Optimization of Sawmill Residues Collection for Bioenergy

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Abstract

The collection of sawmill residues is an important logistic activity for the pulp and paper industry, which use the biomass as a source of energy. We study a vehicle routing problem for a network composed of a single depot and 25 sawmills, in the Lower Mainland region of British Columbia, Canada. The sawmills serve as potential suppliers of biomass residues to the depot, which in turn processes and distributes the residues to the pulp and paper mills. This problem consists of identifying the best daily routing schedule for a fixed number of trucks. The objective is to maximize the ratio of energy returned on energy invested, while satisfying a minimum daily amount of dried biomass residues. There are several random components in the problem, including the availability and moisture content of the biomass residues. We use a combination of scenario analysis and heuristics to solve this stochastic vehicle routing problem.

Keywords: renewable energy systems, routing algorithms, robust estimation, uncertainty, stochastic approximation, logistics modeling.

1. Introduction

The deleterious impacts of climate change coupled with the ongoing urbanization of countries around the world have led to a global effort to reduce greenhouse gas emissions for energy production, especially in the transportation sector. The transport sector is responsible for approximately one quarter of greenhouse gas emissions in both Europe and America, making it the second largest emitting sector after energy (European Commission, 2009; United States Environmental Protection Agency, 2015). A plethora of studies show that urban freight transport could be vastly more efficient. According to the European Commission 24% of commercial trucks that operate in Europe are empty (United States Environmental Protection Agency, 2015). McElroy estimates that commercial trucks drive 19 billion needless miles each year in the United States alone (Jaffe, 2015). Thus, significant economic and environmental savings may be achieved by reducing truck transport.

This paper describes a case study of planning truck routes for the collection of sawmill residues (or waste) in the Lower Mainland region of British Columbia, Canada. A symbiotic relationship exists between sawmills and pulp mills. Approximately 50% of a log, by volume, gets turned into lumber at a sawmill. The residue waste from the process is utilized by the pulp mills to produce both pulp and excess green energy.

Analogously, the majority of pulp mills rely on purchased sawmill residue chips for most, if not all, of their chip supply. Consequently, the sale of residue chips has become an essential revenue stream for the sawmills. The pulp mills have the necessary expertise, infrastructure and potential to be future large scale producers of biomass based transportation fuels (Mercer International Group, 2010). In the past, the design of the residue collection routes has been done manually.

The real-life residue collection problem under consideration may be described as follows. There are a total of 25 sawmills in the region and a single depot. The location of the sawmills and the depot are given along the streets of a defined road network. The biomass residue produced by the sawmills must be collected by a fleet of trucks with known capacities. The average daily amount of residues produced by each sawmill are subject to variability. Each truck may collect residues from several sawmills before returning to the depot to unload. Truck drivers work 8 hour shifts that start at 9am and end at 5pm. The trucks leave the depot at the start of the day at 9am and are allowed to make several, potentially different, routes in a single day. A truck must return to the depot to unload after completing a route. In addition, all trucks must return to the depot before the end of the day at 5pm. The amount of residues that should be collected on a daily basis is determined by the energy demand from the pulp mills that are being supplied by the depot. There are a limited number of identical vehicles available with a capacity of 30 tonnes that are used to collect residues in the considered region.

Information regarding the mass, measured in green tonnes (gt), and energy density, measured in (GJ/tonne) of the residues available at each sawmill is not known and highly variable. The energy density of the residues depends on their moisture content and heating value. The wet basis moisture content is used to describe the water content of biomass and is defined as the percentage equivalent of the ratio of the weight of water to the total weight of the biomass. In this study, the average daily amount of residues produced at each sawmill and their corresponding moisture content are estimated using historical data. Established conversion factors were used to convert from wet to dry weight and energy density (Briggs, 1994).

The time to load the vehicles at the sawmills as well as the time to unload them at the depot are based on estimates provided from earlier studies (Macdonald, 2009). The driving distance and travel time between the sawmills and the depot were calculated using the *RgoogleMaps* package in R (Loecher & Ropkins, 2015). As the residue collection problem includes random parameters and processes, it is stochastic by nature. The objective is to schedule the collection activities and identify collection routes that maximize the total energy returned on energy invested (EROEI). The EROEI is defined as the ratio of the amount of usable energy acquired from a particular energy resource to the amount of energy expended to obtain that energy resource.

The described problem can be viewed as a periodic vehicle routing problem (PVRP) with a limited number of vehicles. The basic vehicle routing problem (PVRP) is a very well known and widely studied problem in combinatorial optimization. The objective is to route the vehicles, with each route starting and ending at the depot, so that all customer supply demands are met and the total travel distance is minimized. As this is a computationally very hard problem, which cannot be solved by exact methods, in practice heuristics are typically used for this purpose (Nuortio et al., 2006). The stochastic periodic vehicle routing problem (SPVRP) arises when some of the elements of the problem are not known exactly, such as the travel times, product availability or customer demands.

