TRUCK ROUTING AND SCHEDULING FOR WOOD CHIP TRANSPORTATION TO A PULP MILL USING SIMULATED ANNEALING

by

FATTANE NADIMI

B.Sc., Industrial Engineering, Sharif University of Technology, 2007
M.Sc., Industrial Engineering, Sharif University of Technology, 2010

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES

(Forestry)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

January 2015

© Fattane Nadimi, 2015
Abstract

Optimization and improvement techniques have been employed to improve truck transportation in the forest industry. Most studies in this area focus on log transportation and there is not much literature available on wood chip transportation which is distinct from log transportation in several ways: chip-truck transportation usually considers a longer planning period, requires a more complex driver scheduling, involves strict limitations on truck unloading capacity, and considers service priorities for major suppliers.

The objective of this thesis is to model and improve truck transportation of wood chips to a pulp mill. To achieve this, a network that transports wood chips from a number of sawmills to a pulp mill with limited truck unloading capacity was studied and an optimization model was developed to consider wood chip production plan at supplier sawmills, transportation of wood chips and unloading at the pulp mill. A simulated annealing metaheuristic was adapted to solve the model and the results for a case study in British Columbia are presented. The results of the metaheuristic showed that the total penalties for truck waiting times could be reduced by 7 percent ($31,000) compared to solutions obtained through simulation. The results also suggested that the fleet size could be reduced by one-third of the actual fleet size used by the pulp mill.

In order to explore the impact of various structural parameters on the transportation network, sensitivity and scenario analyses were used to study the impacts of fleet size, an additional truck dumper, truck types, and switch point locations for truck drivers. The results indicated that the pulp mill could reduce its fleet size and an additional truck dumper could reduce transportation costs. The study also suggested that half of the fleet should be replaced by self-unloading trucks and the investigation of the switch point locations for drivers indicated that the existing switch points were the best available options. The simulated annealing model could assist the pulp mill truck dispatchers to achieve better transportation plans. The scenario and sensitivity analysis could help the pulp mill manager to adapt the most profitable changes in the structure of the transportation network.
Preface

This thesis presents a study that was conducted by Fattane Nadimi during her Master of Applied Science program. This study was designed, conducted, and written by Fattane Nadimi. In this study, the author described the research problem, conducted literature review, developed a model to tackle with the problem, gathered required data from various sources, introduced a case study, applied the designed model on the case study, analyzed the results, and wrote the thesis. The author conducted the research under supervision of her academic advisors, Dr. Gary Bull and Dr. John Nelson. Dr. Gary Bull and Dr. John Nelson advised Nadimi in the process of problem definition, case study identification, model development, results analysis, sensitivity and scenario analysis, and model validation. They also edited the present thesis and are co-authors on any scientific articles that will be submitted to peer-reviewed journals based on this dissertation.

Based on this dissertation, two articles will be submitted for publication in peer-reviewed journals:

- A version of Chapter 2 will be submitted. Literature review on operational-level transportation models in the forest industry.
- A version of Chapters 3, 4 and 5 will be submitted. Development of a weekly truck transportation model for supply of woodchips to a pulp mill with limited truck unloading capacity.
Table of Contents

Abstract........................................................................................................................................... ii
Preface................................................................................................................................................ iii
Table of Contents............................................................................................................................... iv
List of Tables.................................................................................................................................... vi
List of Figures................................................................................................................................... vii
List of Abbreviations......................................................................................................................... ix
Acknowledgments............................................................................................................................. x
1  Introduction..................................................................................................................................... 1
   1.1  Background............................................................................................................................ 1
   1.2  Research Objectives............................................................................................................... 4
   1.3  Thesis Organization............................................................................................................... 4
2  Literature Review.......................................................................................................................... 6
   2.1  Introduction to Pulp Production........................................................................................... 6
   2.2  The Challenges of Truck Transportation in the Forest Sector........................................... 7
   2.3  Lessons Learned from Truck Transportation Models in Other Domains....................... 8
      2.3.1  Capacitated Vehicle Routing Problems........................................................................ 8
      2.3.2  Vehicle Routing Problem with Time Windows............................................................. 10
      2.3.3  Pickup and Delivery Problems....................................................................................... 11
      2.3.4  Summary VRP Solution Approaches......................................................................... 15
   2.4  Forest Truck Transportation Models.................................................................................... 16
      2.4.1  Present State of Operational Log Truck Scheduling Research................................. 17
         2.4.1.1  Using Simulation modeling to Improve Log Truck Scheduling............................. 20
         2.4.1.2  Using Optimization Techniques to Improve Log Truck Scheduling..................... 22
            2.4.1.2.1  Addressing Time Window Constraints............................................................. 22
            2.4.1.2.2  Addressing Backhaul Issues............................................................................. 24
         2.4.1.3  Discussion of Solution Approaches...................................................................... 26
      2.4.2  Wood Chip Truck Scheduling......................................................................................... 27
         2.4.2.1  Wood Chip Truck Scheduling Models................................................................. 29
         2.4.2.2  Discussion............................................................................................................... 30
3  Methods......................................................................................................................................... 33
   3.1  Mathematical Model.............................................................................................................. 33
       3.1.1  The Truck Assignment Problem................................................................................... 34
List of Tables

Table 1: Summary of the studies on simulation and optimization models for log truck scheduling
------------------------------------------------------------------------------------------------- 19

Table 2: Summary of the studies on simulation and optimization models for biomass truck scheduling
------------------------------------------------------------------------------------------------- 29

Table 3: List of indices used in the truck assignment problem------------------------------------------ 35

Table 4: List of parameters used in the truck assignment problem ------------------------------------ 35

Table 5: List of variables used in the truck assignment problem -------------------------------------- 35

Table 6: List of indices used in the truck scheduling problem------------------------------------------ 38

Table 7: List of parameters used in the truck scheduling problem ------------------------------------- 38

Table 8: List of variables used in the truck scheduling problem --------------------------------------- 38

Table 9: One way travel time from the sawmills to the pulp mill (hours)------------------------------- 45

Table 10: Sample data for one week showing the number of daily loads, running days and working hours for sawmills ----------------------------------------------- 46

Table 11: Daily wood chip production plan at sawmills ----------------------------------------------- 47

Table 12: The average solution improvement and solution time for different iteration levels---- 57

Table 13: Probability of accepting deteriorating solutions for different temperature coefficients 58

Table 14: Detailed weekly schedule for one truck for SA run 1----------------------------------------- 61

Table 15: Results of simulated annealing for weekly truck schedule with 60 trucks------------------- 62

Table 16: The number of weekly wood chip loads transported with a fleet of 60 trucks and the productive truck times spent on transportation ----------------------------------- 63

Table 17: Results of simulated annealing for weekly truck schedules with 20, 40, and 60 trucks ----------------------------------------------- 65

Table 18: Fixed and variable costs for wood chips truck and trailer --------------------------------- 111

Table 19: Annual supply plan and travel times ------------------------------------------------------ 114
List of Figures

Figure 1: The wood chip supply and transportation network -------------------------------------------- 44
Figure 2: Overhead bin and truck loading at a sawmill ----------------------------------------------- 49
Figure 3: Flow chart for the assignment of the first trip to each truck ------------------------------ 52
Figure 4: Flow chart for construction of the initial weekly schedule ----------------------------------- 53
Figure 5: Task sequence of a truck before and after applying the delay improvement routine - 55
Figure 6: Task sequence for a truck before and after applying the schedule altering routine -------- 55
Figure 7: Number of daily wood chip loads produced and transported by a fleet of 60 trucks -- 62
Figure 8: The number of weekly wood chip loads production at each sawmill and the number of weekly wood chip load transportation with a fleet size of 20, 40 and 60 ----------------------------- 64
Figure 9: Number of daily wood chip load production and transportation by a fleet of 20, 40 and 60 trucks ------------------------------------------------------------------------------------------ 64
Figure 10: Relationships between number of trucks and time, cost, utilization, and satisfaction levels--------------------------------------------------------------------------------------------------------------- 69
Figure 11: The truck waiting penalty and the transportation delay penalty for the initial solution obtained by simulation------------------------------------------------------------------------------------------ 70
Figure 12: The truck waiting penalty and the transportation delay penalty for the initial solution obtained by simulation and the final solution obtained by the simulated annealing model------ 71
Figure 13: The transportation penalty for the initial solution obtained by simulation and the final solution obtained by the simulated annealing model--------------------------------------------------- 72
Figure 14: The total transportation penalty and trucking cost for different number of trucks ---- 73
Figure 15: The number of weekly truckloads of wood chips with transportation delays ------- 74
Figure 16: The percentage of weekly truckloads of wood chips with transportation delays------ 75
Figure 17: The ratio of each type of truck waiting times to the total truck waiting times ------- 75
Figure 18: The truck waiting penalty and the transportation delay penalty with one truck dumper and two truck dumpers ----------------------------------------------- 77
Figure 19: Truck efficiencies with one truck dumper and two truck dumpers----------------------- 78
Figure 20: The total transportation penalty and trucking cost for different number of trucks and two dumpers------------------------------------------------------------------------------------------ 80
Figure 21: The total cost and penalty function with one truck dumper and two truck dumpers - 80
Figure 22: The percentage of weekly truckloads of wood chips with transportation delays when using two truck dumpers------------------------------------------------------------------------------------------ 81
Figure 23: The truck waiting penalty and the transportation delay penalty of the base scenario compared with the four scenarios developed to assess the impact of truck types --------- 84
Figure 24: The total cost and penalty function for the base scenario compared with the four scenarios developed to assess the impact of truck types----------------------------------------------- 85
Figure 25: The percentage of weekly truckloads of wood chips with transportation delays when half of the trucks were self-unloading

Figure 26: The total cost and penalty function for the base case compared to the conditions when two dumpers were used or half of the trucks were self-unloading

Figure 27: The truck waiting penalty and the transportation delay penalty of the base scenario compared with the four scenarios developed to assess the impact of switch point locations

Figure 28: The total cost and penalty function for the base scenario compared with the four scenarios developed to assess the impact of switch point locations
### List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AA</td>
<td>Ant algorithm</td>
</tr>
<tr>
<td>ACO</td>
<td>Ant colony optimization</td>
</tr>
<tr>
<td>ADMT</td>
<td>Air dry metric ton</td>
</tr>
<tr>
<td>APA</td>
<td>Arc promise algorithm</td>
</tr>
<tr>
<td>ASA</td>
<td>Adapted sweep algorithm</td>
</tr>
<tr>
<td>BDT</td>
<td>Bone dry tonne</td>
</tr>
<tr>
<td>CVRP</td>
<td>Capacitated vehicle routing problems</td>
</tr>
<tr>
<td>DA</td>
<td>Deterministic annealing</td>
</tr>
<tr>
<td>DARP</td>
<td>Dial a ride problem</td>
</tr>
<tr>
<td>DCVRP</td>
<td>Distance constrained vehicle routing problem</td>
</tr>
<tr>
<td>DES</td>
<td>Discrete event simulation</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic algorithms</td>
</tr>
<tr>
<td>IP</td>
<td>Integer programming</td>
</tr>
<tr>
<td>LTSP</td>
<td>Log truck scheduling problem</td>
</tr>
<tr>
<td>MA</td>
<td>Memetic algorithm</td>
</tr>
<tr>
<td>MIP</td>
<td>Mixed integer programming</td>
</tr>
<tr>
<td>NN</td>
<td>Neural networks</td>
</tr>
<tr>
<td>NP-hard</td>
<td>Non-deterministic polynomial-time hard</td>
</tr>
<tr>
<td>PDP</td>
<td>Pickup and delivery problems</td>
</tr>
<tr>
<td>PSO</td>
<td>Particle swarm optimization</td>
</tr>
<tr>
<td>SA</td>
<td>Simulated annealing</td>
</tr>
<tr>
<td>TS</td>
<td>Tabu search</td>
</tr>
<tr>
<td>TSP</td>
<td>Travelling salesman problem</td>
</tr>
<tr>
<td>VRP</td>
<td>Vehicle routing problem</td>
</tr>
<tr>
<td>VRPBTW</td>
<td>Vehicle routing problem with backhauling and time windows</td>
</tr>
<tr>
<td>VRPPD</td>
<td>Vehicle routing problem with pickup and delivery</td>
</tr>
<tr>
<td>VRPTW</td>
<td>Vehicle routing problems with time windows</td>
</tr>
<tr>
<td>VSP</td>
<td>Vehicle scheduling problem</td>
</tr>
</tbody>
</table>
Acknowledgments

First, I would like to acknowledge and offer my endless gratitude to my research advisors, Dr. Gary Bull and Dr. John Nelson, for their invaluable guidance, persistent support, and incessant encouragement during my studies at UBC. This work would have never been possible without their help, critical reviews, and intellectual inputs.

I would also like to express my appreciation to the other member of my supervisory committee, Dr. Taraneh Sowlati, for her time and suggestions for improving the work presented in this dissertation. Additionally, I would like to thank my non-departmental examiner, Dr. Farrokh Sassani for his review and comments on my thesis.

I would like to thank the researchers at FPInnovations in Vancouver, Dr. Mihai Pavel and Mr. Rob Jokai, for kindly sharing their knowledge and providing relevant information for this dissertation. I express my appreciation to the managers at the pulp mill under study, especially the former regional fibre manager who provided the data I needed, facilitated a number of field trips, answered my endless questions, and helped me to understand the wood chip supply and transportation network. I am also thankful to the BC fibre supply manager of the pulp mill who reviewed the results and validated the model developed in this study.

Special thanks are owed to Molly Moshofsky, who assisted me in proofreading and editing my thesis. I am thankful to all graduate students in the Forest Management/Operations Lab for their support and encouragement throughout my program.

I am indeed grateful to all of my wonderful friends who offered me great support and help during my stay in Canada. I am especially thankful to my dear friend, Somaie Salajeghe, for her kindness and support during my most difficult times.

I am always indebted to my dear parents, Mahmood and Mehri, for their unconditional love and support throughout my life. I am sincerely grateful to my sisters, Fatemeh and Fereshteh, and my brother, Ali, for their endless love and moral support.

Last but not least, I would like to express my deepest appreciation to my husband, Kambiz, for his continuous love, support, and encouragement during my studies. He is my best friend and the only family I have in Canada. I could have never finished this work without him.
To my parents, for their enduring support and encouragement

In these years, nothing has been more difficult than being away from them.

To Kambiz, for his endless support and love
1 Introduction

1.1 Background

Although humans have made and used paper since approximately AD 105, the use of wood to produce pulp for papermaking is a relatively recent innovation, which started in the 1840s (Sixta et al., 2006). For centuries, paper was made from linen, hemp, cotton, and other sources of fibre waste from the textile industry (Sixta et al., 2006). In the nineteenth century, the growing demand for paper motivated producers to find another more affordable fibre source to produce larger volumes of paper. This pressure to innovate led to the development of mechanical and chemical approaches that are used to produce pulp from wood chips. Paper made from wood pulp rapidly became the preferred product because it could be made in the large volumes that society increasingly demanded (Sixta et al., 2006).

With a continually growing human population, demand for paper continues to grow, intensifying the need for efficient supply chain management of raw materials, intermediate products, and final products in the pulp and paper industry. In 2012, global fibre used for paper making was approximately 400 million metric tonnes (FAO, 2012) showing a near 60% increase compared to 1993 (Goetzl, 2008). Globally, 54% of wood pulp produced in 2012 was from recovered paper; however, in North America the main source of pulp is virgin fibre and recovered paper is mostly exported to other regions (FAO, 2012). As Canada’s pulp and paper sector struggles to compete with the other wood pulp producing countries, maximizing the efficiency of the wood chip supply chain for virgin pulp production is critical.

