Abstract: The collection of sawmill residuals 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 nearby sawmills in the Lower Mainland region of British Columbia, Canada. The sawmills serve as potential suppliers of residual biomass to the depot, which in turn processes and distributes the sawmill residuals to the pulp and paper mills. The problem consists of identifying the best daily routing schedule for a fixed number of vehicles. The objective is to maximize the ratio of residual dry tonnes collected to kilometers traveled, while achieving a minimum daily amount of residual dry mass. There are several random components in the problem, including the availability and moisture content of the residuals as well as the time spent on the road to retrieve the residuals. We use a combination of scenario analysis and heuristics to solve this stochastic vehicle routing problem (SPVRP).

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

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, especially in the transportation sector. Transport 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 urban freight transport.

This paper describes a study of planning vehicle routes for the collection of sawmill residuals (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 residual 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 residual chips for most, if not all, of their chip supply. Consequently, the sale of residual 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 residual collection routes has been done manually.

The real-life residual 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 residual biomass produced by the sawmills must be collected by a fleet of trucks with known capacities. The average daily amount of residuals produced by each sawmill is subject to variability. Each truck may collect residuals from several sawmills before returning to the depot to unload. 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 residuals 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 tons that are used to collect residuals in the considered region.

* We would like to acknowledge the financial support from MITACS, NSERC, and BioFuelNet NCE (BFN).
Information regarding the mass, measured in green tonnes (gt), and energy density, measured in (GJ/tonne) of the residuals available at each sawmill is not known and highly variable. The energy density of the residuals 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 residuals 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 GoogleMaps package in R (Loecher and Ropkins, 2015). As the residual 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 above 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 optimal (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 a quantile-based scenario analysis (QSA) approach (Zamar et al., 2015). 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 solution model and its input requirements are presented in Section 2. The heuristic routing and scheduling methodologies are explained in Section 3, followed by results in Section 4. The main conclusions of the study are provided in Section 5.
\[ \sum_{l \in L_k} u_{kl} = 1 \quad \forall k \in K \quad (11) \]
\[ \sum_{(i,j) \in A_j} \sum_{l \in L_k} x_{ijkl}(t_{ij} + \alpha_j + \beta_i \delta_{jkl}) + \sum_{i \in V} \sum_{l \in L_k} x_{i0kl}(t_{i0} + \alpha_0 + \beta_0 c_k) + \gamma \leq t^* \quad \forall k \in K \quad (12) \]

The objective function, Equation (1), maximizes the ratio of residual dry mass acquired to distance traveled by the trucks. This is equivalent to maximizing the energy gained per kilometer traveled, whereas stochastic dynamic versions of these 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 \( t \) we would solve an optimization problem using only what we know at that time.

We propose to solve the SPVRP problem using a quantile-based scenario analysis (QSA) approach described in Zaamar et al. (2015), which builds upon the algorithm of Dembo (1991). 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 and ranked based on the quantiles of its performance distributions (i.e., ability to optimize the objective and satisfy the constraints). For this application we maximize the 0.5 quantile (median) of the stochastic objective function shown in equation (1), subject to satisfying two quantile constraints on the resulting procurement amounts given by equation (9).

To reduce the number of under utilized routes and help make the problem more manageable, we first cluster the sawmill nodes based on their traveling distance matrix and restrict attention to routes within each cluster. Thus, our approach does not consider routes that span across clusters.

Our heuristic for solving the PVRP problem is built one route at a time and is summarized as follows:

1. If the current time is past 12pm, then insert a lunch break if it has not been taken yet. Advance the time and update the truck’s logged hours accordingly.

2. Select the optimal route among the cluster of routes. Consider the distance traveled, the residuals available at each sawmill node and their corresponding moisture content.

3. Calculate the time needed to complete the route. This includes the setup and load time at each sawmill node visited, the setup and unload time at the depot, and the travel time.

4. Check if the truck’s logged hours will exceed the maximum allowed when completing the route. If it is not exceeded, continue to Step 5.