The stochastic problem presented in this paper is solved using the quantile-based scenario analysis (QSA) approach (Zamar et al., 2017). This method analyzes the performance of solutions obtained from solving deterministic realizations of the stochastic problem and identifies the solution that optimizes chosen quantiles of the stochastic objective function, subject to satisfying conditions on given quantiles of the constraint distribution. An advantage of this approach is that it requires only that each deterministic version (i.e., scenario) of the stochastic problem be solvable.

The remainder of this paper is organized as follows. The proposed model and its input requirements are presented in Section 2.1. The heuristic routing and scheduling methodologies are explained in Section 2.2, followed by results in Section 3. The main conclusions of the study are provided in Section 4.

2. Methods

2.1. Optimization Model

In this section we formally define the SPVRP model for this study. The problem is defined on a graph $G = \{V, A\}$, where the set of nodes $V = V_d \cup V_s$ consists of a single depot $V_d = \{0\}$, m sawmills, $V_s = \{1, \ldots, m\}$, and a set of arcs $A = \{(i,j) \mid i, j \in V, i \neq j\}$. Let $K = \{1, \ldots, n\}$ be the set of trucks with capacity c_k, $k \in K$. Let d_{ij} and t_{ij} be the travel distance and time associated with arc (i,j), respectively. In addition, each node, $j \in V_s$, has an inventory h_j with an average moisture content ω_j and a mass flow rate β_j for loading a truck. Define the set $R_k = \{1, \ldots, r_k\}$, $k \in K$, where r_k denotes the number of routes assigned to truck k. Let δ_{jkl} represent the mass of residues picked up at node $j \in V_s$ by truck $k \in K$ on its $l \in R_k$ assigned route. Let θ be the required moisture content of the biomass residue for conversion into heat and power at the pulp mills. Let η represent the calorific value of the biomass at a moisture content of θ, and T be the temperature at which it is stored. The time required to load a truck at a given node $j \in V_s$ is given by $\alpha_j + \beta_j \delta_{jkl}$, where α_j is the truck setup time at node j. Similarly, the time required to unload a truck at the depot is given by $\alpha_0 + \beta_0 c_k$. The parameters t_{ij}, α_j, β_j, h_j and ω_j, $\forall (i,j) \in A$, are unknown quantities, which are assumed to be normally distributed. Thus, t_{ij}, α_j, β_j, ω_j and h_j are stochastic variables.

For a specific realization of the random variables t_{ij}, α_j, β_j, ω_j, and h_j, $\forall (i,j) \in A$, the deterministic problem can be modeled using the following additional variables. Let $u_k = 1$, $k \in K$, if and only if the driver of truck k has had a lunch break and $u_k = 0$ otherwise. Let γ be the time alloted for a lunch break. Define the set of arcs between nodes that do not originate from the depot as $A_s = \{(i,j) \mid i \in V, j \in V_s, i \neq j\}$. Let $x_{ijkl} = 1$ if and only if truck $k \in K$ uses arc (i,j) on its lth assigned route and $x_{ijkl} = 0$ otherwise. The optimization model for the SPVRP problem is given in Eq. (1).

$$\text{maximize} \quad J(\boldsymbol{x},\boldsymbol{\delta}) = \frac{\sum\limits_{(i,j)\in A_s}\sum\limits_{k\in K}\sum\limits_{l\in R_k} \delta_{jkl}\cdot\left[1-\left(\omega_j - \frac{\theta(1-\omega_j)}{1-\theta}\right)\left(1+\frac{(100-T)\eta_1+\eta_2}{\eta_4}\right)\right]\cdot x_{ijkl}}{\sum\limits_{(i,j)\in A}\sum\limits_{k\in K}\sum\limits_{l\in R_k} x_{ijkl}\cdot d_{ij}} \propto \frac{e_1}{e_2} \tag{1a}$$

$$\text{subject to} \quad \sum_{j\in V}\sum_{l\in R_k} x_{0jkl} = 1, \quad \forall k\in K \tag{1b}$$

$$\sum_{i\in V}\sum_{l\in R_k} x_{i0kl} = 1, \quad \forall k\in K \tag{1c}$$

$$\sum_{i\in V}\sum_{l\in R_k} x_{ijkl} = \sum_{i\in V}\sum_{l\in R_k} x_{jikl}, \quad \forall j\in V, k\in K \tag{1d}$$

$$\sum_{k\in K}\sum_{l\in R_k} \delta_{jkl} \le h_j, \quad \forall j\in V_s \tag{1e}$$

$$\kappa\cdot c_k \le \sum_{j\in V_s} \delta_{jkl} \le c_k, \quad \forall k\in K, l\in R_k \tag{1f}$$