Truck transportation plays an important role in the forest sector and there is an increasing effort to manage and optimize forestry supply chains by way of improving truck routing and scheduling. This is especially critical for the pulp and paper industry because the pulp mills require a continuous supply of wood chips to operate economically. The advantages of using truck transportation compared to other modes of commercial transportation are its flexibility and capability to transport goods with different specifications, in different volumes, and between various destinations. Truck transportation offers a high level of flexibility in door-to-door transportation. In Canada, there are good road networks, which allow trucks to serve different destinations frequently. Trucks can change routes easily and offer quick loading and unloading times. If the supply and demand points and the load quantities change over short periods, road transportation is the best transportation option. Ultimately, in many forested regions around the
world, rail, ship, and water transportation are not available and truck transportation is the only hauling possibility. This is especially true for many regions in Canada.

When seeking to improve the efficiency of truck transportation, the following factors must be considered: 1) the complexity of the problem; 2) fleet sizes; 3) difficulties in finding efficient work schedules for available machinery, equipment and drivers; 4) cost of transportation; 5) limitations in availability of trucks; 6) limited number of experienced and qualified drivers; and 7) fossil fuel consumption and related environmental issues.

There is a demand for an effective truck routing and scheduling model that balances all of the above factors. The need to reduce transportation costs has motivated many researchers to focus on truck routing and scheduling (Audy et al., 2012). Operational transportation problems are usually modeled as linear, integer, mixed integer, and non-linear mathematical models. Based on the size of the problem and required solution time, the solution approaches may include linear programming methods, branch-and-bound, constraint relaxation, column generation, branch and cut, dynamic programming, heuristics, metaheuristics, and simulation (Rönnqvist, 2003).

Many studies in the literature have considered truck routing and scheduling. Problems of this nature are referred to collectively as vehicle routing problems (VRP) and have been used to optimize supply chains in multiple domains that require transportation of goods. Basic VRPs, referred to as capacitated vehicle routing problems, are characterized by scenarios where vehicles with limited capacities are routed to transport goods from a central supply point to a number of demand points. Another class of VRPs are characterized by scenarios where there are specified time windows, and these are referred to collectively as vehicle scheduling problems (VSP) in which vehicles need to visit the demand points within a pre-specified time window. Pickup and delivery problems are another variation of VRPs in which trucks visits both supply and demand points in a route. In order to solve the truck routing and scheduling problem in the forest wood chip industry, it is important to review related work done to solve VRPs in other domains.

Truck routing and scheduling problems in the forest industry, specifically log truck scheduling problems (LTSP), have received significant attention from industry and researchers. Unlike classic VRPs, daily production at a forest harvest site is much more than the capacity of one truck and forest sites need several daily visits. Moreover, time windows are constraining many forestry operations, which make forestry transportation planning complex. Additionally, forest
mills often have specific constraints and conditions that need specially developed models (Carlsson et al., 2009). In the forest industry, a number of studies have applied simulation models to solve LTSPs, however, the majority of studies have used optimization techniques.

There is little literature available on truck routing and scheduling for transportation of woodchips to pulp mills. The main reason for limited studies in this area is that, wood chips required by pulp mills were generally an inexpensive waste product of sawmills and the pulp industry was able to supply themselves from local sawmills or by whole log chipping at a relatively low price and with procurement methods based on experience and manual planning. However, fiber sourcing issues for pulp mills have increasingly become critical in recent years (Uronen, 2010). This is largely because of the global trend in investing in alternative energies. Wood-based fuels – referred to as biofuels, or bioenergy – are praised for being a carbon-neutral and a renewable energy source (Ragauskas et al., 2006). Biofuels are a rapidly growing market, with bioenergy plants springing up around the world. Consequently, the value and demand for wood chips has increased significantly over the last two decades. Additionally, the growing international demand for pulp is increasing international trade of pulp logs, which consequently makes whole log chipping less available to domestic pulp mills. Moreover, the pulp and paper industry is becoming more dependent on export market; in 2012, the international trade of wood pulp was about 109 million tonnes, which showed a growth rate of 11% compared to 2008 (FAO, 2012). As a result, the survival of the pulp and paper industry depends on increasing competitiveness in different aspects including wood chip supply, which can be accomplished through more efficient and economic transportation planning.

Transporting wood chips to recipient pulp mills is distinct from log truck transportation problems in several ways. Because of the high capital cost, pulp mills work continuously, which results in a very high frequency of transportation. Wood chip truck routing and scheduling problems need to be analyzed weekly in contrast to LTSPs that are done on daily basis. The need for a continuous supply of wood chips to pulp mills requires complicated crew scheduling. Scheduling must account for drivers’ shift starting and ending times, shift changing times, changeover locations, rest times, and the number of weekly shifts for each truck and each driver. In addition, because of high capital cost of truck dumpers, the unloading capacity at pulp mills is usually limited to one truck at a time, which introduces a very strict unloading capacity compared to a LTSP. Finally, pulp mills usually need to consider additional constraints to provide a better transportation service for their major and permanent suppliers, such as wood chip transportation priorities for the main suppliers. A wood chip truck routing and scheduling problem with all these
constraints has not been considered in any of the previous studies and is the subject of this thesis.

1.2 Research Objectives

The primary goal of this dissertation is to develop a model to help pulp mill dispatchers and managers to improve the efficiency of their transportation network. From this goal, two research objectives emerged:

1- To develop a truck transportation model and to improve truck routing and scheduling for transportation of woodchips from a number of sawmills to a single pulp mill while considering the following elements: supply plan, travel times, service times, crew scheduling, and limited truck unloading capacity.

2- To evaluate the effect of changes in some structural parameters such as fleet size, an additional dumper, truck types, and drivers switch points; and to find the most profitable changes that a pulp mill should adapt.

1.3 Thesis Organization

This thesis includes the current introduction chapter, a chapter on literature review, a chapter on methods, a chapter on results for a truck routing and scheduling case study in British Columbia, a chapter on structural improvements for the case study wood chip transportation network and a chapter on conclusions.

In chapter 2, previous studies on truck routing and scheduling in general, truck routing and scheduling in the forest industry and solution approaches applied in the literature are discussed.

In chapter 3, the solution methods available for the wood chip truck routing and scheduling problem are presented and the adopted solution method based on simulated annealing is described.

In chapter 4, the results of a simulated annealing model is presented for detailed weekly truck routing and scheduling for wood chip transportation to a pulp mill. The model is applied to a case study in Canada.

In chapter 5, the simulated annealing model is modified to perform a sensitivity analysis on the structural parameters of the transportation network and investigate their effect on transportation efficiency. The parameters include the fleet size, an additional truck dumper, truck types and drivers’ changeover locations. From the results, the best structural improvements are identified.
In chapter 6, conclusions, benefits of the study, its limitations and suggestions for further research are presented.
2 Literature Review

This chapter provides an introduction to pulp production methods, the challenges of truck transportation in the forest sector, truck transportation models in general, and specific forest truck transportation models. Section 2.1 includes an introduction to wood pulp production methods and the pulp production industry in Canada; Section 2.2 contains the challenges to truck transportation in the forest sector; Section 2.3 overviews relevant studies on vehicle routing and scheduling problems in general, and Section 2.4 outlines the literature on truck transportation planning in the forest industry. Finally, the differences between common log truck scheduling problems and the wood chip truck scheduling problem that is the focus of this thesis are highlighted at the end of this chapter.

2.1 Introduction to Pulp Production

There are three methods of producing pulp from wood: 1) mechanical, 2) chemical, and 3) hybrid. Friedrich Gottlob Keller of Germany discovered the first method of wood pulping during the 1840s. Referred to as mechanical wood pulping, this method works by way of grinding the wood into pulp, which is then used to make paper. It produces high yields but also requires high energy costs. The paper produced from this method contains all wood components and has good printing properties but it is weak, dark in color, and not durable. Shortly after mechanical pulping was discovered, Burgess and Charles Watt developed a chemical soda process for wood pulping in England (Sixta et al., 2006). Chemical pulping methods utilize chemicals to heat and dissolve the lignin – the molecule present in wood that keeps cellulose fibres together and makes wood stiff – while retaining the cellulose, which is ideal for pulp making. Chemical pulping has a pulp yield of 40% to 50%, which is lower than mechanical pulping. However, paper from chemical pulp is strong, with high quality, and can have different brightness levels based on amount of bleach used in the pulping process. Based on chemicals used, chemical pulping is further classified as sulfite pulping or sulfate pulping (Sithole, 1995). Hybrid pulping is a method of producing pulp that utilizes thermal and/or chemical treatments to partially break down wood, which is then pulped mechanically.

Wood required for pulping needs to be in the form of wood chips. These small pieces of wood are produced either as a lumber by-product, or directly from whole log chipping. Wood fibres for the pulping process are supplied from three main sources: sawmill residues, recycled paper, and whole log chipping, respectively accounting for 55%, 24%, and 21% of all wood fibre used in Canadian pulp mills (Government of Canada, 2013). In 2012, total pulp production from virgin
wood fibre was about 170 million tonnes over the globe (FAO, 2012) and Canada was the third largest producer of pulp responsible for 9% of the total production (ranked after USA and China producing 28% and 10% respectively, of the global woody virgin pulp) (FAO, 2014a). However, in 2012, Canada only consumed 4% of global pulp (FAO, 2014a) and was the highest exporter of wood pulp producing 18% of the total worldwide supply of pulp (FAO, 2014b); meaning that the country exported more than half of its pulp production and is highly dependent on international markets. Since survival in the international market requires competitive prices, it is very important for the industry to increase efficiency of its supply chain, including transportation of the wood chip fibre source, which is mainly handled by trucks.

2.2 The Challenges of Truck Transportation in the Forest Sector

Truck transportation is a generalization of the well-known vehicle routing problem (VRP), which is proven to be combinatorial even in simple examples (Cordeau et al., 2007). In the forest industry, transportation problems usually involve a large number of trucks, several sites to visit and many daily transportation demands. Since the transportation problem is combinatorial, as the size of the problem increases, the required solution effort increases exponentially.

A technical barrier the industry faces is limited availability of trucks and drivers. Considering anticipated increase in transportation demand, existing vacancies and retirements, Canada is projected to require 14,100 new truck drivers per year until 2021 (Splinter, 2013). However, since the economic recovery in 2009, it has been very difficult for commercial trucking companies in North America to hire and keep drivers due to long working hours, constant travelling, and low salaries (The Journal of Commerce Magazine, 2014). Moreover, there is strong competition between the forest industry, the oil and gas industry and the mining industry for drivers.

Another challenge in forestry truck hauling is fuel usage and greenhouse gas emissions. Heavy duty trucks account for 41% of fuel consumption for freight transportation in Canada and commercial truck transportation is the source of 19% of total emissions in Canada (Natural Resources Canada, 2013a). These challenges have motivated the industry to increase transportation efficiency and reduce transportation costs.

These challenges contribute to inefficient truck transportation that leads to inefficient utilization of available machinery, equipment, and human resources, resulting in long waiting times, unnecessary idle times, high transportation costs, high fuel consumption, increased emissions, as well as dissatisfaction of drivers, suppliers, and customers. In order to reduce transportation
costs, increase competitiveness, reduce emissions, support human resources, and increase service level satisfaction, optimization methods have been used to improve operational level truck scheduling and improve the design of the transportation network.

2.3 Lessons Learned from Truck Transportation Models in Other Domains

VRPs are one of the most studied combinatorial problems in supply chains. VRPs determine an optimal set of routes for a fleet of vehicles delivering goods to a set of locations. This problem was first introduced by Dantzig and Ramser (1959) to address gasoline delivery from a number of terminals to a number of stations and VRPs have subsequently been used in diverse applications. Based on the constraints for a given problem, VRPs can be categorized into three main groups: 1) capacitated vehicle routing problems (CVRP), 2) vehicle routing problems with time windows (VRPTW), and 3) pickup and delivery problems (PDP). A review of the literature on VRP research, segmented by these three problem groups follows.

2.3.1 Capacitated Vehicle Routing Problems

Capacitated vehicle routing problems (CVRP) are the simplest form of VRPs. These problems focus on situations where vehicles with limited capacities are routed to fulfill specified demands with either the objective to minimize transportation cost or minimize total length of the routes. In traditional CVRPs, each vehicle route starts from a central depot, which is the supplier for all demand nodes and every vehicle visits a number of customers along its route. Only one vehicle can visit each customer along its route, meaning the demand along a given route cannot be split between two vehicles. The sum of total demands for the customers a truck serves needs to be less than or equal to the capacity of the truck.

If the capacity constraint is replaced with a distance constraint, the problem is then classified as a distance constrained VRP (DCVRP). In a DCVRP, the maximum length of the route or the maximum travel time of the route is limited. The distance constraint determines the maximum continuous travel distance or the maximum working hours of a driver. Conversely, a constraint imposed on the total time of a route includes travel time and service time at demand and supply points. In many examples, problems include both capacity and distance constraints.

Some studies have applied exact approaches (e.g. linear programming) to deal with CVRPs. Fukasawa et al. (2006) applied this technique to a CVRP with homogenous vehicles and the objective of minimizing the total length of all routes. They assumed all vehicles were starting and ending their routes at a central hub and the maximum number of demands fulfilled by any
vehicle was limited. They proposed a solution approach based on branch-and-cut and column generation solution methods. Baldacci et al. (2008) considered the same assumptions and employed an alternative mathematical model, also under the category of linear programming approaches, referred to as set partitioning. Due to computational complexities, they relaxed vehicle capacity constraints to be able to use a branch-and-cut method. They tried to implement a near-exact solution approach based on the concepts of dual solution and bounding procedure in linear programming and combined three heuristics to improve the best found solution and take capacity constraints in consideration. Their results showed an improvement to best-found solution lower bound. The works of Laporte (1992), Cordeau et al. (2007), Laporte (2009), and Baldacci et al. (2010) provide a thorough review of the literature on exact solution approaches for capacitated VRPs.

CVRPs are categorized as NP-hard (non-deterministic polynomial-time hard), so, exact methods can only be used to solve small sized and medium sized CVRPs. Many articles have thus focused on developing and applying heuristic and metaheuristic approaches, which are able to find good quality solutions for complicated and practical problems in a reasonable time. Laporte (1992), Gendreau et al. (2001), Laporte (2009), Cordeau et al. (2002), and Cordeau et al. (2007) conducted comprehensive reviews on heuristic methods adopted for capacitated VRPs and the literature in this area is evolving rapidly. Two examples of heuristics-based methods are introduced in this review. First, Lin et al. (2009) developed a hybrid algorithm to solve a capacitated VRP. The algorithm combined two metaheuristics methods: simulated annealing (SA) and tabu search (TS). The computational results proved that for small problems, the hybrid method was able to find the optimum solution and for most large problems, it was able to improve the best-found solution found in the literature. In a second study by Santos et al. (2010), a metaheuristic, referred to as ant colony optimization (ACO), was used to determine the number of vehicles and design vehicle routes that cost for a capacitated VRP. The ACO used two heuristics to build initial solutions. The first heuristic was a constructive algorithm that builds feasible solutions. The second one builds tours that serve all the demand points. Since the routes initially disregarded the capacity constraints, in the second step, each tour was then broken into a number of feasible routes. In the third step, the best initial solutions from the two heuristics were taken to a local search heuristic. The computational results compared to previous studies showed that the ACO produced efficient routes.

If mixed types of vehicles with different capacities are considered, the problem is referred to as a heterogeneous VRP. Brandão (2011) studied a heterogeneous vehicle routing problem with a
fixed number vehicle types. The author argued that even with homogeneous vehicles, the problem of finding a feasible solution can be NP-hard. If the total capacity of vehicles is close to the total customer demands and with mixed fleet types, the problem is a more complicated NP-hard problem. The solution methodology he proposed was using a tabu search metaheuristic. A tabu search works by building a feasible solution and exploring its neighbour solutions through a number of iterations. In order to avoid local optimum solutions, search cycling and induced diversification in the search process, the algorithm makes a list of explored solutions or attributes of explored solutions as tabu feasible solutions. Brandão (2011) tested the proposed method on a number of benchmark test problems and a number of new test problems and concluded that it showed good performance. For more articles on variants of CVRPs with heterogeneous vehicles and their comparisons, readers are referred to a survey by Soonpracha et al. (2014).

