuel	Yard	Customers	All truck types

Daily Cartage Report	
Name of the driver: XYZ	Date: May 28, 2017
Location Name	Biomass Type
From: Supplier 1	Sawdust
To: Customer 1	
From: Supplier 1	Shavings
To: Customer 1	
From: Supplier 1	Clean wood
To: Yard	
From: Supplier 2	Unclean wood
To: Yard	

Fig. 4. Sample of a daily cartage report.

cartage report depicts a truckload delivery which includes details about the product that was transported and the pickup and delivery locations for that truckload. The company keeps record of the cartage reports to determine the total cost of transportation and the total driver working time. Fig. 4 shows a sample of the daily cartage report filled by one driver. The report shows the transportation of four truckloads of biomass. The route adopted by the driver as per the report is (yard, supplier 1, customer 1, supplier 1, customer 1, supplier 1, yard, supplier 2, yard).

Each week, the company receives information about biomass supply and demand for the following week from their suppliers and customers. Based on this information, the weekly comminution schedules and daily truck routes are determined manually by the company. Comminution decisions and transportation decisions are taken separately by the yard manager and the logistics manager, respectively.

4.2. Data retrieval

Data from the company were obtained in the form of driver cartage reports for a span of four weeks. Few drivers did not mention the biomass type that was transported in each truckload in their reports. In such cases, details regarding biomass types available at each supplier and feedstock types demanded by each customer were gathered from the logistics manager of the company. This information was used to assess the product type in each truckload of the cartage reports.

The type of truck driven by each driver is not mentioned in the cartage report. This information is necessary to calculate the total quantity biomass picked up from each supplier and delivered to each customer. However, since drivers usually drive the same truck type, details about the truck type driven by each driver were obtained from the logistics manager of the company. Combining the information from the cartage reports and the logistics manager, the daily supply and demand quantities of biomass were calculated for four weeks. The compatibilities between product type, locations and truck type were retrieved from the cartage reports. The exact routes taken by each driver on each day were also retrieved from the cartage reports.

5. Results

In this section, we present the results obtained from solving the mathematical models presented in Section 2 using the data obtained from the company. The models are run for a planning horizon of one week where the transshipment model is run to determine the weekly transportation decisions and comminution schedules, and the routing model is solved for each day using the results from the transshipment model. Since data were received for a span of four weeks, the models are tested on four problem instances, one for each week.

The models are assessed by determining the total cost of transportation. This cost includes truck routing cost, cost when truck waits for the loader at the yard, cost incurred when trucks wait during loading and unloading operations, and the cost associated with the loader usage. Cost of comminution are disregarded in this comparison since information about the quantity of biomass comminuted at the yard was not available from the cartage reports.

Previous studies which developed transportation optimization models evaluated their results by comparing the cost of the routes obtained from their models with routes which assume that trucks always travel back-and-forth between the supply and demand points [33]. The cost of routes where trucks always travel back-and-forth between

supply and demand points is an upper bound to the optimal cost. However, this may not be a tight bound since these routes do not incorporate backhauling opportunities at all. For the data obtained from the company, it was observed that the cost of the actual truck routes obtained from the cartage reports was on average 7.7% better compared to the cost with truck's back-and-forth movements, indicating that backhauling was already incorporated in the manually-developed routes. We compare the results of our models with the routes implemented by the company as retrieved from the cartage reports.

In Table 5, the total cost from the models is compared with that from the original routes. The total cost includes loaded and empty truck travel cost, trucking cost incurred during loading and unloading operations, cost for trucks when waiting at the yard for the loader, and the loader cost. Loaded travel cost is the cost incurred when a truck travels loaded with biomass, and empty travel cost refers to the cost when the truck travels empty.

The second column of Table 5 shows the cost of the actual routes taken by the trucks. The third column shows the results of running the routing model using truckloads that were originally transported by the drivers. Instead of running the transshipment model to determine the number of truckloads of each truck type and each biomass type, we use the number of truckloads of each truck type and biomass type that were retrieved from driver cartage reports. The fourth column shows the improvement in total cost using the routing model for the original truckloads. The results show an average improvement of 6.6% over the original cost. This means that the routing model can increase the efficiency of the routes by exploiting backhauling opportunities in the pickup and delivery of biomass even when the truckloads were those used by the company.