$$\delta_{jkl} \ge 0, \quad \forall j\in V_s, k\in K, l\in R_k \tag{1g}$$

$$\delta_{0kl} = 0, \quad \forall k\in K, l\in R_k \tag{1h}$$

$$x_{ijkl}\in\{0,1\}, \quad \forall (i,j)\in A, k\in K \tag{1i}$$

$$\sum_{j\in V_s}\sum_{k\in K}\sum_{l\in R_k} \delta_{jkl} \ge \delta^* \tag{1j}$$

$$\sum_{l\in R_k} u_{kl} = 1, \quad \forall k\in K \tag{1k}$$

$$\begin{aligned}&\sum_{(i,j)\in A_s}\sum_{l\in R_k} x_{ijkl}(t_{ij}+\alpha_j+\beta_j\delta_{jkl}) \\ &\quad + \sum_{i\in V}\sum_{l\in R_k} x_{i0kl}(t_{i0}+\alpha_0+\beta_0 c_k) + \gamma \le \tau, \quad \forall k\in K\end{aligned} \tag{1l}$$

The goal is to reduce the EROEI ratio, denoted by the function $J(\boldsymbol{x},\boldsymbol{\delta})$, in Eq. (1a). To simplify the notation, the decision variables are compactly expressed as the route schedule, $\boldsymbol{x}$, and the amount of residues, $\boldsymbol{\delta}$, to pick up from each sawmill visited in each route. We assume that the energy obtained from a green tonne of biomass, e_1, at a moisture content of θ and the energy spent per kilometer (km) traveled, e_2, are both constants. In such case, the EROEI is proportional to the mass of the dried biomass (to the desired moisture content θ) divided by the distance traveled in collecting it. The energy required for drying the biomass is also reflected in $J(\boldsymbol{x},\boldsymbol{\delta})$. This is achieved by subtracting, from the numerator, the quantity of dried biomass that would be required to generate the energy needed to dry the delivered residues to the desired moisture content, θ. Lemma 1 shows how to calculate this quantity. Eqs. (1b) and (1c) ensure that all k trucks must leave and return to the depot at the end of each route. Eq. (1d) ensures that the inflow and outflow must be equal except for the depot node. Eq. (1e) ensures that the trucks cannot pick up more residues than are available at each sawmill node. Eq. (1f) ensures that each truck must come back at least $\kappa\times 100\%$ full at the

Table 1: Optimization Model Notation

	Symbol	Description	Units	Set Notation/Indices
Sets				
	V_0:	depot node	–	$V_0 = \{0\}$
	V_s:	sawmill nodes	–	$V_s = \{1, 2, \ldots, m\}$
	A:	arcs connecting the nodes	–	$A = \{(i, j) \mid i, j \in V_s \cup V_0, i \neq j\}$
	K:	trucks	–	$K = \{1, 2, \ldots, n\}$
	R_k	routes assigned to truck k	–	$R_k = \{1, 2, \ldots, r_k\}$, $k \in K$
Parameters				
	c_k :	truck capacity	tonnes	$k \in K$
	κ_k :	minimum required payload for truck k per route	gt	$k \in K$
	λ :	time allowed for lunch break	hr	–
	τ :	maximum daily operating hours for a truck driver	hr	–
	θ	required moisture content of the dried biomass	%	
	h_j:	inventory at node j	gt	$j \in V_s$
	w_j:	wet basis moisture content of residues at sawmill j	%	$j \in V_s$
	η:	net calorific value of one tonne of biomass at a moisture content of θ	$\text{GJ} \cdot \text{tonne}^{-1}$	–
	α_j	setup time for loading a truck at sawmill j	hr	$j \in V_s$
	β_j	mass flow rate for loading a truck at sawmill j	$\text{gt} \cdot \text{hr}^{-1}$	$j \in V_s$
	α_0	setup time for unloading a truck at the depot i	hr	–
	β_0	mass flow rate for unloading a truck at the depot	$\text{gt} \cdot \text{hr}^{-1}$	–
	d_{ij}	travel distance between nodes i and j	km	$i, j \in V_0 \cup V_s$
	t_{ij}	travel time between nodes i and j	hr	$i, j \in V_0 \cup V_s$
	u_k:	logical value indicating if truck k had lunch	–	$k \in K$
Variables				
	r_k:	number of routes assigned to truck k	–	$k \in K$
	x_{ijkl} :	logical value indicating if truck k uses arc (i, j) on its lth assigned route	–	$k \in K$, $i, j \in V_0 \cup V_s$, $l \in R_k$
	δ_{ikl} :	amount of residues picked up by truck k at node i on its lth assigned route	gt	$k \in K$, $i \in V_s$, $l \in R_k$

end of each route, where $0 < \kappa \leq 1$. Eq. (1f) also ensures that the truck capacity c_k is never exceeded. Eqs. (1g) and (1h) enforce non-negativity and that the trucks are empty when leaving the depot at the start of each route. Eq. (1i) enforces binary variables. Eq. (1j) ensures that the minimum daily amount of required tonnes of sawmill residues, δ^* is met. Eq. (1k) ensures that each truck driver takes a lunch break. Finally, Eq. (1l) ensures that each truck operates a maximum of τ hours. It is convenient to represent the solution to this problem as a set of collection runs. The l^{th} collection run represents the ensemble of routes assigned to each truck on their l^{th} route. As such, solutions to the SPVRP are presented in this form.