2.3.2 Vehicle Routing Problem with Time Windows

Vehicle routing problems with time windows (VRPTW) are a generalization of CVRP in which visits to supply and demand nodes should take place within a specified time window. VRPTWs are also known as vehicle scheduling problems (VSP) because in addition to routing, it also includes vehicle scheduling. The time window constraints can be hard constraints or soft constraints. In both cases, if the vehicle arrives to the site before the required start time, it can wait until the customer becomes available. If the time windows are indicated as hard constraints, the vehicle arrival time cannot be any later than the latest time indicated in the time window. Conversely, if the time windows are indicated as soft constraints, the constraint can be violated and a penalty is applied to all violations. Time constraints are usually incorporated into VRPs where there are restrictions on machine hours at sites, site hours, desired service hours, or technical constraints. The most well-known applications are in the food industry, urban and industrial waste collection and newspaper delivery (Golden et al., 2002).

Savelsbergh (1985) examined a VRPTW where vehicles were located in multiple hubs and formulated the problem as a mathematical model referred to as a multi-commodity network flow problem with the objective of minimizing vehicle waiting times. He argued that the problem is NP-hard and his solution approach was based on column generation, which was able to solve small and medium examples of the problem. Hadjar and Soumis (2009) worked on a multiple depot VRPTW applied in the context of urban bus routing. They modeled the problem as a multi-commodity network flow problem with supplementary time variables and the objective of minimizing total transportation costs. They used an approach based on column generation and
dynamic time window reduction to solve randomly generated test problems. Cordeau et al. (2002) and Cordeau et al. (2007) extensively reviewed exact and heuristic solution methods for VRPTWs and concluded that because of computational complexities, exact methods based on linear programming and branch-and-cut are usually not very efficient in solving VRPs with time window constraints.

The computational complexity that characterizes VRPs with time windows has resulted in a general tendency to using heuristics and metaheuristics as solution approaches. Pureza et al. (2012) modeled beverage and tobacco distribution in crowded urban areas in Brazil as a VRPTW. In addition to the classic assumptions of VRPTWs, they assumed that, if required, some extra vehicles could be added to the fleet to reduce service time. They adopted two solution approaches based on tabu search and ant colony metaheuristics. Çetinkaya et al. (2013) studied a variant of the problem known as two-stage vehicle routing problem with arc time windows for military and urban transportation applications. Their problem assumed that there was a time window constraint that indicated the availability interval for each road (i.e. the arc of the routes). They used a heuristic method called the memetic algorithm (MA), which is an evolutionary search process obtained by updating local search processes within another popular metaheuristic called the genetic algorithm. The method was able to produce good quality solutions with short processing time. A variation of VRPTWs where there is a heterogeneous fleet – i.e. when the number of each type of vehicle is uncertain – was considered by Gan et al. (2014). The researchers used six variants of the particle swarm optimization (PSO) metaheuristic and solved a case problem. Further examples of using heuristics and metaheuristics to solve VRPTWs are comprehensively reviewed in surveys by Cordeau et al. (2002), Cordeau et al. (2007), Bräysy and Gendreau (2005a), Bräysy and Gendreau (2005b), Funke and Tore (2005) and Doerner and Schmid (2010).

2.3.3 Pickup and Delivery Problems

Another generalization of CVRPs considers the pickup and delivery problem. In CPRVs and VRPTWs, a vehicle leaves a depot, loaded with goods required by a number of customers, visits them in its route, then the empty vehicle goes back to the depot. In a pickup and delivery problem, the truck visits both supply and demand points on its route. In the literature, pickup and delivery problems are categorized into two main groups: vehicle routing problems with backhauls (VRPBs) and vehicle routing problems with pickup and delivery (VRPPPDs). A few examples of both cases are reviewed here. Extensive reviews on both problems and their
variations can be found in surveys conducted by Desaulniers et al. (2002), Berbeglia et al. (2007), and Parragh et al. (2008).

In a VRPB, there are two kinds of material flows: regular flow and backhaul flow; and, based on their demand, the customers are either linehaul customers or backhaul customers. Linehaul customers are the individuals to whom goods should be delivered and backhaul customers are the individuals from whom goods should be picked up. If a site has both linehaul and backhaul requests, it is modeled as two separate linehaul and backhaul customers. In a typical VRPB, a loaded vehicle begins the route from a central depot, drops off products at linehaul customer sites, visits some backhaul customers, picks up some other products and delivers them back at the central depot. The objective is to maximize vehicle efficiency or minimize empty travelled distance. VRPBs take customer precedence constraint or deliveries-before-pickups into account, meaning that all linehaul visits should be completed prior to any of the backhaul visits.

The literature contains many articles examining VRPBs and because of computational complexities most researchers implement heuristics and metaheuristics to solve the problems under consideration. Osman and Wassan (2002) worked on a VRPB and developed two fast construction heuristics to build the initial solution. They then used a reactive tabu search heuristic to improve the routes. To test the reactive tabu search, they used two sets of test problems. The first set was generated randomly and the second set was a benchmark problem derived from the literature. The results showed that the algorithm was able to compete with the best algorithms available in literature in terms of both solution quality and solution processing time.

In many examples, the problem considered both backhauling and time windows (VRPBTW) at the same time. A typical VRPBTW deals with vehicle routing for a homogenous fleet that begins and completes routes at a central depot and are applied to perform deterministic linehaul and backhaul transportation demands if deterministic time windows are defined for each pick up or delivery. A number of studies have focused on VRPBTWs. Zhong and Cole (2005) considered the VRPBTW with and without linehaul constraints. The solution method was to use a heuristic called guided local search algorithm (GLSA), which was implemented in two steps. In the first step, a heuristic called adapted sweep algorithm (ASA) built initial infeasible solutions and applied a local search to improve it. For the second step, they developed a heuristic named section planning to adjust routes and customer orders until feasibility was obtained. Like other researchers, Zhong and Cole (2006) demonstrated the performance of their algorithm by solving sample problems.
Vehicle routing problem with pickups and deliveries (VRPPD) is another generalization of VRP in which, each site is the supply point for some goods and the demand point for some other good. The application of the problem is in reverse logistic (Nagy et al., 2013) meaning that it considers the flow of materials and products from typical final destinations to a typical original destination as defected products, low quality materials, or a product that needs remanufacturing or refurbishing. In contrary to deliveries-before-pickups assumption in VRPBs, in a VRPPD, linehaul and backhaul customers can be visited in any order. The problem lies in the decision-making required to determine what travels each vehicle should take on its route, the amount of goods it should deliver to each site, and the amount of goods it should pick from each site. The objective of the problem is to minimize total transportation cost. Mixed linehaul and backhaul visits may cause inconvenience to loading and unloading activities because picked up goods may block delivery goods but in many applications, this mixed pickup-delivery must be taken into account.

In general, it is more difficult to handle a VRPPD compared to a VRPB because it is more difficult to regard truck capacity constraints when mixed pick up deliveries are allowed. In a VRPB, capacity constraint can be obeyed more easily because a vehicle carries either delivery goods or pickup goods. In a VRPB, at the first part of a route, a vehicle only carries linehaul goods and the load decreases with each delivery and during the second leg, the vehicle only carries backhaul goods and the load increases with each pickup. Therefore, the total delivery goods and the total pickup goods must be less than the vehicle’s capacity. In a VRPPD, a vehicle is allowed to carry a mixture of delivery and pickup goods. At each visit the total load on board may increase or decrease and the total deliveries and/or pickups along the route may ultimately exceed vehicle’s capacity. This means that the capacity constraint needs to be assessed at each customer site.

Ropke and Pisinger (2006) developed a solution method based on a heuristic referred to as large neighbourhood searching and applied it to solve different classes of VRPPD. These included: a classic problem and problems featuring one, or a combination of the conditions, of heterogeneous vehicles, time windows, multiple depots, and precedence constraints. Zachariadis and Kiranoudis (2011) examined a VRP characterized by simultaneous pickup and delivery, a central depot, and homogenous vehicles. For the solution approach, a simple construction heuristic was first applied to obtain a feasible solution, and then a local search improvement heuristic called Arc Promise Algorithm (APA) was implemented. The proposed heuristic used a filtering approach to increase the probability of moving toward improving
neighbour solutions and the results were tested against a number of available large test problems with good computational results. Belmecheri et al. (2013) used a particle swarm optimization method to solve a VRP with a heterogeneous fleet type, time windows, and linehaul orders. Nagy et al. (2013) modeled a general VRP that included both VRPB and VRPPD as special cases. Their model did not consider any transportation between customers meaning that all delivery goods were supplied from a central depot and all delivery goods were delivered to the same depot. The main constraints of their model were vehicle capacity and demand satisfaction. A solution method based on tabu search metaheuristics was used to minimize the total travel costs. The results of applying the tabu search to test problems showed that more cost savings could be obtained by allowing simultaneous pickup and delivery.

A special case of VRPPD with unit load requests is referred to as a dial-a-ride-problem (DARP). The DARP is a vehicle routing and scheduling problem for door-to-door transportation of people. The problem is actually a VRPPD that is applied for collection and distribution of people in place of goods. It consists of a number of pick-up and delivery requests within specified time windows. The problem was first studied in 1980 and has been widely studied in literature since then. The problem can be considered as a taxi company or a courier service provider for elderly or patients and in most examples it is assumed that the vehicles are of the same type and are located in a central hub. In a deterministic DARP, all demands are known from the beginning while in a dynamic one, demands are gradually submitted as time passes. Other constraints could be limited vehicle capacity or route travel time. In some cases, the goal of the problem is to determine the number of vehicles that can satisfy all demands and in other cases, the goal is to minimize the transportation cost with a fixed number of trucks while satisfying as many demands as possible. Since the problem is addressing human transportation, maximizing service convenience could also be identified as an objective.

Most studies have addressed deterministic DARPs in which the transportation requests, travel times, and other components of the problem are known in advance. Cordeau (2006) formulated a deterministic DARP as a mixed integer model and used a branch-and-cut method as an exact method to solve small and medium sized examples of the problem. The problem is NP-hard even when there is a single vehicle and deterministic demands (Savelsbergh and Sol, 1995). The majority of studies on this subject have used heuristic and metaheuristic methods as solution approaches. Cordeau and Laporte (2003) used a tabu search heuristic to solve a deterministic and multi-vehicle DARP.
A dynamic DARP considers uncertainties and request updates such as traffic, travel time fluctuations, new requests, request cancellation, customer delays, and vehicle breakdowns. In recent years, the literature addressing dynamic DARP has grown. Xiang et al. (2008) studied a dynamic DARP with the objective of minimizing transportation costs and delays. Their approach was to use a fast heuristic and reschedule the vehicles in real time if a new event occurred. To evaluate the performance of the solution method, the results were compared with a simulation model. In another example, Schilde et al. (2011) studied a DARP with dynamic new request submissions for patient transportation to Austrian Red Cross. The same authors (Schilde et al., 2014) studied the same problem with stochastic travel times and used two metaheuristics as solution approaches. For further references, detailed reviews on DARP are provided by Desaulniers et al. (2002), Cordeau and Laporte (2003) and Cordeau and Laporte (2007).

2.3.4 Summary VRP Solution Approaches

Truck routing and scheduling problems are the most studied combinatorial problem in optimization literature. Mathematical programming and optimization techniques have been widely used in literature to deal with VRPs and VSPs. General VRPs and VSPs consider different constraints related to capacity of vehicles, time windows at supply and demand points, pickups, and deliveries. In many cases, these problems assume that demands are less than the capacity of one truck, each supply and demand point can only be visited once, and a transportation demand cannot be split between two vehicles. The objectives of the models are usually to find truck routes and/or schedules with the minimum transportation cost. The solution approaches mainly included column generation, heuristics, and metaheuristics with increasing tendency toward metaheuristics.

Mathematical formulations of different classes of VRPs are based on binary, integer, or mixed integer linear programming. In integer formulations, binary variables are used to indicate if a vehicle moves between two demand and/or supply points in the final solution or not. A review of the literature revealed that the main mathematical formulations for capacitated vehicle routing problems were based on vehicle flow formulation, two-commodity flow formulation, and commodity flow formulation (Baldacci et al., 2010). Vehicle routing problems with time windows constraints are usually formulated as a mixed integer programming (MIP) model referred to as a multi-commodity network flow model with time windows and capacity constraints (Cordeau et al., 2002). Pickup and delivery problems are generally formulated either as an extension of the travelling salesman problem (TSP) if the problem considers only one vehicle and as adapted
three index vehicle routing problem formulations if the problem considers multiple vehicles (Parragh et al., 2008).

Vehicle routing and scheduling problems are NP-hard. Consequently, the most basic vehicle routing problem with capacitated vehicles is proven to be NP-hard. The computational complexities of VRPs with time windows and pickup-deliveries make them generalizations of capacitated VRP and so, they too are NP-hard. For VRPs with time windows and pickup-deliveries even the problem of finding a feasible solution or determining whether a feasible solution exists is NP-hard (Savelsbergh, 1985).

As a result of computational complexities, many studies used metaheuristic methods to address vehicle routing problems. The most popular metaheuristics applied to variations of VRPs include: simulated annealing (SA), deterministic annealing (DA), tabu search (TS), genetic algorithms (GA), ant algorithm (AA), and Neural Networks (NN) (Cordeau et al., 2007). Many studies on vehicle routing problems consider the same problems, with the same assumptions and mathematical formulations and try to develop solution algorithms that outperform previous studies in terms of solution processing time and quality. Since the VRPs are combinatorial, for medium and large sized problems there is often no guarantee that the optimal solution has been found. As a result, there are many publicly available test problems that researchers use as benchmarks.

2.4 Forest Truck Transportation Models

Supply chain management in the forest industry includes transportation and storage of raw materials, work-in-process, and final products between supply and demand points. Supply chain planning is difficult because keeping costs low so often compromises other priorities. Dynamic changes in the products, supply, demand, and technologies require frequent planning and management updates. Operations research and optimization methods have been used in the field of forestry since the 1950’s (Martell, 2007) to address diverse issues including: plantation planning, road building, harvesting, transportation planning for flow of raw materials and products, production planning, decision making for supply and demand, and assisting in export and import decisions. There is intensifying pressure to make forestry supply chains more efficient and the recent research indicates advances in efficiency can be obtained through higher integration across points in the supply chain as well as increasing the utilization of existing resources and production capacity (Carlsson and Rönnqvist, 2005). A significant portion of operational costs in a supply chain is associated with transportation making it an obvious choice for increasing efficiency. Transportation includes hauling of products and by-products.
such as timber, lumber, wood chips, pulp, and paper. Leading countries in the forest industry such as Canada, Chile, The United States, Sweden, Australia, and New Zealand reported that 25-45% of all procurement costs were related to transportation (Audy et al., 2012). There are three main reasons that have motivated many studies on transportation improvement: 1) increasing machine utilization and cost saving by reducing idle times or lineup waiting times; 2) reducing environmental impacts – typically means reducing total transportation time and/or travelled distance, which subsequently reduces greenhouse gas emissions and environmental impacts; and 3) supporting truck drivers and improving employee satisfaction specifically for drivers who possess enough experience for heavy loads and adverse weather conditions.