The fifth column of Table 5 shows the results of the models where truckloads obtained from the transshipment model are used in the routing model. The sixth column shows the reduction in cost from the models as compared to the company's original cost. An average improvement of 12% can be observed in the total cost. This can be attributed to better full-truckload transportation decisions between different locations of the network and the resultant routes which incorporate backhauling as much as possible.

Trucks and loaders consume fuel during operation. The cost parameters used in the models for trucks and loaders include the cost of fuel.

Table 5
Total and weekly costs obtained by summing the costs for each routes per day.

Week	Cost from driver's reports (CDN\$)	Truckloads from driver's reports & routes from the routing model		Truckloads from the transshipment model & routes from the routing model	
		Cost (CDN \$)	% improvement	Cost (CDN \$)	% improvement
Week 1	55895.00	51646.40	7.6	48242.33	13.7
Week 2	47467.00	44306.50	6.7	41992.57	11.5
Week 3	70085.70	66103.10	5.7	62620.25	10.7
Week 4	73063.10	68288.40	6.5	64045.30	12.3
Total	246510.30	230344.40	4.6	217105.90	12.0
Average	61627.70	57586.10	6.6	54276.50	12.0

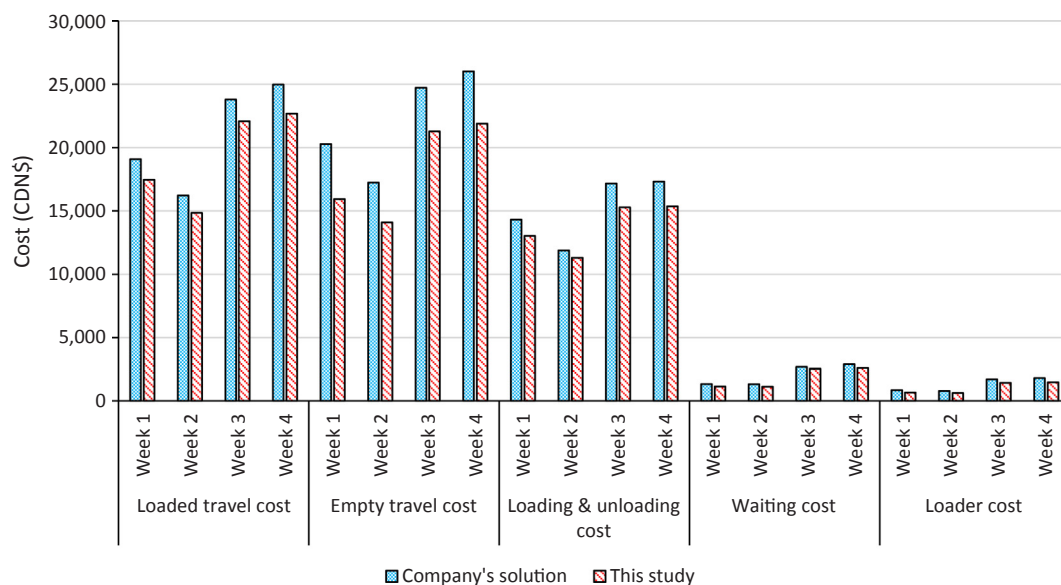


Fig. 5. Comparison of different cost components in the company's original routes and the routes obtained from our models.