Lemma 1. *Let δ be a delivered amount of biomass in green tonnes and ω be its corresponding wet basis moisture content. Let $\theta \leq \omega$ be the required moisture content of the biomass for conversion into energy and T be the temperature at which the biomass is stored. If the net calorific value of the biomass at a moisture content of θ is η $GJ \cdot tonne^{-1}$, then the net energy gained after drying (assuming 100% burner efficiency) is equivalent to that stored in*

$$\delta \left[1 - \left(\omega - \frac{\theta(1-\omega)}{1-\theta}\right)\left(1 + \frac{(100-T)4.19 \times 10^{-3} + 2.26}{\eta}\right)\right] \tag{2}$$

tonnes of biomass at a moisture content of θ, where 4.19×10^{-3} and 2.26 represent the specific heat and latent heat of vaporization of water in $GJ \cdot tonne^{-1}$, respectively (Perrot, 1998).

Proof. The wet basis moisture content of biomass is the percentage equivalent of the ratio of the weight of water to the total weight of the biomass. We can write

$$\omega = \frac{\delta\omega}{\delta\omega + \delta(1-\omega)}, \tag{3}$$

where $\delta\omega$ is the weight of water in the delivered biomass, in tonnes. Let y be the allowed weight, in tonnes, of the dried biomass where θ is the required moisture content, then y satisfies

$$\frac{y}{\delta(1-\omega) + y} = \theta. \tag{4}$$

From Eq. (4) we have:

$$y = \delta\theta(1-\omega) + \theta y \tag{5}$$

$$\Rightarrow \quad y(1-\theta) = \delta\theta(1-\omega) \tag{6}$$

$$\Rightarrow \quad y = \frac{\delta\theta(1-\omega)}{1-\theta}, \tag{7}$$

thus the amount of water, in tonnes, that must be evaporated from the delivered biomass is

$$\delta\omega - y = \delta\omega - \frac{\delta\theta(1-\omega)}{1-\theta}. \tag{8}$$

If T is the temperature (in degrees Celsius) at which the biomass is stored and η is the net calorific value (in $\text{GJ} \cdot \text{tonne}^{-1}$) of the biomass at a moisture content of θ, then the number of tonnes of biomass that would be required to generate the energy needed to evaporate $\delta\omega - y$ tonnes of water is given by:

$$z = \frac{(100 - T)4.19 \times 10^{-3} + 2.26}{\eta} \left[\delta\omega - \frac{\delta\theta(1-\omega)}{1-\theta} \right], \tag{9}$$

where the first term in the product corresponds to the energy required to heat one tonne of water to its boiling point plus the energy to change its state all divided by the energy stored in one tonne of biomass at a moisture content of θ. From Equations (8) and (9) we have that the net energy gained (assuming 100% burner efficiency) is equivalent to that stored in

$$\begin{aligned} \delta - (\delta\omega - y) - z &= \delta - \left(\delta\omega - \frac{\delta\theta(1-\omega)}{1-\theta} \right) - \frac{(100 - T)4.19 \times 10^{-3} + 2.26}{\eta} \left(\delta\omega - \frac{\delta\theta(1-\omega)}{1-\theta} \right) &(10) \\ &= \delta \left[1 - \left(\omega - \frac{\theta(1-\omega)}{1-\theta} \right) \left(1 + \frac{(100 - T)4.19 \times 10^{-3} + 2.26}{\eta} \right) \right] &(11) \end{aligned}$$

tonnes of biomass at a moisture content of θ. □

2.2. *Simulation Model*

Deterministic versions of the SPVRP (where all parameter values are known in advance) are generally solved using heuristics, whereas stochastic dynamic versions of these problems are typically solved using simulation, where at time t one would solve an optimization problem using only what is known at that time.

We solve the SPVRP problem presented earlier using the quantile-based scenario analysis (QSA) approach described in Zamar et al. (2015). A discrete even simulation model based on the heuristic illustrated in