Based on the length of the planning horizon, four main planning levels are identified in forestry transportation: strategic planning (more than five years), tactical planning (six month to five years), operational planning (one day to six month), and online planning (less than one day) (Rönnqvist, 2003). In general, strategic planning involves long term planning and it can be very long because it depends on the rotation age of a trees (80 years) or the profitable life of a mill (30 years) (D’Amours et al., 2008). Examples of strategic planning include road construction and the selection of transportation mode for a given activity. Tactical planning is the next level of planning and the link between strategic planning and operational planning. It includes decisions such as road upgrades and maintenance. Operational planning is short term planning such as decisions about what volumes are to be picked up and delivered between supply and demand points, truck routing, and scheduling. Online planning involves planning with horizons less than a day such as truck dispatching. Surveys on forest transportation in different planning levels are presented by Rönnqvist, 2003), Epstein et al. (2007), D’Amours et al. (2008) and Audy et al.(2012).

In recent years, truck scheduling problems in forestry have been the subject of many studies. However, the majority of studies focused on log truck transportation with only a few papers considering wood chip truck transportation. Sections 2.4.1 and 2.4.2 overview literature considering daily truck transportation in forestry.

2.4.1 Present State of Operational Log Truck Scheduling Research

LTSPs are a generalization of vehicle routing problems that usually consider time windows, multiple supply points, multiple demand points, multiple products, multiple daily visits to each site, and in many cases, one load to be delivered to one customer at a time. Audy et al. (2012)
extensively reviewed literature available on LTSP including the available decision support systems and application issues.

A number of log truck routing and scheduling studies focused on simulation approaches, although most studies applied linear optimization techniques, heuristics, and metaheuristics. In this section, literature on log truck scheduling is reviewed. The studies are sorted based on the year of the study. Table 1 presents a summary of studies on simulation and optimization models used for log truck scheduling. Table 1 includes the objective function of the study, decision variables, the solution method applied, and the country of the study.
Table 1: Summary of the studies on simulation and optimization models for log truck scheduling

<table>
<thead>
<tr>
<th>Author-year</th>
<th>Region</th>
<th>Objective function</th>
<th>Decision variables</th>
<th>Solution method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shen (1988)</td>
<td>China</td>
<td>Minimizing transportation cost</td>
<td>Flow between forest and mills</td>
<td>LP with a method based on primal-dual problem</td>
</tr>
<tr>
<td>Rönnqvist and Ryan (1995)</td>
<td></td>
<td>Minimizing empty truck driving time and loaded driving time</td>
<td>Truck routes and schedules</td>
<td>Hybrid greedy heuristics and column generation</td>
</tr>
<tr>
<td>Weintraub et al. (1996)</td>
<td>Chile</td>
<td>Minimizing transportation cost</td>
<td>Flow between forest and mills, number of trucks and cranes, work schedule for each truck and crane</td>
<td>Simulation</td>
</tr>
<tr>
<td>Barrett (2001)</td>
<td>United States</td>
<td>Maximize logging and transportation productivity</td>
<td>Flow between forest and mills, truck routes and schedules</td>
<td>Simulation</td>
</tr>
<tr>
<td>McDonald et al. (2001)</td>
<td>United States</td>
<td>Maximizing the amount of logs transported from forest to mills</td>
<td>Truck routes and schedules</td>
<td>Simulation</td>
</tr>
<tr>
<td>Murphy (2003)</td>
<td>New Zealand</td>
<td>Minimizing transportation cost</td>
<td>Truck routes and schedules</td>
<td>Integer programming</td>
</tr>
<tr>
<td>Palmgren et al. (2003)</td>
<td>Sweden</td>
<td>Minimizing transportation cost</td>
<td>Truck routes and schedules</td>
<td>Column generation</td>
</tr>
<tr>
<td>Palmgren et al. (2004)</td>
<td>Sweden</td>
<td>Minimizing transportation cost</td>
<td>Truck routes and schedules</td>
<td>Column generation</td>
</tr>
<tr>
<td>Mendell et al. (2006)</td>
<td>United States</td>
<td>Minimizing transportation cost</td>
<td>Truck routes and schedules</td>
<td>Simulation</td>
</tr>
<tr>
<td>Epstein (2007)</td>
<td>General formulation</td>
<td>Minimizing transportation cost</td>
<td>Truck routes and schedules</td>
<td>Column generation and heuristics</td>
</tr>
<tr>
<td>Gronalt and Hirsch (2007)</td>
<td>Austria</td>
<td>Minimizing empty truck driving time</td>
<td>Truck routes and schedules</td>
<td>Tabu Search</td>
</tr>
<tr>
<td>Andersson et al. (2008)</td>
<td>Sweden</td>
<td>Minimizing transportation cost and penalty for unfulfilled demand</td>
<td>Flow between forest and mills, truck routes and schedules</td>
<td>Hybrid LP and tabu search</td>
</tr>
<tr>
<td>Flisberg et al. (2009)</td>
<td>Sweden</td>
<td>Minimizing transportation cost and unfulfilled demands</td>
<td>Truck routes and schedules</td>
<td>Hybrid method based on linear programming and tabu search</td>
</tr>
<tr>
<td>Rey et al. (2009)</td>
<td>Chile</td>
<td>Minimizing transportation cost</td>
<td>Flow between forest and mills, number of trucks and truck routes and schedules</td>
<td>Column generation</td>
</tr>
<tr>
<td>Author-year</td>
<td>Region</td>
<td>Objective function</td>
<td>Decision variables</td>
<td>Solution method</td>
</tr>
<tr>
<td>----------------------</td>
<td>------------</td>
<td>------------------------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------</td>
</tr>
<tr>
<td>Rummukainen et al. (2009)</td>
<td>Finland</td>
<td>Minimizing transportation cost</td>
<td>Load collection plan, truck assignment to loads, truck routes and schedules</td>
<td>Tabu search, mixed integer goal programming</td>
</tr>
<tr>
<td>El Hachemi et al. (2011)</td>
<td>Canada</td>
<td>Minimizing the total cost of the nonproductive activities such as waiting times and empty truck driving time</td>
<td>Truck routes and schedules</td>
<td>Hybrid method based on integer programming and constraint programming</td>
</tr>
<tr>
<td>Derigs et al. (2012)</td>
<td></td>
<td>Minimizing empty truck driving time</td>
<td>Truck routes and schedules</td>
<td>Multiple neighbourhood search</td>
</tr>
<tr>
<td>Zazgornik et al. (2012)</td>
<td>Austria</td>
<td>Minimizing total travel time consists of driving times, service times and waiting times</td>
<td>Truck routes and schedules</td>
<td>Tabu search</td>
</tr>
<tr>
<td>El Hachemi et al. (2013)</td>
<td>Canada</td>
<td>Minimizing loaded truck travel time and minimizing the total cost of the nonproductive activities such as waiting times and empty truck driving time</td>
<td>Flow between forest and mills, truck routes and schedules</td>
<td>Hybrid method based on integer programming, local search and constraint programming</td>
</tr>
<tr>
<td>Haridass et al. (2013)</td>
<td>United States</td>
<td>Minimizing empty truck driving time</td>
<td>Truck routes and schedules</td>
<td>Simulated annealing</td>
</tr>
</tbody>
</table>

A brief discussion of each paper is presented in the following sections.

### 2.4.1.1 Using Simulation modeling to Improve Log Truck Scheduling

In forestry transportation, a number of studies have used simulation models for log truck routing and scheduling. A simulation is an imitation of a system over time that provides researchers with a general image of how the system works. Simulation models work based on conditions and rules identified in the real problem and are thus very good at providing a general view of the performance of a system. Simulation models also usually have fewer simplifying assumptions compared to optimization models. A popular approach in simulation is called discrete event simulation (DES), which assumes the activities of a problem are a discrete sequence of events in time. Discrete event simulation calculates the time of occurrence for each event and jumps from one event to the next in order of time. Another simulation approach, which is very powerful for analyzing a system, is called stochastic simulation in which the activities can be stochastic (random events). A number of studies have used DES models for daily truck scheduling.
Weintraub et al. (1996) developed a computerized tool based on a simulation model that employs heuristic rules in order to provide help with scheduling daily activities of log trucks transporting timber from stands to pulp mills, sawmills, sort yards, and ports in Chile. The simulation model produces daily schedules and updates it hourly to address unexpected events. The simulation tool is successfully used in the Chilean forest industry and has resulted in a 10-20% reduction in transportation costs across the industry.

McDonald et al. (2001) investigated the benefits of sharing log trucks between different logging companies using a simulation model. Empty trailers were left at harvest sites where trucks switched empty trailers with loaded trailers. In one case, they assigned a fixed number of trucks to serve each logging group and in the other case, all trucks were shared between all loggers. They developed a simulation model that showed the second case was more efficient and economical.

Barrett (2001) applied a simulation model to evaluate the productivity of forest harvesting and log transportation to a number of mills in the Appalachian forest region of the United States. They expressed the productivity of the system based on the number of daily truckloads of logs produced and transported and investigated the effect that truck trip time, harvesting rate, loading time at forest areas, unloading time in mills, variations in travel times, and multiple log types had on the productivity of the system. They concluded that truck turn times were the most effective factor that could limit the productivity of the system.

Mendell et al. (2006) evaluated the benefits of log truck sharing between independent logging companies working in adjacent forest areas to supply logs for multiple sawmills in central Georgia, US. They used a simulation approach to obtain daily truck routes and schedules, which reduced empty truck travel times and loaded trailer waiting times at forest areas.

All four simulation models introduced here generated daily truck schedules for a fleet between forest areas and mills and dealt with the complicated problem of log truck routing and scheduling. Two of the studies evaluated benefits of truck sharing between different logging companies while the other two focused on truck scheduling improvements for one logging company.

Simulation models provide a deeper understanding of systems, making them ideal for solving strategic and tactical level problems, as well as operational level problems that are nonlinear or involve stochastic parameters. Simulation models are well-suited for analyzing the performance
of a transportation network or different scenarios. However, the majority of studies in the area of transportation have used optimization techniques in which they start by building an initial solution (using exact methods, approximation methods or simulation methods) and then apply some improvement or optimization techniques to obtain more efficient transportation plans.

2.4.1.2 Using Optimization Techniques to Improve Log Truck Scheduling

Most log truck scheduling studies used optimization techniques to improve truck routing and scheduling. Based on constraints in the problems, LTSPs are categorized according to problems with time windows and problems with backhauling.

2.4.1.2.1 Addressing Time Window Constraints

Time window constraints arise from the nature of log harvesting which usually takes place over the course of one or two working shifts. Time constraints related to driver hours limit the length of a route and site visit time constraints are related to working hours of supply and/or demand points or working hours of machinery at each site.

In the simplest versions of LTSPs, the time constraints are only related to driver hours. An early study in log truck scheduling comes from the work performed by Shen (1988), who formulated a small example of log transportation problem in China as a network flow problem with capacitated vehicles. He employed a linear programming method based on primal-dual method called “out-of-kilter” to calculate the number of trucks required and subsequently determined the daily truck schedules.

Murphy (2003) worked on a log truck routing and scheduling problem in New Zealand and tried to reduce the number of trucks with a mixed integer linear model. In another study, Rey et al. (2009) used a dynamic column generation method to solve a LTSP with a time span of one day in the Chilean forest industry. They included time constraints for maximum working hours of drivers, multiple supply and demand points, and developed a mixed integer model to reduce transportation costs of daily truck routing and scheduling.

One of the most often studied time window constraints in the area of LTSPs is related to working hours of forest loggers and mills. If a truck arrives to a site before the opening time or after the closure time, it needs to wait for the site to start working. Palmgren et al. (2003) studied a LTSP with time windows for working hours of supply and demand points in the Swedish forest industry. They modeled the problem as a mixed integer problem in which each column represented a daily truck route. To solve the model, they relaxed integer constraints, then used
a column generation method to produce truck routes, and applied composite pricing to solve the linear model. To achieve integer results, they used a branch-and-price algorithm on the linear model outcome. The same authors subsequently investigated the same problem later using a shortest path algorithm to solve the linear relaxed problem and obtained better results (Palmgren et al., 2004).

Andersson et al. (2008) developed a decision support system called RuttOpt for log truck routing and scheduling. RuttOpt had three modules; the first module contained the Swedish road database and a tool to calculate truck travel distances; the second module did log truck routing and scheduling; and the third module was tasked with information storage. In the second module, the truck routing and scheduling, was deconstructed into a log flow problem and a truck routing and scheduling problem. The log flow problem was modeled and solved as a linear programming problem and the LTSP was solved using a tabu search method.

Truck routing and scheduling problems for timber transportation from forest stands to sawmills, pulp mills and paper mills in Finland were considered by Rummukainen et al. (2009). They developed a three-stage planning method for the load collection problem, the load assignment problem, and the truck routing problem. In the load collection problem, large wood batches were broken into a number of truck loads. A tabu search method was used to minimize total driving time and loading time for all truckloads. The load assignment problem considered a time span of a few weeks and produced a rough estimation of load assignments to trucks, ships, and trains while minimizing transportation costs and unfulfilled demand penalties. A mixed integer programming model was developed for this stage. Finally, the truck routing problem was dealing with detailed time schedule of trucks and drivers and was solved by a tabu search metaheuristic. The authors only explained the problem and approaches applied and no case problems or results were presented.

Zazgornik et al. (2012) considered wood transportation between forest areas, mills, and customers (wholesalers or wood processing units) and assumed that mills were providing the transportation services for both roundwood and sawnwood. They discussed that due to their specifications, log trucks could not transport sawnwood from mills to wholesalers, and as a result, two vehicle types were used between forest-mill and mill-wholesalers. This situation used two separate routing loops and did not allow for truck sharing between suppliers and customers of a mill. They considered four truck and container types and used a tabu search metaheuristic
to solve the problem. The results showed that the total transportation cost could be reduced if trucks and containers could be used to move both roundwood and sawnwood.

2.4.1.2.2 Addressing Backhaul Issues

The concept behind backhauling is to increase truck utilization by decreasing empty truck travel times. Without backhauling, a truck travels back empty from the mill to the forest to pick up another load. With backhauling, after log delivery, the empty truck is directed to a second forest area near the first mill to pick up logs that are destined for a second mill located near the first forest area. In this way, transportation efficiency can be improved (Carlsson and Rönnqvist, 2007).

Rönnqvist and Ryan (1995) worked on a real time log truck dispatching problem with the objective of minimizing empty truck travel times while keeping loaded truck travel time as low as possible. They assumed that log supply and demand was changing during the planning day and after each delivery, a dispatcher was assigning the truck to its next destination. Their solution approach was based on using two greedy heuristics to produce truck schedules and one optimization step based on column generation and branch-and-price to improve the initial schedule. The solution method produced a transportation plan for one working shift and the plan was revised whenever a new event happened, such as log pickup, log delivery, new supply level, or new demand level. They proposed a solution approach that included a sequential greedy method, a column generation method, and a branch-and-bound method.

Epstein et al. (2007) classified log truck transportation planning problems into three categories: 1) log destination problems (wood flow problems); 2) log destination problems with backhauling; and 3) scheduling and dispatching issues. The first two models were focused on weekly and monthly assignment of logs between forest areas and mills while the third model included daily truck routing and scheduling. All three problems were formulated as MIPs and because of computational complexities, they suggested column generation as the solution method for the first two models and column generation or heuristics for the third. The scheduling formulation they presented did not actually contain time constraints and they mentioned that timing constraints must be considered in the column generation process. They also discussed integration of truck transportation with ship or train transportation and organizational aspects with loggers and transporters.

Gronalt and Hirsch (2007) presented an algorithm based on tabu search to provide truck schedules for roundwood transportation in the Austrian forest sector. The transportation was
based on full truck loads with the objective of minimizing empty truck trips. They used a greedy heuristic to find an initial solution and applied three variants of tabu search methods with different neighborhood investigation approaches to improve it. After each step of tabu search, a post-optimization heuristic was applied in an attempt to improve the solution.

In another example, a routing problem for log trucks in Sweden was considered by Flisberg et al. (2009) and a two-phase hybrid solution approach for daily truck routing was proposed. In the first phase, a linear programming model was used to represent a simplified version of the problem and to determine wood flow from forest stands to sawmills. In the second phase, a tabu search was adopted to solve truck schedules between supply and demand points and to find truck routes for the wood flow plan generated in phase one.