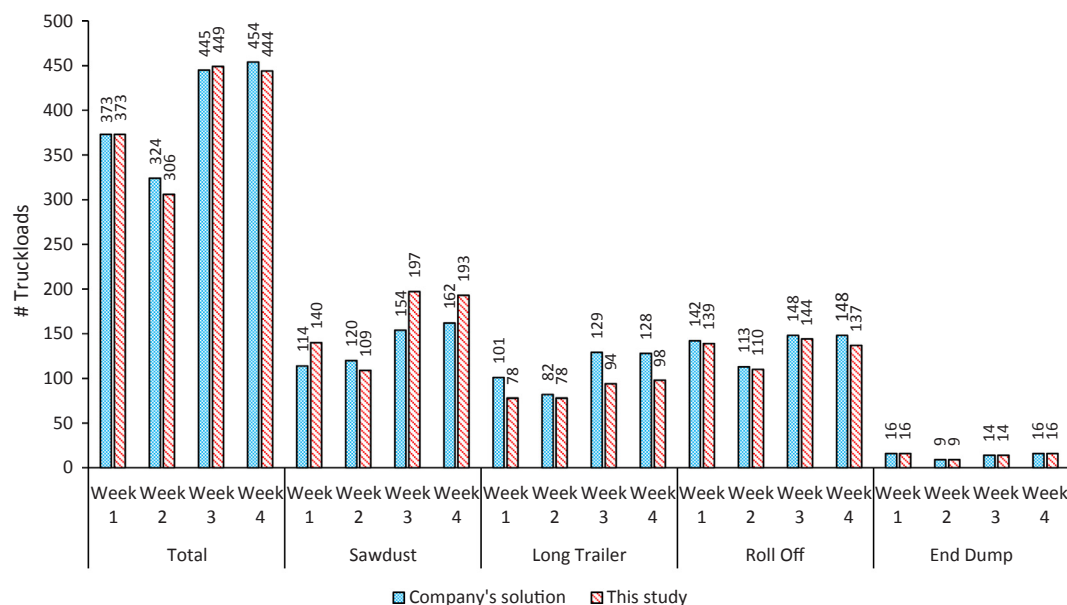


Fig. 6. Number of truckload for each type of truck.

Therefore, the cost optimization models also contribute to a reduction in the total fuel consumption. Using the truck fuel consumption rates from the literature [34], the total fuel consumption during each week is calculated. The results suggest that the improvement in fuel consumption during each week relates to the improvement in total cost. The average reduction in total fuel consumption using the optimization models for four weeks was 11.7%.

Fig. 5 compares different cost components of our solutions and the driver's original routes. It can be observed that the cost of each component has reduced using the optimization models as compared to the company's original routes. It can also be observed that the empty travel cost is relatively lower than loaded travel cost in the optimal solutions

while it is the opposite in the original routes. In the drivers' original routes, loaded travel cost was on average 34% of the total cost while empty travel cost was 36% of the total cost. In the routes obtained from our solutions, loaded travel cost was 36% and empty travel cost was 34% of the total cost.

The total number of truckloads transported during each week and the distribution of the number of truckloads with respect to the truck type from the company's original routes and the solution from our models can be seen in Fig. 6. Except for week 2, the total number of truckloads in both the solutions is more or less the same. In addition, except for week 2, the number of truckloads of the sawdust truck increased in the optimal solutions. The number of truckloads of long

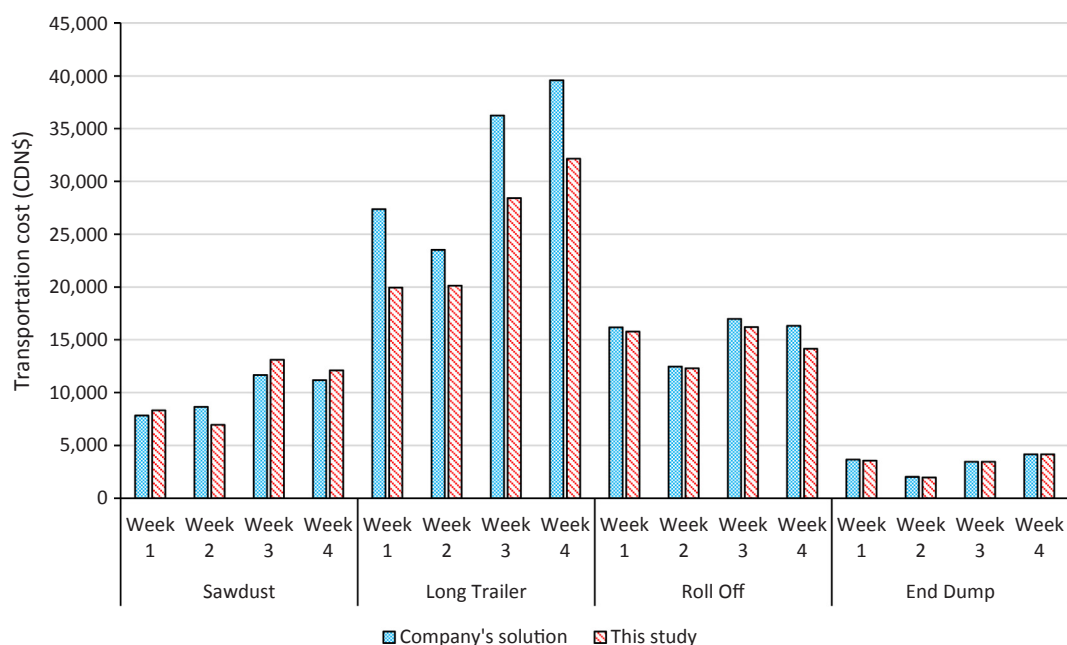


Fig. 7. Transportation cost per week for each truck type.