5. Reduce the residual biomass available at each sawmill node visited in the route according to the amount that will be picked up by the truck.

6. Advance the time according to that required to complete the route.

7. Update the truck’s logged hours, and go to Step 1.

We built a discrete event simulation model that uses the heuristic described above to identify a solution for each simulated scenario. The optimal schedule identified by our heuristic for each scenario are evaluated across the set of sampled scenarios using the QSA method to obtain both an objective and constraint distribution for each scenario solution. The objective distribution corresponds to the EROEI while the constraint distribution represents the fulfilled portion of the demand as described in Equations (1), and (9), respectively. We restrict attention to solutions that have a 90% probability of satisfying at least 90% of the demand across scenarios.

### 3. METHODOLOGY

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 \( t \) we would solve an optimization problem using only what we know at that time.

We propose to solve the SPVRP problem using a quantile-based scenario analysis (QSA) approach described in Zaamar et al. (2015), which builds upon the algorithm of Dembo (1991). The QSA method samples scenarios from their underlying distribution and solves each scenario separately.

### 4. RESULTS

In this section we apply our heuristic coupled with the QSA approach to the previously described SPVRP problem. A map of the study region is shown in Figure 1, which identifies the locations of the 25 sawmills and the single depot. The depot requires a minimum of 180 residual dry tonnes per day.
The random parameters that distinguish the scenarios are (1) the residual biomass available at each sawmill node; (2) the moisture content of the residual biomass available at each sawmill node; (3) the time required to navigate each route; and (4) the setup, load and unload time at the sawmills and depot, respectively. The random parameters $h_i$ and $\omega_i$, representing the residual biomass availability and moisture content at each sawmill node, were obtained from published summary data (BC Bioenergy Network and Biomass Availability Study Working Group, 2012). The random parameters $\alpha_i$ and $\beta_i$, $i \in V$, describing the setup, load and unload times are 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, $d_{ij}$, $\forall(i, j) \in A$, $i \in V$, between nodes were calculated using the RgoogleMaps package in R (Loecher and Ropkins, 2015).

Table 1. Stochastic Input Data

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Available Residue (gt)</td>
<td>1010.168</td>
<td>31.568</td>
</tr>
<tr>
<td>Residue Per Node (gt)</td>
<td>40.407</td>
<td>10.265</td>
</tr>
<tr>
<td>Moisture Content (%)</td>
<td>38.00</td>
<td>3.787</td>
</tr>
<tr>
<td>Setup Time (hrs)</td>
<td>0.100</td>
<td>0.010</td>
</tr>
<tr>
<td>Load Time Rate (hrs/tonne)</td>
<td>0.023</td>
<td>0.002</td>
</tr>
<tr>
<td>Unload Time Rate (hrs/tonne)</td>
<td>0.012</td>
<td>0.001</td>
</tr>
<tr>
<td>Travel Time (hours)</td>
<td>1.486</td>
<td>0.599</td>
</tr>
</tbody>
</table>

A summary of the distributions of the random parameters included in the model are shown in Table 1. The average available residual biomass 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 theoretical average wet basis moisture content of the residual biomass available at each sawmill node (Bivand et al., 2008). The travel time between a pair of nodes was modeled as an exponential random variable with a mean equal to their expected travel time. The mean and standard deviation of travel time, averaged across all pairs of nodes, are included in Table 1. Similarly, the mean and standard deviation of the residual biomass available at each sawmill node, averaged across all the sawmill nodes, are included in Table 1. For completeness, the mean and standard deviation of the total available residual biomass across all the sawmill nodes are also included in Table 1. 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 simulation model was implemented using the R system for statistical computing (Team et al., 2012). A total of 1000 scenarios were simulated by sampling from the appropriate distribution of each random parameter included in the model. To control the amount of residual dry mass procured on a daily basis, we restrict attention to solutions that have a 90% chance of satisfying 90% of the target daily demand of 180 tonnes. Moreover we only consider solutions with a probability of 10% of exceeding the demand. This will compel the optimal 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 (6).