Synchronization between log trucks and log loaders has been considered in a few studies. Bredström and Rönnqvist (2008) discuss the need to consider synchronization and temporal precedence in vehicle routing and scheduling with applications in homecare services, the airline industry, and the forest industry and present an integer programming model for the problem. In regard to log truck scheduling, they explained the need to synchronize log loader availability and log trucks schedules when trucks do not have a crane and log-loaders are used to serve several sites.

El Hachemi et al. (2011) assumed that the number of trips between each forest stand and each mill were known and all trucks needed a log-loader for loading and unloading activities. The objective of the study was to minimize truck waiting times, log-loader waiting times, and empty truck travel times. To solve the problem, they used a hybrid method based on deconstructing the problem into a weekly truck routing and a daily truck scheduling problem. They proposed an integer programming model to minimize empty truck travel times. The number of empty truck trips was used to impose some constraints on a constraint programming model to determine daily truck schedules with the minimum waiting times. The same authors used a tabu search and a constraint programming method for the same problem in an earlier study (El Hachemi et al., 2009).

El Hachemi et al. (2013) considered the same problem with an additional decision to determine log allocation between forest areas and mills. They proposed a two-phase method to solve the problem. In the first phase, they used a MIP model to determine the daily load allocation between forests and mills with the minimum empty truck travel time. In the second phase they
addressed daily log truck scheduling and synchronization of trucks and log-loaders. For the second phase, they used two solution approaches based on constraint programming.

Another example of LTSPs with time windows at forest areas and mills was studied by Haridass et al. (2013). The objective was to minimize the empty truck travel times and the solution method was based on a simulated annealing metaheuristic. Derigs et al. (2012) applied a number of variations of a heuristic method named multiple neighbourhood search (MNS) based on a local search, large neighbourhood search and metaheuristic control to solve a log truck routing and scheduling problem to transport wood from forest sites to a biomass power plant.

2.4.1.3 Discussion of Solution Approaches

Truck transportation in forestry is a generalization of vehicle routing and scheduling problems and the primary focus of research in this area is on log truck routing and scheduling. The main difference between general VRPs and forest truck scheduling problems is that the daily supply and demand at each site exceeds the capacity of one truck and as a result, each site is usually visited several times by several trucks in every working day. Additionally, the forest industry is characterized by having diverse mills that have specific constraints that make mill-specific customized planning methods necessary (Carlsson et al., 2009). The objective functions of forest truck scheduling problems mainly include minimizing transportation costs and minimizing empty truck driving times. The decision variables are mainly log flow between supply and demand points, truck routes, and truck schedules. A careful look at the literature shows that approaches were mostly based on column generation and metaheuristics.

The most popular exact-based methods applied to log truck transportation problems are based on applying constraint relaxation and boundary techniques. Even the simplest formulations of VRPs result in NP-hard problems. As a result, lower bounds are usually obtained by employing linear programming techniques like column generation or a cutting plane. After finding a lower bound, some bounding techniques are employed to find a feasible and integer solution. The most popular bounding techniques are branch-and-cut and branch-and-cut-and-price. In forestry truck scheduling, a combination of linear relaxation, column generation, and bounding methods have been used as the most popular algebraic solution method (Rönnqvist and Ryan, 1995; Palmgren et al., 2003; Palmgren et al., 2004; Epstein et al., 2007; Rey et al., 2009). To evaluate the quality of results obtained by exact-based methods, the solution quality is defined based on the gap between the lower bound and the best found solution. In fact, there is no guarantee that a solution method has really found the exact solution unless it finds the lower bound.
As the problems become more complicated, they become more difficult to solve by an exact method. Moreover, for these cases, relaxation problems generate weak lower bounds and final solutions show low quality. Many studies therefore, used metaheuristic methods as solution approaches and the two metaheuristics that were most often used for LTSPs were tabu search and simulated annealing. Metaheuristic methods are able to find good quality solutions for complicated problems in a reasonable time. They work based on a local search of the solution space and apply some variation techniques to escape local optima and guide the search process towards the global optimum. Gronalt and Hirsch (2007), Andersson et al. (2008), Flisberg et al. (2009), Rummukainen et al. (2009), and Zazgornik et al. (2012) have used tabu search methods and Acuna et al. (2012), Han and Murphy (2012), and Haridass et al. (2013) used simulated annealing methods to solve LTSPs.

2.4.2 Wood Chip Truck Scheduling

There is not much literature available on truck routing and scheduling for the transportation of woodchips to pulp mills. The main reason for the limited number of studies in this area is that in the past wood chips required by pulp mills were a waste product of sawmills. There was no competition for wood chips, they had low value, and there was no need to demonstrate efficiency for their supply. As a result, the pulp industry was able to acquire wood chips from local sawmills or by whole log chipping at a relatively low price. Planning methods were based on experience and manual methods.

In recent years, traditional pulp and paper producers, especially in North America felt a need to improve their competitiveness by increasing the efficiency of their supply chain activities. Because of the downturns in Canadian and American housing markets, many sawmills had to shut down which resulted in reduced lumber production (Statistics Canada, 2013). Decline in lumber production caused decline in wood chips production at sawmills, fibre shortage and increased competition for wood fibre. New competitors have emerged in tropical and subtropical regions who possess advantages of high technology plants, lower wood costs and lower labour costs compared to North American pulp facilities (Bajpai, 2013). Moreover, because of increased use of electronic devices, paper production and consumption in North America has declined for a number of paper grades in recent years. In Canada, pulp production has decreased by 16% between 2008-2012 but the export of pulp has increased by about 2% in the same period which shows that the industry is becoming more dependent on export markets (FAO, 2012). In addition, the global market for wood chips, pulp log and wood pulp has grown significantly (Goetzl, 2008); and the competition for wood chip supply has increased between
pulp mills and bioenergy plants (Uronen, 2010). In spite of the increased international and local demands for wood chips and pulp logs, in recent years the competition for available land between wood plantation and food production has intensified; Also, since the 1990’s, environmental organizations increased social awareness and subsequent pressure to preserve forests and limit wood harvest (Uronen, 2010). As a result, fibre sources required for the pulp and paper industry are becoming more expensive and less available. As wood chips become scarcer, the survival of the pulping industry depends on securing wood chip supply and more efficient transportation planning. As a result, the wood chip truck routing and scheduling problem is attracting the attention of more researchers. Table 2 presents a summary of simulation and optimization models used for wood chip and biomass truck scheduling. It includes the objective function of the study, the decision variables, the solution method applied, and the country of focus.
Table 2: Summary of the studies on simulation and optimization models for biomass truck scheduling

<table>
<thead>
<tr>
<th>Author-year</th>
<th>Region</th>
<th>Objective function</th>
<th>Decision variables</th>
<th>Solution method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Väätäinen et al. (2005)</td>
<td>Finland</td>
<td>Minimizing truck waiting before unloading, balancing the use of two unloading bays, increasing uniformity of truck arrivals</td>
<td>Truck schedules and truck assignment to one of the two unloading bays</td>
<td>Simulation</td>
</tr>
<tr>
<td>Acuna et al. (2012)</td>
<td>Australia</td>
<td>Minimizing transportation cost</td>
<td>Truck routes and schedules</td>
<td>Simulated annealing</td>
</tr>
<tr>
<td>Han and Murphy (2012)</td>
<td>USA</td>
<td>Minimize transportation cost and working time</td>
<td>Truck routes and schedules</td>
<td>Simulated annealing</td>
</tr>
</tbody>
</table>

The rest of section 2.4.3 overviews the main differences between log truck scheduling problems and wood chip truck scheduling problems, and provides a short summary of the studies in this area.

2.4.2.1 Wood Chip Truck Scheduling Models

The principle difference between log transportation and biomass transportation is that the daily volume transported in biomass transportation is larger than the daily volume in log transportation. The reason is that demand at biomass demand points is larger than the demand at log demand points. Sawmills usually work for one or two shifts in four or five days of a week but pulp mills and heating plants usually run 24/7. This is true especially for pulp mills because of the high capital cost and the high costs of stopping and resuming production.

Moreover, biomass demand points usually have limited unloading capacity and truck waiting times at delivery points are common. The main reason is that the dumpers used to unload chip trucks have a very high capital cost and hence, there are a limited number of dumpers (only one dumper in many cases). Some studies in log truck transportation have considered a limited number of cranes for log loading and unloading (El Hachemi et al., 2011; El Hachemi et al., 2013; Haridass et al., 2013). The crane constraint is similar to the dumper constraint because a log truck cannot be loaded or unloaded unless a crane is available to serve it. However, since the capital cost of a crane (or a wheel loader) is much less than a truck, many studies assume that enough cranes are serving the studied log truck fleet. Additionally, in log truck transportation, some trucks carry their own crane and can load or unload logs independently.
Väätäinen et al. (2005) studied solid biofuel (peat and woodchips) transportation from a fuel storage area to bio-power plants in the Finnish forest industry with a focus on improving solid fuel transportation at the power plant. They considered the winter conditions of the power plant when energy production and fuel transportation are at their maximum levels. The truck transportation activities were taking place between a storage bay and the power plant. After arrival to the power plant, trucks were weighed and directed to one of the two unloading bays. The objective of the study was minimizing truck waiting times before unloading, increasing the usage balance between the two unloading bays, and increasing the uniformity of truck arrivals to the power plant. They used a discrete event simulation model to analyze the problem.

Acuna et al. (2012) developed a software tool named FastTRUCK to optimize truck schedules for chip-vans transporting in-field produced wood chips to a shipping port in an Australian case study. The study assumed that in-field chippers were producing wood chips at roadsides and they were able to work only if a truck was available for direct loading. The trucks then hauled the wood chips to a port where a hydraulic dumper was used to unload them. They also evaluated the effect of chipper utilization, chipping sites available for each truck, truck loading and unloading times, and load weights on the transportation system in the context of daily transportation costs, number of trucks, truck utilization, and the volume of daily wood chip production.

A truck scheduling problem for woody biomass transportation was discussed by Han and Murphy (2012). According to the authors, production and transportation cost improvements are necessary to make biomass utilization for energy production economically viable. The study focused on transportation of woody biomass from sawmills to heating plants, pulp mills, or export terminals. The authors developed a model based on simulated annealing to optimize woody biomass truck scheduling in western Oregon to evaluate the effect of different components on total transportation costs and total travel times.

2.4.2.2 Discussion

Chips-to-pulp mill transportation problems are distinct from log transportation problems in several ways. These problems have been rarely studied in the forestry literature and despite the interest and effort in developing log truck scheduling models, only a few studies considered biomass transportation to heating plants or wood chip transportation to a pulp mill. There are four differences between LTSPs and the chip truck scheduling problem.
First, since a pulp mill runs 24/7, wood chip truck routing and scheduling must consider a time span of one week. In contrary, LTSPs are usually performed on a daily basis and with consideration of one shift or two shifts according to loggers' working hours and sawmill working hours. A pulp mill never stops production and although chip supplier mills have limited working hours, chip storage yards are made available to chip trucks to accommodate a continuous schedule.

Second, weekly scheduling must consider maximum hours for drivers and plan for shift starting and ending times, shift changing times, changeover locations, rest times, and the number of weekly shifts for each truck and each driver.

Third, truck unloading capacity at a pulp mill is limited, so usually there are long waiting times that need to be minimized. Limited loading and unloading capacity have been considered in some LTSPs but since log cranes or loaders are much cheaper than dumpers the comparison is not appropriate.

Fourth, pulp mill wood chip transportation problems usually feature priorities for certain wood chip suppliers. In many cases, pulp mills have some major wood chip suppliers and several smaller suppliers. The pulp mill often prioritizes pickup at these major suppliers over the smaller suppliers.

A wood chip truck routing and scheduling problem with all these constraints has not been considered in any of the previous studies and is the subject of this thesis. It is clear from the review of the literature that there is a need for an effective tool for managing wood chip truck routing and scheduling. Two research objectives emerged to address this gap in the literature:

1- To improve truck routing and scheduling for transportation of wood chips from a number of sawmills to a single pulp mill while considering: the production rate of chips, travel times, service times, crew scheduling, and limited unloading capacity. To fulfill this objective, a simulated annealing method was adapted to provide detailed weekly truck routing and scheduling to minimize transportation delays and truck waiting times. The model is intended to be used as an operational level tool to help truck dispatchers plan routing and scheduling.

2- To evaluate the effect of changes in some structural parameters such as fleet size, drivers switch points, truck types, and an additional dumper. To achieve this objective,
the simulated annealing model was used to conduct sensitivity analysis and scenario analysis on these parameters.

Chapter 3 outlines the methodologies used to address these objectives.
3 Methods

The objective of this section is to describe the method used in this study to model transportation of wood chips from multiple sawmills to a central pulp mill, and the method applied to improve truck routes and schedules for the transportation fleet. The transportation planning model produces detailed, weekly working routes and schedules for each truck and each truck driver by considering wood chip production rates, travel times, service times, crew scheduling regulations, and limited unloading capacity at the pulp mill.

The remainder of this chapter is organized as follows: Section 3.1 outlines the development of a mathematical model that minimizes transportation delays and truck waiting times for a wood chip transportation network serving a pulp mill. Section 3.2 describes the solution method used to tackle the truck routing and scheduling planning and includes a general simulated annealing algorithm. Section 3.3 describes the solution approach for evaluating the impact of changes in structural parameters which include sensitivity and scenario analysis. In Section 3.4, the wood chip transportation case study including the suppliers, the transportation network, and the consumer are introduced. In Section 3.5, the adapted simulated annealing method and its parameters are explained.

3.1 Mathematical Model

Operational level truck transportation problems are usually modeled as a linear programming (LP) model with integer variables (integer programming (IP) model) or with both continuous and integer variables (mixed integer program (MIP) model). In this section, a mathematical model for the wood chip transportation problem with limited truck unloading capacity is presented. The model has several supply points, a transportation fleet, one demand point with limited unloading capacity, and a scheduling period of one week. The objective function was defined to minimize the unfulfilled transportation penalty and the truck waiting times. The case specific objective function will be described in section 3.4.4.

The model was built under the following assumptions:

Scheduling and Routing Assumptions:

- Travel time between each sawmill and the pulp mill is known and considered to be a constant number;
- Service priorities for regular suppliers are in effect, meaning that the transportation penalties for unfulfilled transportation demands are different for different sawmills.
Trucking Assumptions:
- Trucks are the same type (regular trucks unloaded by a dumper) and the fleet size is fixed;
- Trucks are equipped with the same capacity, which is equal to the size of one wood chip load produced at a sawmill;
- All trucks in fleet are able to visit all sawmills;
- Trucks are able to visit sawmills at any time;
- Truck unloading time at the pulp mill is deterministic;
- There are no truck breakdowns or transportation delays in the planning week;
- There are no delays in truck unloading and the dumper does not need any maintenance during the planning week.

Loading Assumptions:
- Wood chips are the only wood product being transported and the transportation of different species does not affect the transportation time, loading, or unloading time;
- The number of weekly loads and the sawmill production plans are known;
- Moisture content of wood chips at all sawmills is the same;
- Loading time is deterministic and is constant for all sawmills;
- There are no delays in wood chip production and loading at sawmills.

The problem is decomposed into two sub-problems: 1) the truck assignment problem and 2) the truck scheduling problem. The truck assignment model minimizes the penalty associated with unfulfilled transportation demands in a week. The model determines the number of trips and the number of loads picked up from each sawmill by each truck in a weekly period. The truck scheduling model is designed to determine the task sequence for every truck and detailed weekly time schedules with the goal of minimizing the total waiting times while satisfying results of the truck assignment problem.