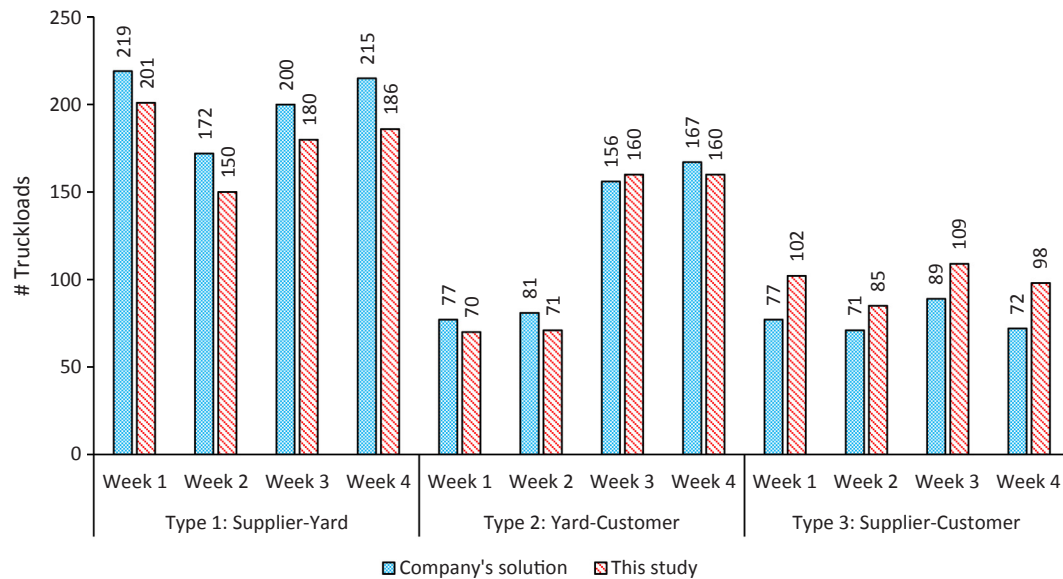


Fig. 8. Number of truckloads per week in of each truckload type in the supply chain.

trailer decreased in the optimal solutions. The number of truckloads of roll off trucks and end dump trucks are more or less the same for all four weeks.

Fig. 7 shows the average cost incurred by each truck type from the company's original routes and the solutions obtained from the optimization models. Even though Fig. 6 shows that the number of truckloads of sawdust trucks is greater than that of long trailer trucks, the average total cost of long trailer trucks is much greater than that for sawdust trucks. This trend of higher cost for long trailer trucks and lower cost for sawdust trucks can also be observed in the company's original routes.

There are three types of loaded truckloads: truckload from a supplier to the yard (type 1), truckload from the yard to a customer (type

2), and truckload directly from a supplier to a customer (type 3). The total number of truckloads of each type is shown in Fig. 8. It can be observed that the optimization models suggest transporting less number of truckloads of the type 1 and more number of truckloads of type 3. Except for week 3, the number of truckloads of type 2 also decreased using the optimization models.

The average number of truckloads of each truck type and each truckload type are shown in Fig. 9. Similar to the observations made in Fig. 8, Fig. 9 suggests that the average number of truckloads of type 1 reduced using our models for all truck types, while the number remains the same for end dump truck type. Similarly, the number of truckloads of type 3 increased on average for all truck types. With respect to the