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 and Rousseeuw, 1990) with the maximum number of cluster set equal to five. The four clusters are depicted in Figure 1 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 2. Each row in Table 2 corresponds to a collection run. From the first row, we see that the heuristically optimized 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 residual dry mass accumulated in the first collection run is 57.0 tonnes, which yields a performance ratio of 1.05 tonnes per kilometer traveled. Similarly, the performance of collection runs 2, and 3 are shown in the corresponding rows of Table 2. Notice the big drop in performance ratio between the first and second collection runs. This is attributed to the fact that the closest nodes 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 residuals with a low moisture content. The QSA solution collects on average 172.4 residual dry tonnes per day with an EROEI of 0.44 dry tonnes per kilometer 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 2. Similarly, the distribution of the residual dry tons collected is shown in Figure 3. 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 tonnes). In addition, we can see from Figure 3 that the QSA solution seldom exceeds the demand by much.

<table>
<thead>
<tr>
<th>Truck 1</th>
<th>Truck 2</th>
<th>Truck 3</th>
<th>Distance (km)</th>
<th>Dry Weight (Tonne)</th>
<th>Ratio (Tonne/km)</th>
<th>Time (hrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S22</td>
<td>S19, S20</td>
<td>S18, S15, S22</td>
<td>54.3</td>
<td>57.0</td>
<td>1.05</td>
<td>4.6</td>
</tr>
<tr>
<td>S20, S23, S25</td>
<td>S22, S14, S25</td>
<td>S2</td>
<td>118.3</td>
<td>57.1</td>
<td>0.48</td>
<td>5.6</td>
</tr>
<tr>
<td>S2</td>
<td>S17, S16</td>
<td>S24</td>
<td>217.4</td>
<td>58.3</td>
<td>0.27</td>
<td>9.0</td>
</tr>
</tbody>
</table>
To validate the QSA solution, we applied it to a new set of 1000 randomly generated scenarios and evaluated its performance in terms of the EROEI and total residual dry mass collected. The probability density function for each of these performance measures is shown in Figures 4 and 5, respectively. 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. In cross-validation, the QSA solution obtained a 90% probability of collecting 90% of the demand and a median EROEI of 0.44 residual dry tonnes per kilometer 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 residual dry tonnes per kilometer traveled. However, as can be seen in Figure 5, the MS approach tends to excessively over collect and has an estimated 75% probability of exceeding the required demand of 180 residual dry tonnes per day. In contrast, the QSA approach collects between 162 and 180 residual dry tonnes 75% of the time (area enclosed between the dotted lines in Figure 5) 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.

5. DISCUSSION

We presented a simulation approach to solve a stochastic periodic vehicle routing problem, where the goal is to efficiently collect biomass residuals from a set of sawmills that are distributed in the Lower Mainland region of British Columbia, Canada. The sawmill residuals are being brought to a single depot for processing. Several key factors, such as the amount of residuals available at the sawmills is assumed to be random as well as their average moisture content. The distributions of the stochastic model parameters were empirically determined using data from the literature and the depot’s records. The daily amount of residual dry mass required by the depot is 180 dry tonnes per day. The optimal routing schedule was obtained by maximizing the ratio of residual dry tonnes collected per kilometer traveled. Our simulation results indicated that a minimum of three trucks are needed in order to obtain the required daily amount of biomass residuals in dry tonnes. A scenario analysis approach was used to obtain the solution across a set of 1000 randomly generated scenarios. The solution obtained from our heuristic approach in combination with the QSA was evaluated on a separate set of 1000 scenarios and was found to efficiently meet the demand. As one may expect, the closest sawmills to the depot are visited before the more distant sawmills. In this case study, it happens that the sawmills more proximate to the depot have a lower moisture content, which makes them even more attractive. Although it was not considered by our model, it would be useful to account for the energy spent on drying the residual biomass along with other preprocessing done at the depot.

REFERENCES