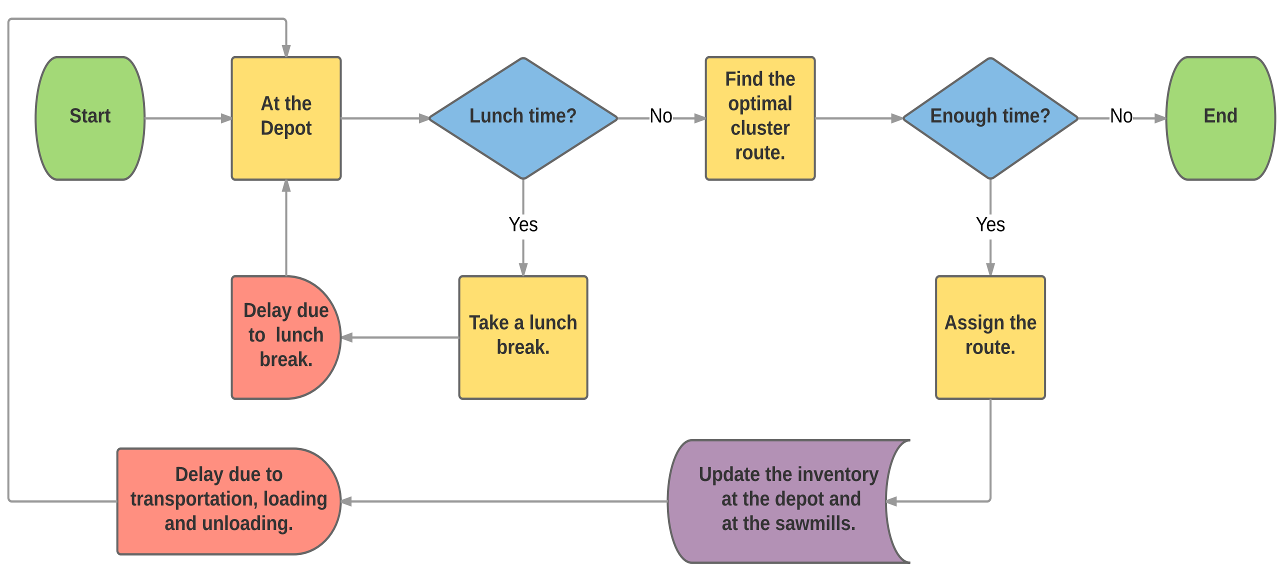


Figure 1: The Logic Flowchart for Truck Operations in the Simulation Model.

Figure 1 was implemented to solve each scenario. To make the problem more manageable, we first cluster the sawmill nodes based on their distance matrix and restrict attention to routes within each cluster. Thus, our approach does not consider routes that span across clusters, which are unlikely to be selected due to their Hamiltonian distance. The Hamiltonian distance of a set of nodes is the shortest path, made up from the edges connecting the nodes, which passes through each node. The QSA method samples scenarios from their underlying distribution and solves each scenario separately. The solution of each deterministic scenario problem is evaluated across the sampled scenarios to provide an estimate of the objective and constraint satisfaction distribution of each solution. Solutions are then ranked based on their corresponding objective and constraint distribution quantiles. For this application we maximize the 0.5 quantile (median) of the stochastic objective function shown in equation (1a), subject to satisfying two quantile constraints on the resulting procurement amounts given by equation (1j).

The objective distribution corresponds to the EROEI while the constraint distribution represents the fulfilled portion of the demand as described in Eqs. (1a), and (1j), respectively. We restrict attention to solutions that have a 90% probability of satisfying at least 90% of the demand across scenarios.

3. Results and Discussion

We applied our simulation model coupled with the QSA approach to solve the previously described SPVRP problem. A map of the study region is shown in Figure 2, which identifies the locations of the 25 sawmills and the single depot. The depot requires a minimum of 180 dry tonnes of biomass. Here, dry tonnes refers to the mass of the biomass at a moisture content of $\theta = 0.3 \times 100\%$. The net calorific value of one tonne of biomass, η, is assumed to be fixed at 12.2 $\text{GJ} \cdot \text{tonne}^{-1}$ (FAO, 2013). The temperature, T, at which the biomass is stored at the depot is assumed to be fixed at 20 °C.

The random parameters that distinguish the scenarios are categorized as follows: (1) the residue available at each sawmill, h_j; (2) the moisture content of the residue available at each sawmill, ω_j; (3) the time required to travel between the nodes (sawmills and the depot), t_{ij}; (4) the truck setup time at the depot and the sawmills, α_0 and α_j; and (5) the load and unload flow rates at the sawmills and the depot, β_0 and β_j. The random parameters h_j and ω_j are modeled based on published summary data (BC Bioenergy Network and Biomass Availability Study Working Group, 2012) on biomass residue availability and moisture content at each of the sawmill nodes. The random parameters α_j and β_j, $i \in V$, describing the setup, load and unload times, are modeled based on the values calculated by FPInnovations in their assessment of economically viable biomass (Macdonald, 2009). The expected travel time, t_{ij}, and the exact travel distance, d_{ij}, $\forall (i, j) \in A$, between nodes were calculated using the *RgoogleMaps* package in R (Loecher & Ropkins, 2015).