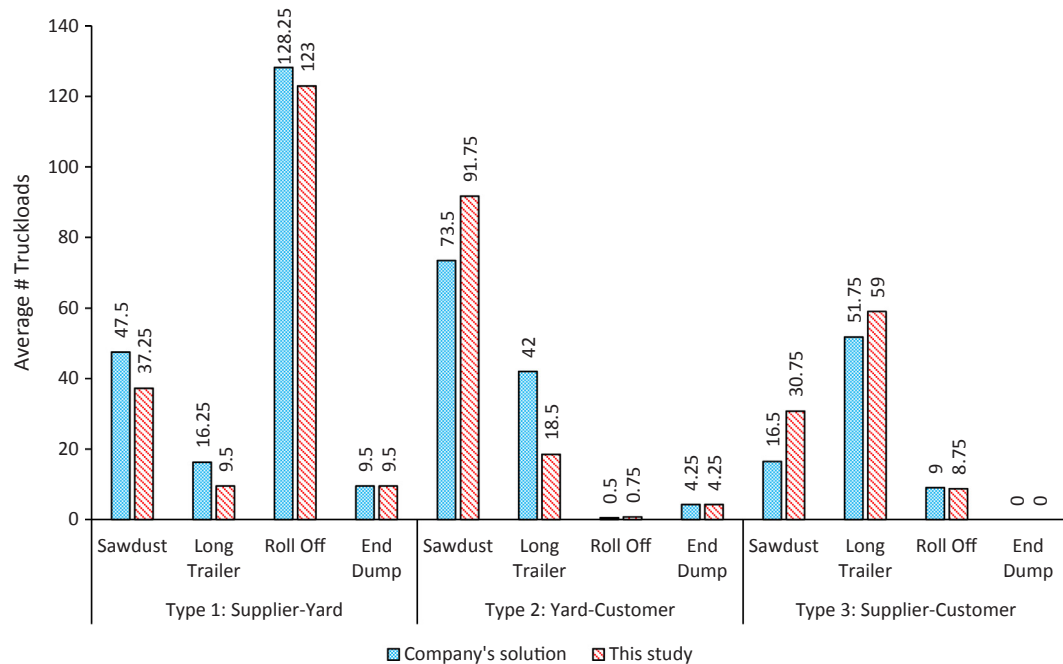


Fig. 9. Average number of truckloads of each truck type and each truckload type in the supply chain.

use of sawdust trucks, the models suggest decreased usage for type 1 loads and increased usage for type 2 loads from the yard to customers.

The durations of chipping and grinding of clean wood and unclean wood, respectively, are determined by the transshipment model. Since the quantity of unclean wood ground daily is equal to the quantity of hog fuel demanded by the customers that day, there is no flexibility in scheduling the grinding operations. On the other hand, inventory of clean wood chips is maintained at the yard, therefore, chipping schedules can be flexible in terms of the day it takes place. According to the optimal solution obtained from the transshipment model, chipping takes place every Monday and Tuesday such that the total quantity of wood chips produced is equal to their demand over the week. The inventory of clean wood chips at the end of each week is equal to the safety stock maintained by the company. No chipping happens during the weeks when clean wood chips are not demanded by customers.

6. Discussion

The results presented in Section 5 indicate that an average reduction of 12% in total cost can be achieved using the optimization models developed in this study compared to the routes taken by the drivers. This reduction in total cost can be attributed to the decisions related to the truck type and the truckload type transported between different locations of the network, and the resultant routes of each truck incorporating backhauling as much as possible. This can be observed from the difference in the number of truckloads of each truck type and each truckload type, and the reduction in cost of empty truck travel compared to that of loaded truck travel in the optimal solutions.

The optimization models also resulted in a reduction of 11.7% in total fuel consumption on average. This reduction in fuel consumption corresponds to the reduction in total cost as the cost parameters used in the model include fuel consumption cost. This observation is in accordance with the literature [35] which indicate that cost minimization in transportation models also contribute to a reduction in fuel consumption.

The total number of truckloads transported in the driver's original routes is similar to that suggested by the optimization models. Roll-off and end dump trucks are mainly used to pick up clean and unclean wood from suppliers which have little flexibility in the type of truck that can visit them. Therefore, the number of truckloads of roll-off and end dump trucks is almost the same in the optimal solution of the models and the driver's original routes. On the other hand, several suppliers and customers dealing with sawdust, shavings, wood chips and hog fuel have flexibility in the type of truck that can visit them. Therefore, the number of truckloads of sawdust and long trailer trucks which carry these types of biomass are different using the optimization models compared to the company's solution. The models suggested transporting more truckloads of the sawdust truck and fewer truckloads of the long trailer truck. Due to the increased number of sawdust truckloads, the total cost of using sawdust trucks is greater in the optimal solutions of the models. Similarly, due to the decrease in the number of long trailer trucks, the total cost of using long trailer trucks is lower in the optimum solutions suggested by the models compared to the costs in driver's original routes.