3.1.1 The Truck Assignment Problem
The truck assignment model determines the number of loads that each truck should pick up from each sawmill during the week. Here, the formulation and components of the mathematical models are introduced. Table 3, Table 4, and Table 5 respectively show the list of indices, parameters, and variables used in the truck assignment problem.
Table 3: List of indices used in the truck assignment problem

<table>
<thead>
<tr>
<th>Indices of parameters and variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i$</td>
</tr>
<tr>
<td>$j$</td>
</tr>
</tbody>
</table>

Table 4: List of parameters used in the truck assignment problem

<table>
<thead>
<tr>
<th>Parameters of the model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$ Number of sawmills</td>
</tr>
<tr>
<td>$M$ Number of trucks</td>
</tr>
<tr>
<td>$DelPen_i$ Penalty associated with a full truckload left at sawmill $i$ at the end of a week ($/load$)</td>
</tr>
<tr>
<td>$MaxTrHour$ Maximum allowed weekly hours for each truck</td>
</tr>
<tr>
<td>$L_i$ The numbers of truck loads produced at sawmill $i$ in one week</td>
</tr>
<tr>
<td>$TripTime_i$ Travel time from the pulp mill to sawmill $i$ or reverse</td>
</tr>
<tr>
<td>$PickUpDur$ Duration of loading at a sawmill</td>
</tr>
<tr>
<td>$UnLoadDur$ Duration of unloading at the pulp mill</td>
</tr>
<tr>
<td>$WaitTime_{ij}$ The average wait time of truck $j$ for transportation of all loads at sawmill $i$</td>
</tr>
</tbody>
</table>

Table 5: List of variables used in the truck assignment problem

<table>
<thead>
<tr>
<th>Variables of the model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$LeftLoads_i$ A non-negative integer variable denoting the number of truckloads left at sawmill $i$ at the end of the week</td>
</tr>
<tr>
<td>$x_{ij}$ A non-negative integer variable showing the number of loads truck $j$ hauls from sawmill $i$</td>
</tr>
</tbody>
</table>

The objective function (1) was calculated by multiplying the number of truckloads left at a mill at the end of the week by the penalty per truckload. Some sawmills clear their wood chip inventory at the end of each week by selling loads left in the yard to other customers, while other sawmills hold the wood chips in inventory and let the trucks transport it the following week. In the first case, the delay penalty is high because the profit that could have been gained from that load is lost forever but in the second case, the penalty is low and equal to weekly inventory holding cost.
The model includes the following constraints:

− Equation (2) determines the number of truckloads left at a sawmill at the end of each week based on number of truckloads produced in that sawmill and the total number of truckloads that were hauled by the fleet.
− Equation (3) ensures that the total number of loads to be picked up does not exceed the total sawmill production.
− Equation (4) ensures that the total working hours of a truck are less than the maximum hours permitted. The total working hours are calculated by multiplying the number of loads a truck hauls from each sawmill by the total trip time for that sawmill. The total trip time for each mill includes two-way travel time, loading time at the sawmill, unloading time at the pulp mill and average truck waiting time. The truck waiting time is assumed to be zero at first and later it is fixed based on results of the second model.

**Objective function**

\[
\text{Min } Z = \sum_{i=1}^{N} (\text{DelPen}_i \times \text{LeftLoads}_i)
\]

**Constraints**

\[
\text{LeftLoads}_i = L_i - \sum_{j=1}^{M} x_{ij}, \quad \forall i = 1, 2, ..., N
\]

\[
\sum_{j=1}^{M} x_{ij} \leq L_i, \quad \forall i = 1, 2, ..., N
\]

\[
\sum_{i=1}^{N} x_{ij} \times (2 \times \text{TripTime}_i + \text{PickUpDur} + \text{UnloadDur} + \text{WaitTime}_{ij}) \leq \text{MaxTrHour}, \quad \forall j = 1, 2, ..., M
\]

**3.1.2 The Truck Scheduling Problem**

Once the transportation assignment is completed, the truck scheduling model is applied to minimize waiting times. Like the truck assignment problem, the truck scheduling problem was formulated as a mixed integer programming model.
In a mathematical programming approach, the truck assignment and the truck scheduling models can be connected by feeding results of one model to the other model. At first, the truck assignment model should assume that truck waiting times are zero and calculate the number of weekly trips of each truck to each sawmill. Then the results should be used as input parameters in the scheduling model, which calculates truck schedules and waiting times. The schedules would violate the maximum weekly truck hours in the first model because waiting times are inevitable as a consequence of limited unloading capacity, gradual wood chips production at mills, and driver working hours. The average waiting times obtained in the truck scheduling model should be used to update parameters in the truck assignment model. The model should be solved again and the results could be used to update the number of weekly trips and destinations in the truck scheduling model. This exchange of results should be continued until the results of the two models converge. The approach explained here is based on exact methods and because of the size and complexity of the truck scheduling model, it is not practical. As a result, the solution approach in this study is based on a metaheuristic method called Simulated Annealing and it further described in Sections 3.2 and 3.5.

In the case study it was assumed that the dumper has an unloading capacity of one truck at a time and each unloading task takes fifteen minutes. For the purpose of modeling, the weekly transportation period was broken into $7 \times 24 \times 4 = 672$ fifteen-minute time segments starting from Monday 12:00 am and ending at Sunday 11:45 pm. In this way, Monday 12:00 am was considered as $t = 1$, Monday 12:15 am was considered as $t = 2$, ..., Tuesday 12:00 am was considered as $t = 97$, ..., and Sunday 11:45 pm was considered as $t = 672$. All the time units used in the following model were based on this time segment concept. For example, if the travel time from sawmill 1 to the pulp mill is 2:30 hours, this parameter was equal to 10 time units or if a truck arrived to the pulp mill on Monday 9:00 am, the arrival time was $t = 37$.

Some of the modeling components that are common with the previous model and are not repeated here. These components include $i$ and $j$ (available in Table 3), $N$, $M$, $L_i$, $TripTime_i$, $PickUpDur$ and $UnloadDur$ (available in Table 4). The other indices, parameters, and variables used in the truck scheduling model, are displayed in Table 6, Table 7, and Table 8.
Table 6: List of indices used in the truck scheduling problem

<table>
<thead>
<tr>
<th>Indices of parameters and variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k$</td>
</tr>
<tr>
<td>Represents the index of $k$th load of wood chips at a sawmill</td>
</tr>
<tr>
<td>$u$</td>
</tr>
<tr>
<td>Represents the index of $u$th trip of truck $j$</td>
</tr>
<tr>
<td>$t$</td>
</tr>
<tr>
<td>Represents the index of $t$th weekly time segment ($t \in T$)</td>
</tr>
</tbody>
</table>

Table 7: List of parameters used in the truck scheduling problem

<table>
<thead>
<tr>
<th>Parameters of the model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$U_j$</td>
</tr>
<tr>
<td>The total number of trips assigned to truck $j$ during the week (This parameter is the result of the assignment problem being fed into the sequencing and scheduling problem and it is equal to $\sum_{i=1}^{N} x_{ij}$)</td>
</tr>
<tr>
<td>$T$</td>
</tr>
<tr>
<td>The total number of time quarters in a week that the dumper is available</td>
</tr>
<tr>
<td>$WaitPen$</td>
</tr>
<tr>
<td>The penalty associated with the waiting time of a truck ($/\text{time segment}$)</td>
</tr>
<tr>
<td>$Assigned_{ij}$</td>
</tr>
<tr>
<td>The total number of loads truck $j$ picks from sawmill $i$ (This parameter is the result of the assignment problem being fed into the sequencing and scheduling problem and it is equal to $x_{ij}$)</td>
</tr>
</tbody>
</table>

Table 8: List of variables used in the truck scheduling problem

<table>
<thead>
<tr>
<th>Variables of the model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$WaitLoadedPM_{ijk}$</td>
</tr>
<tr>
<td>Waiting time of loaded truck $j$ at the pulp mill carrying load $k$ from sawmill $i$ during trip $u$</td>
</tr>
<tr>
<td>$WaitLoadedSM_{ijk}$</td>
</tr>
<tr>
<td>Waiting time of loaded truck $j$ at sawmill $i$ if carrying load $k$ from the mill during trip $u$</td>
</tr>
<tr>
<td>$WaitEmptyPM_{ijk}$</td>
</tr>
<tr>
<td>Waiting time of empty truck $j$ at the pulp mill if intended to carry load $k$ from sawmill $i$ during trip $u$</td>
</tr>
<tr>
<td>$WaitEmptySM_{ijk}$</td>
</tr>
<tr>
<td>Waiting time of empty truck $j$ at sawmill $i$ before picking load $k$ from the sawmill during trip $u$</td>
</tr>
<tr>
<td>$y_{ijk}$</td>
</tr>
<tr>
<td>Binary variable equal to 1 if truck $j$ is assigned to load $k$ of sawmill $i$ during trip $u$</td>
</tr>
<tr>
<td>$Seg_{ijkut}$</td>
</tr>
<tr>
<td>Binary variable equal to 1 if truck $j$ is assigned to load $k$ of sawmill $i$ during trip $u$ and is unloaded by the dumper at time segment $t$</td>
</tr>
<tr>
<td>$MillTime_{ijk}$</td>
</tr>
<tr>
<td>Arrival time to sawmill $i$ if truck $j$ is assigned to load $k$ of the sawmill during trip $u$</td>
</tr>
<tr>
<td>$Dep_{ijk}$</td>
</tr>
<tr>
<td>Pulp mill departure time if truck $j$ is assigned to load $k$ of sawmill $i$ during trip $u$</td>
</tr>
<tr>
<td>$PickUp_{ijk}$</td>
</tr>
<tr>
<td>Pick up time of load $k$ of sawmill $i$ if truck $j$ is assigned it during trip $u$</td>
</tr>
<tr>
<td>$Pr_{tk}$</td>
</tr>
<tr>
<td>Production time of the $k$th load at sawmill $i$</td>
</tr>
<tr>
<td>$Arr_{ijk}$</td>
</tr>
<tr>
<td>Truck arrival time to the pulp mill if truck $j$ is assigned to the $k$th load of sawmill $i$ in its $u$th trip</td>
</tr>
<tr>
<td>$UnTime_{ijk}$</td>
</tr>
<tr>
<td>Unloading time of the $k$th load of sawmill $i$ if truck $j$ is assigned to it in its $u$th trip</td>
</tr>
</tbody>
</table>

The objective function minimizes the truck waiting cost, which is calculated by multiplying the waiting cost per unit time by the total waiting time (5). The waiting cost per unit time included
truck ownership and operating costs, including fuel consumption, maintenance, and drivers wages. The total waiting times included the waiting times of loaded or empty trucks at the pulp mill or one of the sawmills.

The truck waiting time was minimized subject to the following constraints:

- Equations (6), (7), (8) and (9) express the waiting times as functions of other variables and parameters. They calculate the waiting times for empty trucks at a sawmill, loaded trucks at a sawmill, loaded trucks at the pulp mill and empty trucks at the pulp mill, respectively.
- Equation (10) ensures that the truck assignment specified by the first model is taken into account.
- Equation (11) specifies that if a truck is not responsible for hauling a load, then no departure time should be considered for that load and that truck.
- Equations (12), (13), (14) and (15) define time constraints and relations between pulp mill departures, travel to the sawmill, loading, return trip and unloading.
- Equations (16) and (17) constrain the dumper to one truck to be unloaded every time unit
- Equation (18) indicates that a truck can only be scheduled for a new departure after its unloading is complete.
- Equation (19) ensures that each truck is assigned to only one load from a sawmill during each trip.
- Equation (20) assigns every load produced in a mill to at most one trip of one truck.

The objective function

\[
\text{Min } Z = \text{WaitPen} \\
= \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{L_i} \sum_{u=1}^{U_j} \left( \text{WaitLoadedPM}_{ijk} + \text{WaitLoadedSM}_{ijk} \\
+ \text{WaitEmptySM}_{ijk} + \text{WaitEmptyPM}_{ijk} \right) \\
\times \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{L_i} \sum_{u=1}^{U_j} \left( \text{WaitLoadedPM}_{ijk} + \text{WaitLoadedSM}_{ijk} \\
+ \text{WaitEmptySM}_{ijk} + \text{WaitEmptyPM}_{ijk} \right) 
\]

Constraints

\[
\text{WaitEmptySM}_{ijk} = \text{PickUp}_{ijk} - \text{MillTime}_{ijk}, \quad \forall i = 1, 2, ..., N, \quad \forall j = 1, 2, ..., M, \quad k = 1, ..., L_i, \quad u = 1, 2, ..., U_j 
\]

\[
\text{WaitLoadedSM}_{ijk} = \text{Arr}_{ijk} - \text{PickUp}_{ijk} - \text{PickUpDur} \times \text{y}_{ijk} - \text{TripTime}_i \times \text{y}_{ijk}, \\
\forall i = 1, 2, ..., N, \quad \forall j = 1, 2, ..., M, \quad k = 1, ..., L_i, \quad u = 1, 2, ..., U_j 
\]
\( \text{WaitLoadedPM}_{ijk} = \text{UnTime}_{ijk} - \text{Arr}_{ijk}, \quad \forall i = 1, 2, \ldots, N, \quad \forall j = 1, 2, \ldots, M, \quad k = 1, \ldots, L_i, \quad u = 1, 2, \ldots, U_j \) \hfill (8)

\[ \sum_{k} \sum_{u} y_{ijk} \geq \text{assigned}_{ij}, \quad \forall i = 1, 2, \ldots, N, \quad \forall j = 1, 2, \ldots, M \] \hfill (10)

\[ \text{Dep}_{ijk} \leq M \times y_{ijk}, \quad \forall i = 1, 2, \ldots, N, \quad \forall j = 1, 2, \ldots, M, \quad k = 1, \ldots, L_i, \quad u = 1, 2, \ldots, U_j \] \hfill (11)

\[ \text{MillTime}_{ijk} \geq \text{Dep}_{ijk} + \text{TripTime}_i \times y_{ijk}, \quad \forall i = 1, 2, \ldots, N, \quad \forall j = 1, 2, \ldots, M, \quad k = 1, \ldots, L_i, \quad u = 1, 2, \ldots, U_j \] \hfill (12)

\[ \text{PickUp}_{ijk} \geq \max(\text{Pri}_k \times y_{ijk}, \text{Dep}_{ijk} + \text{TripTime}_i) \], \quad \forall i = 1, 2, \ldots, N, \quad \forall j = 1, 2, \ldots, M, \quad k = 1, \ldots, L_i, \quad u = 1, 2, \ldots, U_j \] \hfill (13)

\[ \text{Arr}_{ijk} \geq \text{PickUp}_{ijk} + \text{PickUpDur} \times y_{ijk} + \text{TripTime}_i \times y_{ijk}, \quad \forall i = 1, 2, \ldots, N, \quad \forall j = 1, 2, \ldots, M, \quad k = 1, \ldots, L_i, \quad u = 1, 2, \ldots, U_j \] \hfill (14)

\[ \text{UnTime}_{ijk} \geq \text{Arr}_{ijk}, \quad \forall i = 1, 2, \ldots, N, \quad \forall j = 1, 2, \ldots, M, \quad k = 1, \ldots, L_i, \quad u = 1, 2, \ldots, U_j \] \hfill (15)

\[ \text{UnTime}_{ijk} = \sum_{t \in T} t \times \text{Seg}_{ijk, t}, \quad \forall i = 1, 2, \ldots, N, \quad \forall j = 1, 2, \ldots, M, \quad k = 1, \ldots, L_i, \quad u = 1, 2, \ldots, U_j \] \hfill (16)

\[ \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k} \sum_{u} \text{Seg}_{ijk, t} \leq 1, \quad t \in T \] \hfill (17)

\[ \sum_{i=1}^{N} \sum_{k} \text{Dep}_{ijk(u+1)} \geq \sum_{i=1}^{N} \sum_{k} \text{UnTime}_{ijk} + \text{UnLoadDur}, \quad \forall j = 1, 2, \ldots, M, \quad u = 1, 2, \ldots, (U_j - 1) \] \hfill (18)

\[ \sum_{i=1}^{N} \sum_{k} y_{ijk} = 1, \quad \forall j = 1, 2, \ldots, M, \quad u = 1, 2, \ldots, U_j \] \hfill (19)

\[ \sum_{j=1}^{M} \sum_{u} y_{ijk} \leq 1, \quad \forall i = 1, 2, \ldots, N, \quad k = 1, \ldots, L_i \] \hfill (20)
The two models presented here are both integer programming models and hence, are among the most computationally difficult optimization problems. As a result, the solution approaches suggested by literature mainly consist of approximation methods that apply column generation, heuristics, and metaheuristics with increasing tendency toward metaheuristics. This research utilized a simulated annealing algorithm adapted for the wood chip truck assignment and scheduling problem under consideration.