A summary of the distributions of the random parameters included in the model are shown in Table 2. The average available biomass residue at each sawmill node was modeled as a multivariate normal distribution based on their average annual production. Spatial variogram models were fit using the *sp* package in R to represent the wet basis moisture content of the biomass residue available at each sawmill node (Bivand

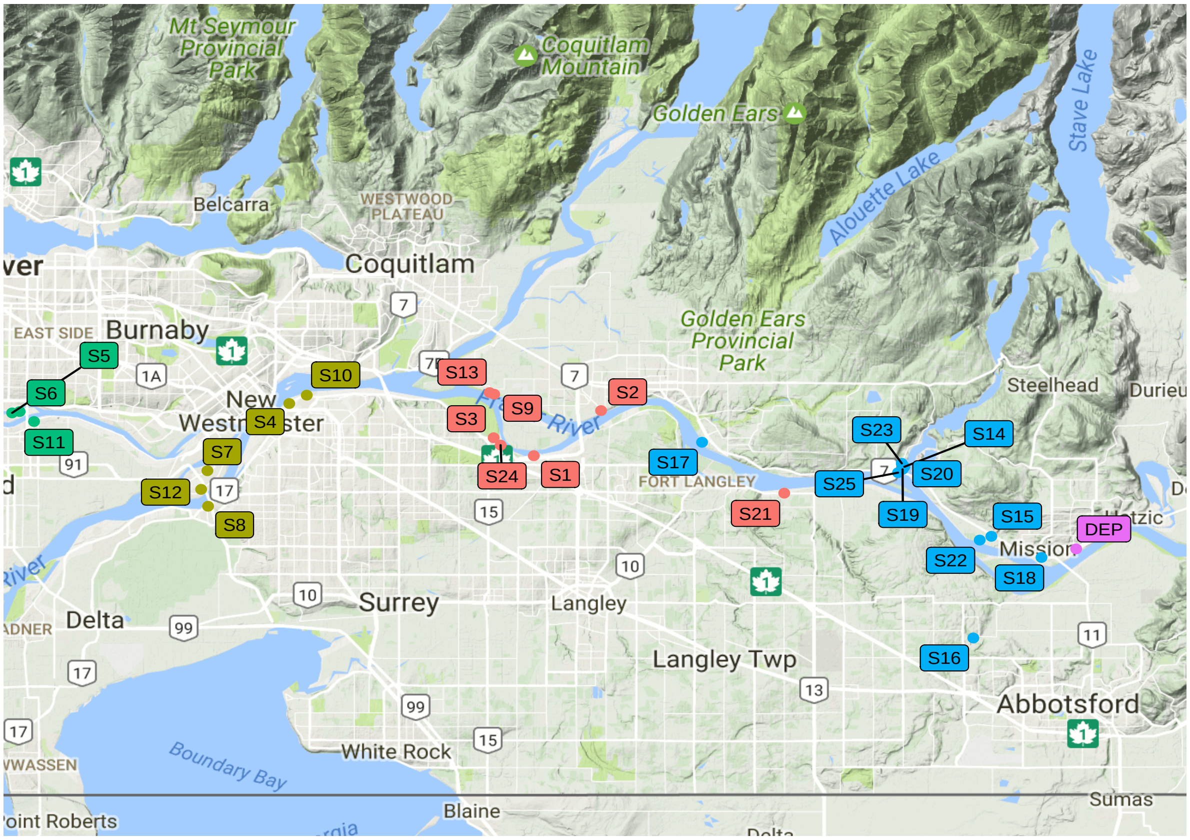
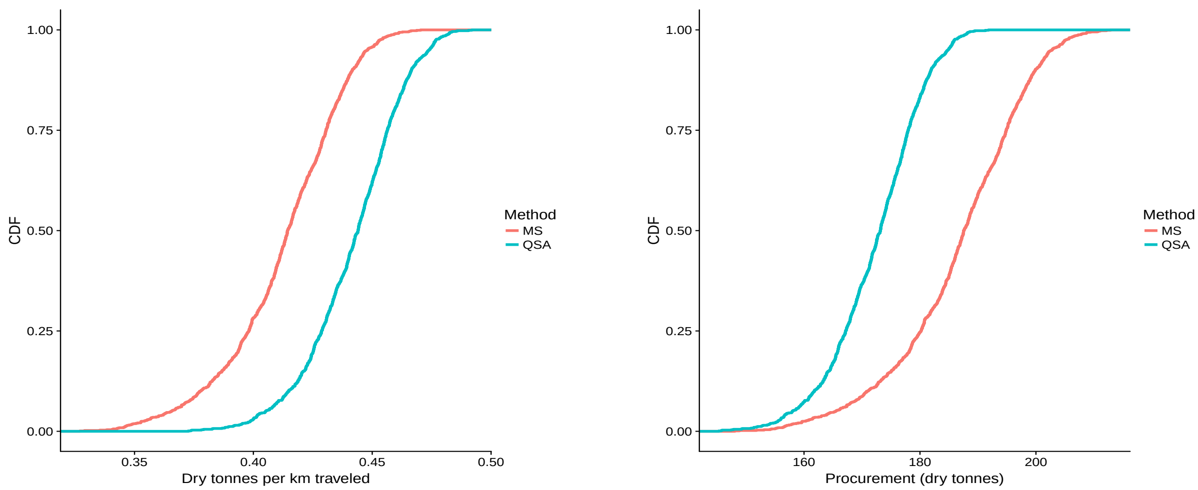


Figure 2: The study region comprises 25 sawmills (S1–S25) across the Lower Mainland of BC, and a single depot (DEP) located in Mission. The sawmills have been spatially clustered into four distinct color-coded groups.