Although fewer number of long trailer truckloads is transported compared to that of sawdust trucks, the total cost of using long trailer trucks is much greater than that of sawdust trucks in the optimum solutions of the models. This indicates that more truckloads of sawdust trucks are used for shorter distance transportation, and long trailer trucks are used for longer distances. Although sawdust trucks have higher cost per unit volume of biomass (1.68 \$/hour-m³) compared to

that of long trailer trucks (1.16 \$/hour-m³), they have shorter loading and unloading times. Due to this reason, depending on the quantity of biomass and the distance traveled, the model selects sawdust trucks for short distances and long trailer trucks for long distances. This trend of higher cost for long trailer trucks and lower cost for sawdust trucks can also be observed in the company's original routes.

Since clean and unclean wood must be comminuted at the yard before delivering the respective feedstock to customers, the truckloads carrying clean and unclean wood, and clean wood chips and hog fuel cannot bypass the yard. All the truckloads carrying clean and unclean wood are of truckload type 1 (from suppliers to the yard, shown in Fig. 3), and those carrying clean wood chips and hog fuel are of type 2 (from the yard to customers, shown in Fig. 3). Depending on the quantities of biomass supplied and demanded, truckloads carrying sawdust and shavings can bypass the yard by performing a direct delivery. A reduction in the number of truckloads from the supplier to the yard (truckload type 1, shown in Fig. 3), which is compensated by the increase in the number of direct deliveries from the suppliers to the customers (truckload type 3), can be observed in the optimum solutions. Since direct deliveries, which avoid multiple loading and unloading operations, are cost efficient, the optimization models select more truckloads of type 3 compared to those in the company's solution.

7. Decision support tool

A decision support tool is developed for the company using the Solver Studio [36] add-in in Microsoft Excel® to make their weekly transportation and comminution decisions. The model is written in the PuLP language. The tool is made as simple as possible, and only the inputs that vary on a regular basis are to be modified by the user. These inputs include the date of the beginning of the planning horizon, the inventory of biomass at the yard at the beginning of the planning horizon, the number of vehicles available and the quantities of biomass to be picked up and delivered. Once all the required data have been entered, the user presses the optimize button located on the spreadsheet to run the tool. The button executes the model and writes back the results in the workbook. Figures of the user interface and the workbook within the tool to display the results are shown in Appendix A.

8. Conclusions

This paper focused on optimization of the forest-based biomass logistics over a short-term planning horizon. Current literature on biomass logistics optimization over a short-term is limited, and focuses only on optimizing daily truck routes without including decisions related to storage and comminution of biomass, which are important steps in the conversion of biomass to energy and fuels. Previous models did not include intermediate storage sites in their networks. The study that included decisions related to allocation of biomass from different suppliers to customers considered homogeneous fleet of trucks, while biomass logistics systems may be more complicated due to multiple biomass types and heterogeneous fleet of trucks. We addressed these gaps by developing transshipment and routing models to determine optimal decisions related to transportation, storage and comminution of biomass for short-term planning. The models were applied to a large biomass logistics company based in Lower Mainland region, British Columbia, Canada.

The transshipment model was solved to determine weekly comminution and transportation decisions, and the results of the transshipment model were used within a routing model to determine the routes

for each truck on a daily basis. The results of the developed models indicated an improvement of 12% on average for the total logistics cost, and 11.7% on average for the total fuel consumption of trucks and loaders. The models suggested direct delivery of biomass from suppliers to customers where possible, and larger trucks were used more for the direct delivery of biomass. The results of the routing model indicated a reduction in relative cost of empty truck travel compared to the relative cost of loaded truck travel, where as it was the opposite in the company's original routes. A decision support tool based on the transship-model was provided to the company.

This study assumed that the supply and demand quantities of biomass were deterministic and the resultant models were static. As a result, the models are not readily applicable under situations with unexpected truck failures, mill breakdowns and traffic jams. Incorporating such dynamics, and including uncertainties in supply and demand quantities of biomass may enhance the applicability of the models.