3.2 Objective 1 Methods

The approach implemented in this thesis to solve the weekly chip truck routing and scheduling problem is using Simulated Annealing (SA). The reason for choosing a simulated annealing method is that the most recent studies on log truck scheduling, wood chips, and biomass truck scheduling have used simulated annealing methods and have obtained very good results.

Simulated annealing (SA) is a metaheuristic for solving complex optimization problems in a short time. It is a generic heuristic that was first introduced in 1983, and is mostly used for discrete optimization (Dowsland, 2012). Simulated annealing is designed to search the solution space for optima by progressively improving the solution through a number of iterations.

SA is an improved version of local search heuristics. In a local search process a neighbour solution is allowed to replace the current solution only if it introduces an improvement to the objective function. Consequently, the search process terminates once a local optimum is obtained. SA tries to find a global optimum and in order to escape local optimums, it also allows for acceptance of some non-improving solutions. However, in order to direct the total search process towards improvement, the non-improving solutions should be accepted in a controlled manner. The control rules in SA are inspired from a metal cooling process aimed to obtain ideal molecular arrangements.

The SA algorithm is designed to search the solution space for optima by progressively improving the solution through a series of iterations and accomplishes the following steps (Dowsland, 2012; Hillier & Lieberman, 2005):

1- Build an initial solution: As the first step, SA starts at an initial temperature value \( T_0 \); sets the current temperature value equal to initial temperature value \( T_c = T_0 \) and builds a feasible and random solution using a simulation model that takes into account all resources and constraints in the problem. The current objective function value \( Z_c \) is set equal to the objective function value for the initial solution.
2- Build a neighbour solution: During each iteration, the algorithm explores movement from one feasible answer to another. For each movement, all feasible neighbours of the current solution are candidates and one of them is randomly selected as the potential new solutions. Neighbour solutions are mostly identical except for minor attributes. The objective value of the potential new solution is calculated ($Z_n$).

3- Decide on movement: In this step, the algorithm decides whether to substitute the current solution with the potential new solution or not. If the potential solution improves the objective value, the algorithm accepts it as the new solution and continues the search by exploring its neighbors. If the potential new solution does not introduce an improvement to the objective function, it is accepted by a probability which depends on a parameter named temperature value ($T'$) and the level of damage to the objective function. Equation (21) shows the probability of acceptance of a non-improving solution as a new solution.

$$ Z_c: \text{Objective function value of current solution}, $$

$$ Z_n: \text{Objective function value of potential next solution} $$

$$ T_c: \text{Temperature value, a parameter that shows the tendency to accept the potential solution as the new solution if it does not improve the objective function, for a maximization objective value.} $$

If $Z_n \geq Z_c$, accept the potential solution,

If $Z_n < Z_c$, accept the potential solution with the probability of:

$$ \text{Prob(acceptance)} = e^x, \quad \text{where} \quad x = \frac{Z_n - Z_c}{Z_c \times T_c} $$

4- Complete the current stage: Whether the system has moved to a new solution or not, Steps 2 and 3 should be repeated for a certain number of iterations. The number of iterations is an analogy for the time length the metal should be held at each temperature value and it is a parameter that should be set before beginning the simulated annealing process.

For large problems, the feasible region can be searched more accurately by using a large number of iterations at each temperature value and by decreasing temperature value more slowly.

5- Move to the next temperature value: Lower the temperature to the next value defined by the annealing procedure and using the current solution, start again from Step 2, while
considering the current temperature value to be equal to the new temperature value. Simulated annealing usually starts with a large temperature value, which allows for worse solution easily, just as metal annealing process allows for a lot of molecular disarrangements in high temperatures. This strategy in simulated annealing is designed to prevent the solution from being limited to a local optimum and facilitates a process similar to random search at early solving stages. As the search goes further and after a certain number of iterations, the temperature value is decreased and the probability of acceptance of non-improving solutions decreases. This gradual temperature reduction gives higher priority to improving candidates in advanced steps of the search process.

6- Terminate the algorithm: After the algorithm completes the required steps for the final temperature value, it reports the best solution found in the search process for the optimization problem.

3.3 Objective 2 Methods

The approach implemented to identify important structural parameters and evaluate their impact on wood chip transportation network is based on sensitivity analysis and scenario analysis. In order to evaluate the feasibility of an investment that improves a business, managers should make decisions that maximize the profit or minimize the cost (Berk et al., 2012). Sensitivity analysis and scenario analysis can help managers to assess different improvement plans and their effect on transportation cost (Beaudoin et al., 2007); both methods can aid managers to decide whether or not to make an investment.

The main difference between sensitivity analysis and scenario analysis is that sensitivity analysis investigates the effects of changing one parameter while scenario analysis investigates the effects of changing a number of interrelated parameters. To conduct a sensitivity analysis, a certain variable in the model is changed to see how the revenues or costs are affected. To conduct scenario analysis, a number of related variables are changed at a time to create a number of alternative scenarios and evaluate their effect on revenues or costs (Brealy et al., 2014).

In Chapter 5, a sensitivity and scenario analysis is performed producing results that can be used as a tactical or strategic tool to help managers of pulp mills to improve the structure of the wood chip transportation network. Sensitivity analysis is performed to assess the impact of the number of trucks and the number of dumpers on transportation costs, waiting times, and unmet transportation tasks. Scenario analysis along with simulated annealing was used to calculate
transportation costs, waiting times, and unmet transportation demands as a result of changes in truck types and drivers’ switch point locations.

### 3.4 Case Study Data and Description

This section describes the conditions and constraints related to suppliers, the transportation network, and the pulp mill. Figure 1 provides an overview of the wood chip supply and transportation network.

![Figure 1: The wood chip supply and transportation network](image)

A case study was conducted on a pulp mill located in the interior of British Columbia (BC), Canada. Specifically, the case featured a pulp mill producing northern bleached softwood kraft pulp (NBSK). The pulp mill is a cogeneration plant with a wood waste boiler and produces both pulp and electricity. Wood chips needed by the pulp mill are provided by truck transportation mainly from eight to ten sawmills. Some of these sawmills are located in Canada and some are located in the United States. Wood chip loads transported to the pulp mill are dumped and kept in inventory before being used to produce NBSK.
A series of informal interviews were conducted with the case study mill personnel, specifically the fibre supply manager of the corporation that owned the pulp mill, the pulp mill manager, and the pulp mill dispatchers. To protect confidentiality of the pulp mill and its personnel, this study does not disclose the names of interviewees. The specifications of the wood chip supply and transportation network for the case study are presented below.

3.4.1 Suppliers

Sawmills are the dominant suppliers of wood chips to pulp mills. A secondary source of wood chips is whole log chipping using an industrial chipper. In this study, wood chip sources are sawmills. The pulp mill under study may have up to thirty wood chip suppliers at a time but eight to ten sawmills are the main suppliers. To access each sawmill, the shortest paths are known and taken by the trucks; the travel time for each sawmill is calculated based on truck speed limits and experience of actual travel time and it is assumed to be the same for all trips made to a sawmill. The average one-way travel times between the pulp mill and the main supplier mills are presented in Table 9 and the travel time is the same in either direction.

Table 9: One way travel time from the sawmills to the pulp mill (hours)

<table>
<thead>
<tr>
<th>Sawmill</th>
<th>A2</th>
<th>A3</th>
<th>CA2</th>
<th>B9</th>
<th>B10</th>
<th>P31</th>
<th>U21</th>
<th>U41</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel time</td>
<td>0:45</td>
<td>1:45</td>
<td>0:45</td>
<td>4:45</td>
<td>3:45</td>
<td>4:00</td>
<td>2:30</td>
<td>5:00</td>
</tr>
</tbody>
</table>

Sawmills have different wood chip production rates, which depends on their working schedule, sawing patterns, and capacity. The main suppliers usually have one-year-contracts with pulp mills based on bone dry tonnes of wood chip supply. However, the demand is assessed on a weekly basis and at the end of each week, sawmills announce their approximate production rate of wood chips for the following week and based on that, the dispatcher at the pulp mill forecasts when and where a new load will be ready for pick up. For the purpose of model testing, pulp mill supply data from a week in March 2012 was used. The reason that this time of year was selected is that it is when the wood chip supply and production is in its peak and the need for efficient transportation planning is greatest. Table 10 shows the number of daily load produced in the sawmills, the working days, and working hours for each supplier for this sample week. Sawmills run four or five days a week and they worked for ten, twelve, or twenty-four hour shifts. Despite restricted sawmill working hours, wood chip storage areas were open to trucks at any time during the week. The wood chip transportation cost is based on a load-by-load basis (calculated in bone dry tonnes); however, for transportation planning wood chips are generally
expressed as truckloads. One truckload of wood chips is the weight of a load that a truck can carry and normally the maximum weight limit of a load is met before the maximum volume limit.

Table 10: Sample data for one week showing the number of daily loads, running days and working hours for sawmills

<table>
<thead>
<tr>
<th>Sawmill</th>
<th>Number of daily truckloads of wood chips produced</th>
<th>Running days and working hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>A2</td>
<td>28</td>
<td>28</td>
</tr>
<tr>
<td>A3</td>
<td>42</td>
<td>42</td>
</tr>
<tr>
<td>CA2</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>B9</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>B10</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>P31</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>U21</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>U41</td>
<td>7</td>
<td>7</td>
</tr>
</tbody>
</table>
Based on Table 10, the production plan of wood chip loads at each sawmill was calculated and is shown in Table 11.

**Table 11: Daily wood chip production plan at sawmills**

<table>
<thead>
<tr>
<th>A2</th>
<th>A3</th>
<th>CA2</th>
<th>B9</th>
<th>B10</th>
<th>P31</th>
<th>U21</th>
<th>U41</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>Daily</td>
<td>Daily</td>
<td>Daily</td>
<td>Weekly</td>
<td>Daily</td>
<td>Daily</td>
<td>Daily</td>
</tr>
<tr>
<td>6:22 AM</td>
<td>6:15 AM</td>
<td>6:21 AM</td>
<td>7:39 AM</td>
<td>10:07 AM</td>
<td>7:35 AM</td>
<td>7:30 AM</td>
<td>7:30 AM</td>
</tr>
<tr>
<td>6:45 AM</td>
<td>6:30 AM</td>
<td>6:42 AM</td>
<td>8:48 AM</td>
<td>2:15 PM</td>
<td>9:10 AM</td>
<td>9:00 AM</td>
<td>9:00 AM</td>
</tr>
<tr>
<td>7:07 AM</td>
<td>6:45 AM</td>
<td>7:03 AM</td>
<td>9:57 AM</td>
<td>6:22 PM</td>
<td>10:46 AM</td>
<td>10:30 AM</td>
<td>10:30 AM</td>
</tr>
<tr>
<td>7:30 AM</td>
<td>7:00 AM</td>
<td>7:24 AM</td>
<td>11:06 AM</td>
<td>10:30 PM</td>
<td>12:21 PM</td>
<td>12:00 PM</td>
<td>12:00 PM</td>
</tr>
<tr>
<td>7:52 AM</td>
<td>7:15 AM</td>
<td>7:45 AM</td>
<td>12:15 PM</td>
<td>2:37 AM</td>
<td>1:57 PM</td>
<td>1:30 PM</td>
<td>1:30 PM</td>
</tr>
<tr>
<td>8:15 AM</td>
<td>7:30 AM</td>
<td>8:06 AM</td>
<td>1:24 PM</td>
<td>6:45 AM</td>
<td>3:32 PM</td>
<td>3:00 PM</td>
<td>3:00 PM</td>
</tr>
<tr>
<td>8:37 AM</td>
<td>7:45 AM</td>
<td>8:27 AM</td>
<td>2:33 PM</td>
<td>10:52 AM</td>
<td>5:08 PM</td>
<td>4:30 PM</td>
<td>4:30 PM</td>
</tr>
<tr>
<td>9:00 AM</td>
<td>8:00 AM</td>
<td>8:48 AM</td>
<td>3:42 PM</td>
<td>3:00 PM</td>
<td>6:43 PM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9:22 AM</td>
<td>8:15 AM</td>
<td>9:09 AM</td>
<td>4:51 PM</td>
<td>7:07 PM</td>
<td>8:19 PM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9:45 AM</td>
<td>8:30 AM</td>
<td>9:30 AM</td>
<td>6:00 PM</td>
<td>11:15 PM</td>
<td>9:54 PM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10:07 AM</td>
<td>8:45 AM</td>
<td>9:51 AM</td>
<td>3:22 AM</td>
<td>11:30 PM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10:30 AM</td>
<td>9:00 AM</td>
<td>10:12 AM</td>
<td>7:30 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10:52 AM</td>
<td>9:15 AM</td>
<td>10:33 AM</td>
<td>11:37 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11:15 AM</td>
<td>9:30 AM</td>
<td>10:54 AM</td>
<td>3:45 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11:37 AM</td>
<td>9:45 AM</td>
<td>11:54 AM</td>
<td>7:52 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12:00 PM</td>
<td>10:00 AM</td>
<td>11:36 AM</td>
<td>12:00 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12:22 PM</td>
<td>10:15 AM</td>
<td>11:57 AM</td>
<td>4:07 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12:45 PM</td>
<td>10:30 AM</td>
<td>12:18 PM</td>
<td>8:15 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1:07 PM</td>
<td>10:45 AM</td>
<td>12:39 PM</td>
<td>12:22 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1:30 PM</td>
<td>11:00 AM</td>
<td>1:00 PM</td>
<td>4:30 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1:52 PM</td>
<td>11:15 AM</td>
<td>1:21 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2:15 PM</td>
<td>11:30 AM</td>
<td>1:42 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2:37 PM</td>
<td>11:45 AM</td>
<td>2:03 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3:00 PM</td>
<td>12:00 PM</td>
<td>2:24 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3:22 PM</td>
<td>12:15 PM</td>
<td>2:45 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3:45 PM</td>
<td>12:30 PM</td>
<td>3:06 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4:07 PM</td>
<td>12:45 PM</td>
<td>3:27 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4:30 PM</td>
<td>1:00 PM</td>
<td>3:48 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1:15 PM</td>
<td>4:09 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Sawmills do not have equal priorities in terms of pickup schedules. Wood chip transportation networks quickly become complex because of their unique attributes. For example, sawmills with high production rates that are close to the pulp mill may be considered high priority mills. In the case study, a high service level must be provided for sawmills A2, A3, and CA2.

Sawmill wood chip storage systems are also varied. Wood chips can be stored in a bin, stockpiled on the ground or stored in trailers left at the sawmill. The primary method is using an overhead wood chip bin with a capacity of a few truckloads (Figure 2). Many sawmills prefer their bin to be emptied by the end of each week. The secondary option for wood chips storage is to make a stockpile on the ground that can store wood chips for up to two months. Stockpiling provides more flexibility for the transportation system but it is not favourable to sawmills because it is more expensive – largely because it requires more labour and equipment resources compared to bin storage – and it results in fibre quality degradation and volume losses. Moreover, in most cases sawmills will not stockpile wood chips on the ground if they have alternate chip customers. The third and final option for wood chip storage is to leave extra trailers at sawmills. Extra trailers can temporarily increase the storage capacity without stockpiling. Like bin storage, extra trailer storage should be cleared at the end of every week. In the case study, all sawmills have enough storage capacity and wood chip storage is not a constraint. All sawmills utilize a wood chip bin with the storage capacity of a few truckloads. A
number of them allow stockpiling and the rest increase storage capacity as needed by leaving extra trailers at the mills.