Table 2: Stochastic Input Data

	Mean	SD
Total Available Residue (gt)	1010.2	31.6
Residue Per Node (gt)	40.4	10.3
Moisture Content (%)	38.0	3.8
Setup Time (hrs)	0.1	0.01
Load Time Rate (hrs/tonne)	0.02	0.002
Unload Time Rate (hrs/tonne)	0.01	0.001
Travel Time (hours)	1.5	0.6

et al., 2008). The travel time between a pair of nodes was modeled as an exponential random variable with a mean equal to the expected travel time. The mean and standard deviation of the travel time, averaged across all pairs of nodes, are included in Table 2. Similarly, the mean and standard deviation of the biomass residue available at each sawmill node, averaged across all the sawmill nodes, are provided in Table 2. For completeness, the mean and standard deviation of the total available biomass residue across all the sawmill nodes are also given in Table 2. The number of sawmills, $m = 25$, the number of available trucks, $n = 3$, and the distance between nodes, d_{ij}, $\forall(i,j) \in A$, are all known and assumed to be fixed. The The number of trucks needed was established by adding one truck at a time and repeating the simulation until the required dry tonnes of daily biomass residues was achieved.



(a) CDF of the EROEI

(b) CDF of the Procurement

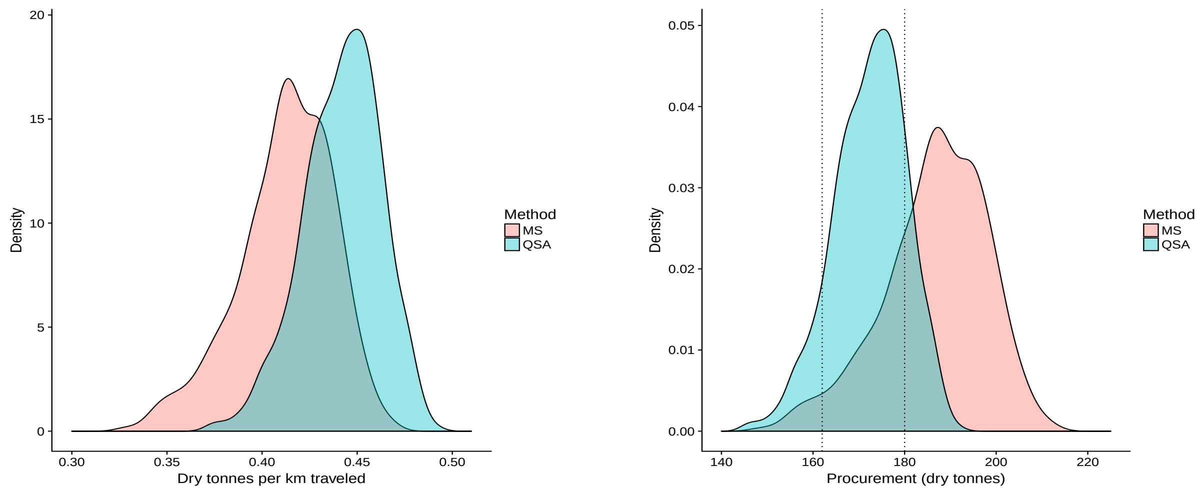
Figure 3: Performance distributions of the QSA and MS solutions. (a) shows the cumulative distribution function of the energy returned on energy invested (EROEI). The QSA solution is more efficient as it consistently delivers more dry tonnes of biomass per km traveled. (b) shows the cumulative distribution function of the total amount of biomass procured. The MS solution consistently delivers more dry tonnes of biomass than required thereby producing a surplus at the depot.

The simulation model was implemented using the R system for statistical computing (Team et al., 2016). A total of 1000 scenarios were simulated by sampling from the appropriate distribution of each random parameter included in the model. The parameters were considered to be statistically independent. To control the amount of biomass procured on a daily basis, we restrict attention to solutions that have a 90% chance of satisfying 90% of the daily demand of 180 dry tonnes of biomass. Moreover we only consider solutions with a probability of 10% of exceeding the demand. This will compel the QSA solution to seldom exceed the required daily demand, but at the same time consistently meet at least 90% of the demand. Each truck was required to come back at least 70% full at the end of each route, thus $\kappa = 0.70$ in equation (1g).