Appendix A. Appendix A

Fig. A.1 shows the user interface of the tool provided to the company.

Fig. A.2 displays the main results given by the tool. It contains the quantity of biomass to be comminuted on each day, the level of inventory of biomass for each day and a list of orders indicating all the information required for each truckload. To facilitate the interpretation of the results, the tool displays maps showing the relative quantities of biomass to be picked up and delivered at each supplier and customer locations.

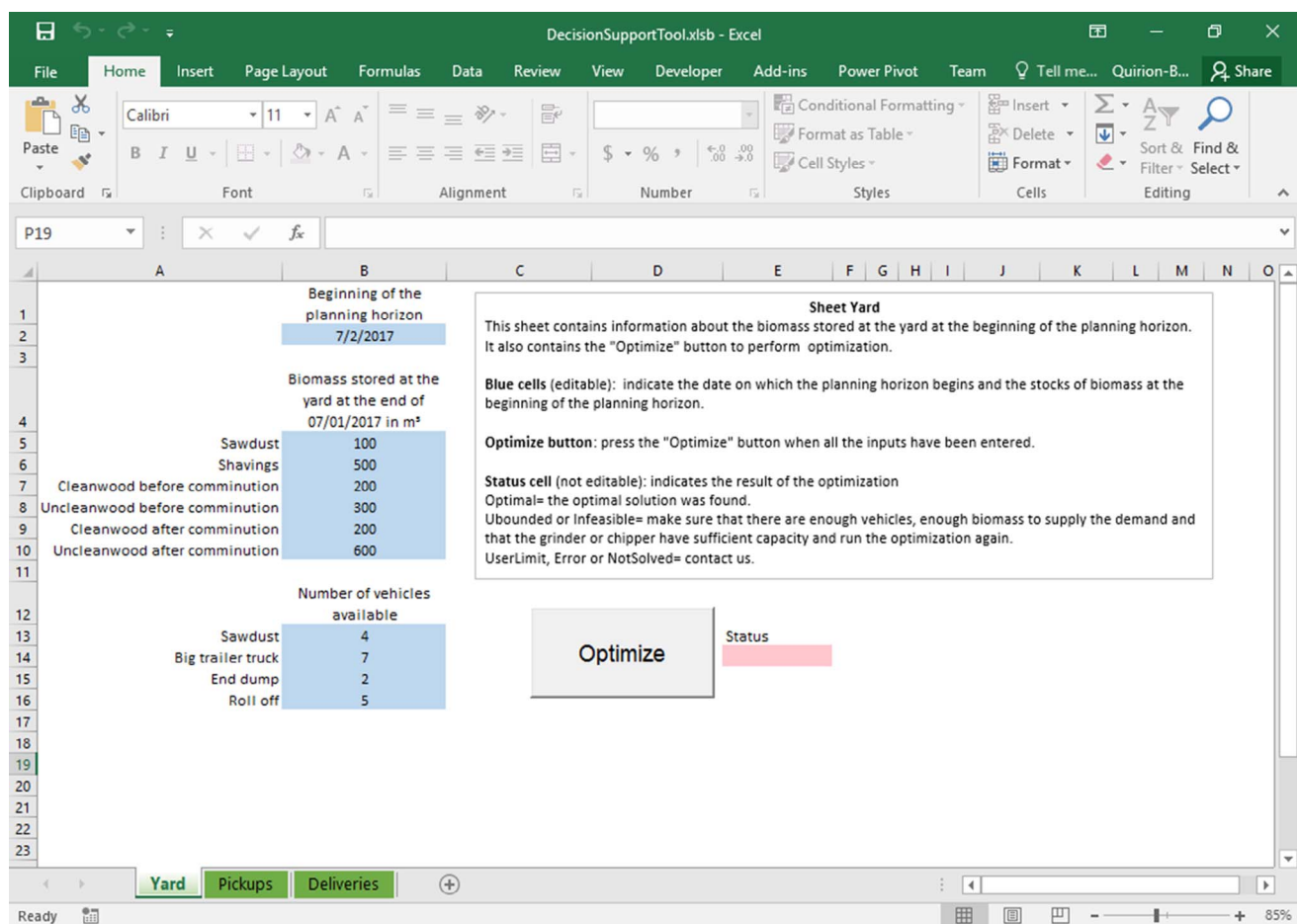


Fig. A.1. Snapshot of the main worksheet of the decision support tool.

While the cost minimization models resulted in reducing the total fuel consumption, models focusing solely on minimizing fuel consumption, and the resultant trade-offs between economic and environmental objectives may also be interesting to investigate.

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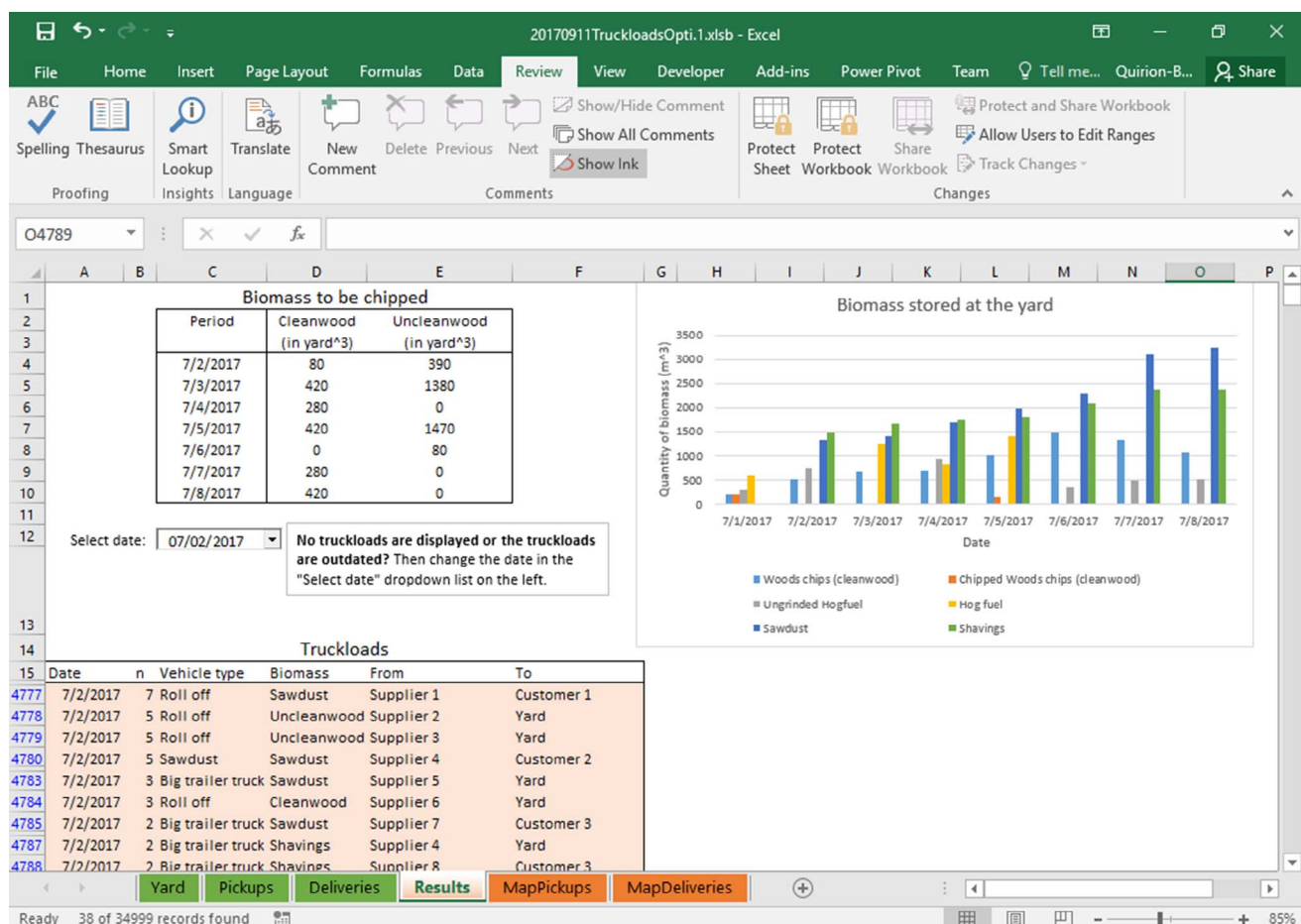


Fig. A.2. Snapshot of the results sheet obtained from the decision support tool.

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