The sawmill nodes were clustered into four groups based on their travel distance matrix using the k-medoids method implemented in the package *cluster* (Maechler et al., 2015). The number of clusters was estimated by the method of optimum average silhouette width (Kaufman & Rousseeuw, 1990). The four

Table 3: QSA Optimal Schedule

Truck 1	Truck 2	Truck 3	Distance (km)	Weight (tonne)	Ratio (tonne/km)	Time (hrs)
S22	S19,S20	S18,S15,S22	54.3	57.0	1.05	4.6
S20,S23,S25	S22,S14,S25	S2	118.3	57.1	0.48	5.6
S2	S17,S16	S24	217.4	58.3	0.27	9.0



(a) PDF of the EROEI

(b) PDF of the Procurement

Figure 4: Out of sample performance of the QSA and MS solutions. (a) shows the probability density function of the energy returned on energy invested (EROEI). The QSA solution is more efficient as it has a consistently larger ratio of dry tonnes delivered per km traveled. (b) shows the probability density function of the total amount of biomass procured. The dotted lines show where 90% and 100% of the demand is met. The MS solution consistently delivers a great deal more than the required 180 dry tonnes of biomass thereby producing a surplus at the depot. In contrast, the QSA solution is much more accurate and precise in delivering the required amount of biomass.

clusters are depicted in Figure 2 and the cluster sizes are 3, 5, 7 and 10, respectively. Given the time constraints imposed by the sawmills and the truck drivers operating hours, each truck was able to perform a maximum of 3 routes per day. This fact was learned from the simulation results. The optimal routes selected for each truck by the QSA method are shown in Table 3. Each row in Table 3 corresponds to a collection run. From the first row, we see that the first collection run consists of sending the first truck to sawmill S22, the second truck to sawmills S19 and S20, and the third truck to sawmills S18, S15 and S22, in this order. We denote this route combination as [S22,(S19,S20),(S18,S15,S22)]. The total distance traveled in the first collection run is 54.3 km and an accumulated time of 4.6 hours is required on average. The average amount of biomass obtained in the first collection run is 57.0 dry tonnes of biomass residue per day. Thus, the first collection run yields a performance ratio (EROEI) of 1.05 tonnes per km traveled. Recall, that EROEI has been adjusted for the energy spent during collection. Similarly, the performance of collection runs 2, and 3 are shown in the corresponding rows of Table 3. Notice the big drop in the EROEI between the first and second collection runs. This is attributed to the fact that the sawmills closest to the depot are nearly depleted after the first collection run. Sawmill nodes S22 and S2 are repeatedly visited as they are relatively close to the depot and have a large production of residues with a low moisture content. The QSA solution collects on average 172.4 dry tonnes of biomass residue per day. This gives an EROEI of 0.44 tonnes per km traveled. A computation time of 3.91 minutes was required by the QSA method to solve this problem running on an Intel Xeon 3.6 GHz processor.

The cumulative distribution function of the EROEI for the QSA solution is shown in Figure 3a. Similarly, the distribution of the amount of residue collected is shown in Figure 3b. As can be seen in these figures, the QSA solution has an EROEI that ranges between 0.40 and 0.50 and consistently meets at least 90% of the demand (i.e., 162 dry tons). In addition, we can see from Figure 3b that the QSA solution seldom exceeds the demand by much. The corresponding distributions obtained using the mean scenario (MS) are also included for comparison. The MS solution is obtained by taking the expected value of the sampled scenarios and solving the resulting deterministic problem. As can be seen in Figure 3a, the QSA solution is able to consistently obtain a lower EROEI than that of the MS solution while meeting 90% of the demand at least 90% of the time. Figure 3b shows that the QSA solution stays much closer to the target demand than that of the MS solution, which has a tendency to over collect.

To validate the QSA solution, we applied it to a new set of 1000 randomly generated scenarios and evaluated the performance of its solution based on the EROEI and total dry tonnes of delivered biomass to the depot. The probability density function for each of these performance measures are shown in Figures 4a and 4b, respectively. In cross-validation, the QSA solution obtained a 90% probability of collecting 90% of the demand and a median EROEI of 0.44 residue dry tonnes per km traveled. On the other hand, the MS solution obtained a 90% probability of collecting 95% of the demand and has a median EROEI of 0.41 residue dry tonnes per km traveled. As can be seen in Figure 4b, the MS approach tends to excessively over collect and has an estimated 75% probability of exceeding the required demand of 180 dry tonnes of residue per day. In contrast the QSA approach collects between 162 and 180 dry tonnes of residue 73% of the time (area enclosed between the dotted lines in Figure 4b) and only exceeds the demand 17% of the time. This is a convenient feature of the QSA solution because the depot has a limited storage capacity and throughput.

4. Conclusion

In this case study, a simulation approach was used to solve a stochastic periodic vehicle routing problem, where the goal is to efficiently collect biomass residues from a set of sawmills. Several key factors, such as the moisture content and the amount of available residues are uncertain. The optimal routing schedule was obtained by maximizing the energy returned on energy invested (EROEI). Our approach was found to be more efficient in terms of minimizing the EROEI and more accurate and precise in terms of meeting the daily demand than by simply solving the expected value or mean scenario.

Acknowledgments

We would like to acknowledge the financial support from MITACS, NSERC, and BioFuelNet NCE (BFN).

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