![Photo by case study pulp mill manager](image)

**Figure 2: Overhead bin and truck loading at a sawmill**

### 3.4.2 The Transportation Fleet

The transportation fleet consists of trucks rented from a hauling company. Most trucks are of the same type with common trailer capacity. Each truck is operated by two drivers alternating shifts during the week. For each driver there are working hour constraints that must be respected. In Canada, the normal shift length is ten to twelve hours and it is acceptable to vary the length of a shift by two hours from one day to the next. However, the maximum allowed driving time is fourteen hours and each working shift should follow ten consecutive hours off duty. The drivers should work an average of 55 hours per week followed by 34 or more consecutive hours off duty (Ministry of Transportation and Infrastructure, 2011). A driver starts his working shift at the pulp mill (or an acceptable driver switch point) then heads toward a sawmill specified by the truck dispatcher. After a maximum number of hours, the driver leaves the truck at the pulp mill or at an acceptable switch point for the next driver. In the case study, the switch points include the pulp mill, sawmill A2, sawmill CA2, and sawmill B10.

### 3.4.3 The Consumer

For the purposes of this study, the pulp mill is considered as the only consumer in the wood chip transportation network. Presently, the pulp mill's production capacity is 750 ADMT (air dry metric tonne) of pulp per day but the pulp mill can be utilized to produce up to 900 ADMT of pulp per day. Considering the pulp yield of 0.48 ADMT per bone dry tonne (BDT) (Biermann, 1996) and average truckload weight of 20 BDT based on pulp mill's historical data, the pulp mill consume an average of 80 truckloads of wood chips every day. The wood chip storage at the
pulp mill is facilitated in three chip piles. Wood chips can be stored in stockpile on ground for up to two months. The surplus storage in piles can supply wood chips if there are delays in deliveries, which is common during the winter months.

The pulp mill has a limited truck unloading capacity. It utilizes a single hydraulic dumper for truck unloading that can serve one truck at a time with the average service time of fifteen minutes. If the dumper is busy at the arrival time of a truck, the truck waits in a line. The dumper is the main bottleneck of the supply network and the major source of truck waiting. Often, the truck arrival rate exceeds the dumper’s service rate, which results in delays for trucks and drivers. These waiting times are the major source of inefficiency and result in increased number of trucks, working hours, and transportation costs. Other than the annual maintenance period, the pulp mill operates 24/7. The dumper is down twice a day, each time for half an hour for operator shift changing and there are about four hours of preventive maintenance every week, with a twenty-four-hour notice. The dumper has unexpected breakdowns once or twice a week for an average of two to four hours. Taking these factors into consideration, the dumper can unload 92 trucks in a day if no maintenance takes place.

In this case study, transportation planning relies on the experience of the truck dispatchers and is performed manually. This system is time consuming and dependent on a highly skilled dispatcher. A better approach for quickly updating the system in near real time would be to re-assign a series of optimal destination sequences and time schedules to each truck.

A system for truck routing and scheduling improvement can help truck dispatchers to increase transportation efficiency. It can also reduce transportation costs, increase sawmill satisfaction by providing improved transportation service levels, and provide a better work environment for drivers.

This study developed a system to support weekly wood chip truck routing and scheduling decisions and to address some key inefficiencies. The objective of the model was to minimize transportation costs, which translated into minimizing truck waiting times and transportation delays. The weekly time schedule for each truck included the number of trips as well as the destination mill for each trip, pulp mill departure time, load pickup time at the sawmill, arrival time to the pulp mill, and unloading time. It also tracked drivers for each trip, the number of working hours for each driver, locations where drivers should meet for shift changeovers (switch points), and waiting times for loaded and unloaded trucks either at the pulp mill or the sawmills.
3.4.4 The Objective Function

The objective function for the case study was to minimize the total penalty related to unmet transportation demands and truck waiting times in the planning week. In this study, the transportation tasks are known and fixed at the start of each week, which means that some cost components would not affect the solution. These factors include: costs related to truck times spent on travel between the pulp mill and the sawmills, service at the sawmills (loading and pre-trip check-ups) and service time at the pulp mill – unloading (excluding waiting times), check-ups, and truck weighing before and after unloading. As a result, it was sufficient to minimize the total penalties related to transportation delays and truck waiting times in order to increase the transportation service level to high priority sawmills and at the same time increase the trucks productivity. The objective function for the case study is displayed in Equation (22) and is the summation of the functions presented in Equations (1) and (5).

\[ \text{Objective function} = \text{Truck Waiting Penalty} + \text{Transportation Delay Penalty} \] (22)

In which, the truck waiting penalty and the transportation delay penalty are:

\[ \text{Truck waiting penalty for each truck} = 115.27 \times \text{total truck waiting hours} \]

\[ \text{Transportation delay penalty for each mill} = 6,645 \times \text{Number of delayed truckloads from mills A2, A3, CA2} + 9 \times \text{Number of delayed truckloads from mills B9, B10, P31, U21, U41} \]

See Appendix A for detailed calculations on the cost coefficients presented above.

3.5 Case Study Simulated Annealing Model

A general SA procedure was explained in Section 3.2. For the rest of this section, the details of each step for the simulated annealing adapted for wood chip truck routing and scheduling are explained.

3.5.1 Building an Initial Solution

In the initiation phase, a discrete event and deterministic simulation model is used to build a feasible starting solution. The simulation model is based on constraints introduced at the beginning of Chapter 4. Each time the model needs to assign a destination sawmill to a truck, it
checks to see which sawmills are eligible for the next trip and selects one at random. Figure 3 shows how the first trip is assigned to each truck.

Figure 3: Flow chart for the assignment of the first trip to each truck

After assigning the first trip to each truck, the simulation continues truck routing and scheduling considering the relations between truck arrival times to the pulp mill, dumper unloading capacity, unloading duration, travel time to sawmill, load availability at sawmill, load pick up time, loading duration, travel time to pulp mill, and driver working hour limitations. Trucks are assigned to transportation trips until all loads are transported or all drivers work up to their maximum allowed weekly hours. Figure 4 shows how the weekly schedule is built after determination of the first trips.
Once, the initial solution is built, it is passed to the improvement phase to start the optimization process. In addition to truck routes and schedules, the following measures are calculated and passed to the next step: truck waiting times for loaded and empty trucks at the pulp mill or at a sawmill, the total unfulfilled demand orders (transportation delays), and the total hauling cost.
3.5.2 Constructing a Neighbour Solution

The improvement phase begins by building a second feasible solution in the neighbourhood of the initial solution space identified in the initiation phase. In the proposed SA method, the following routines are applied in the neighbour construction process: delay improvement, schedule altering, inventory controller, and driver hour controller. The delay improvement routine is used to decrease the transportation delay penalty and the schedule altering routine is used to decrease truck wait times. The inventory controller routine keeps track of trucks assigned to tasks in order to prevent duplicate task assignments. The driver hour controller routine is applied to make sure that total shift duration and total weekly hours of a driver is in accordance with regulations. The first two routines are used to adjust an existing solution to a new solution and are applied sequentially. The remaining two routines are applied to ensure that the solutions are feasible and they are implemented several times inside the first two routines. A more detailed description of the four routines is provided below.

The delay improvement routine is beneficial when there is an unfulfilled demand from a high priority sawmill. The weekly surplus is referred to as a transportation delay and specifically refers to the number of loads that are not planned for transport in the weekly schedule due to limited truck availability. Transportation of those loads is, by default, postponed to the following week or the sawmill may choose to sell to another customer and the pulp mill loses out on those loads. When the delay improvement routine is implemented, it randomly selects a delayed order from a high priority mill, then randomly selects a truck and one of its trips to a lower priority mill, removes the low priority task from the schedule and inserts the high priority task in its place. Figure 5 shows an application of this routine to a truck. Diagram (a) shows the sequence of trips for one truck. Assume that based on the existing truck routes, three loads are left in each of the sawmills 1 to 5. Since it is important to provide a good transportation service to sawmill 1 (the sawmill with the highest priority level), one of the lowest priority trips (to sawmill 5) is selected randomly and its destination is altered with a visit to sawmill 1. Diagram (b) shows the sequence of trips for the same truck after applying the delay improvement routine. The delay improvement routine always reduces the total delay penalty because it never switches the sawmills if the result is not an improvement. However, it may increase the total truck waiting times.
Figure 5: Task sequence of a truck before and after applying the delay improvement routine

The schedule altering routine changes the sequence of visited sawmills for a single truck in the hope of reducing the total waiting times. The routine randomly select a truck and switches the order of visits to two sawmills. Figure 6 shows an example of the visits sequence for a truck before (diagram (a)) and after applying the schedule altering routine (diagram (b)). The order of the third and the sixth sawmills in the sequence has been switched. The routine does not affect weekly unfulfilled demands and it only affects truck waiting times.

Figure 6: Task sequence for a truck before and applying the schedule altering routine

The inventory controller routine is implemented to ensure that the feasibility of a solution is not violated because of double allocation of one load to more than one truck and one visit. It keeps track of sawmill production plans and their inventory levels. When a truck is assigned to a load, the routine puts a label on it to prevent double booking.

The driver hour controller routine schedules the shift start time and shift end time for a driver based on hours on duty, hours off duty, relevant partners’ hours, production plans, and load availability at sawmills. The first shift of a truck begins at the pulp mill and the last shift ends at the pulp mill. However, during the week, drivers can change shifts at either the pulp mill or one of the switch point sawmills. When a driver wants to start a new trip, the controller may not allow...
assigning a new task or it may restrict the destinations based on driver’s hours on duty, travel times, and inventory levels at the sawmills. The routine also decides on driver shift changing locations and whether a task should be accomplished by one or two drivers. For example, a driver may take a load to the pulp mill and leave the loaded truck in the yard because of his working hour restrictions. Then, his partner can start his shift by unloading a loaded truck. Taken together, these routines help to identify a possible neighbour solution in the local solution space. Then, the algorithm needs to decide whether to accept the revised solution or not.

3.5.3 Deciding on the Movement
After building a new feasible solution, the algorithm has to evaluate whether to accept it or not. The decision to move to a new feasible solution is based on the quality of the neighbour solution, which is evaluated based on its objective function value. When a new feasible solution is built, the objective function is calculated based on transportation delays and truck waiting times. If a potential new solution shows an improvement to the objective function, it is accepted as the new current solution. However, if it deteriorates the objective value, SA accepts it as the new current solution with a probability defined in equation (21). Then the algorithm continues the search process with the current solution.

3.5.4 Completing the Current Stage
At each stage of SA, the temperature value is kept constant and the steps related to neighbourhood construction, neighbourhood evaluation and decision about the movements are repeated for a number of iterations. According to Kendall (2014), one obvious approach is to use a constant number of iterations at each temperature value. This method is simple and results in a predictable solution time; consequently, this research uses a constant number of iterations at each temperature value. In order to determine the suitable number of iterations for each temperature level, a series of sample runs were conducted to test the following iteration levels: 10, 50, 100, 300, 500 and 1000. For each iteration level, SA was conducted for 10 independent runs.

Table 12 shows the average level of improvement obtained in the final objective function compared to the initial objective function and the average solution time for the test runs.
Based on the results, as the number of iterations increases, both the level of improvements in the solution and the solution time increases. However, it seems that the level of improvement from 300 iterations to 500 or 1000 iterations does not change significantly but the solution times for 500 iterations and 1000 iterations are almost twice and four times as the solution time for 300 iterations. As a result, in this study, 300 iterations for each temperature value were used.

### 3.5.5 Moving to the Next Temperature Value

Upon completing a stage, a new stage is initiated by moving to the next temperature value. The temperature values are identified in the temperature schedule, which uses an initial temperature, the cooling rate, and the final temperature value to discern what values will be used. The selection of the initial temperature value is very important. A very low initial temperature value does not allow SA to reach the global optimum solution because it only permits very limited acceptance of non-improving solutions and limits the search to a local search around the initial solution. On the other hand, a very high temperature value results in waste of valuable solution time (Dowsland, 2012).

The initial temperature value determines the chance of admitting a deteriorating solution in the first iterations of the algorithm. A frequently used method to calculate the appropriate initial temperature value is based on using a priori information about the problem. In this method, a number of sample runs for the problem are performed, the objective function values are calculated, and $T_0$ is defined in a way that the maximum variation to the objective function is accepted with a probability close to one (Dowsland, 2012). Based on the probability of acceptance of a non-improving solution, $T_0$ for the wood chip truck with a minimization objective function is calculated based on equation (23). A number of sample runs for the wood chip truck routing and scheduling problem were performed and the results showed a maximum variation of

<table>
<thead>
<tr>
<th>Number of iterations</th>
<th>Number of trucks: 20</th>
<th>Number of trucks: 40</th>
<th>Number of trucks: 60</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Solution imp. (%)</td>
<td>Solution time (h:mm:ss)</td>
<td>Solution imp. (%)</td>
</tr>
<tr>
<td>10</td>
<td>25</td>
<td>0:00:19</td>
<td>10</td>
</tr>
<tr>
<td>50</td>
<td>72</td>
<td>0:01:34</td>
<td>20</td>
</tr>
<tr>
<td>100</td>
<td>80</td>
<td>0:03:03</td>
<td>25</td>
</tr>
<tr>
<td>300</td>
<td>83</td>
<td>0:09:09</td>
<td>41</td>
</tr>
<tr>
<td>500</td>
<td>83</td>
<td>0:15:43</td>
<td>41</td>
</tr>
<tr>
<td>1000</td>
<td>83</td>
<td>0:34:20</td>
<td>41</td>
</tr>
</tbody>
</table>
10% in randomly produced objective values. Considering an acceptance probability of 90%, the appropriate value of the initial temperature value was equal to $T_0 = 0.95$.

$$T_0 = -\frac{\text{Maximum Variation in the objective function}}{\text{Ln(Prob(acceptance))}} \quad (23)$$

The cooling rate determines how the temperature values are decreased in the SA. Like the initial temperature value, it is important to use the right cooling rate. A very fast cooling schedule may transform SA to a local search process and a very slow cooling rate wastes computational time. A popular cooling schedule used in practice is the geometric schedule in which the temperatures are calculated according to equation (24). The literature suggests $\alpha$ to be in the range of 0.8-0.99 (Dowsland, 2012). In this study, $\alpha = 0.8$ was used.

$$T_k = \alpha^k \times T_0 \quad (24)$$

The final temperature value defines the probability of acceptance of a non-improving solution in the final runs of SA. In the final steps, the temperature value should be reduced to a value close to zero. In this study, the final temperature value is defined in a way that near the end, the deteriorating solutions that are only 10% worse than the previous solution are accepted with a probability of less than 10%. Based on the cooling schedule described in this section, the temperature coefficients for the proposed SA are presented in Table 13. The table also shows the probability of accepting a deteriorating solution that is 10%, 20%, or 50% worse than the previous solution based on temperature coefficients defined in the table.

<table>
<thead>
<tr>
<th>Probability of</th>
<th>Temperature coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>acceptance</td>
<td>0.95 0.76 0.61 0.49 0.39 0.31 0.25 0.2 0.16 0.13 0.1 0.08 0.07 0.05 0.04</td>
</tr>
<tr>
<td>Deterioration</td>
<td>10%</td>
</tr>
<tr>
<td>level compared to previous solution</td>
<td>20%</td>
</tr>
<tr>
<td></td>
<td>50%</td>
</tr>
</tbody>
</table>

### 3.5.6 Terminating the Algorithm

For each temperature value, the algorithm is repeated 300 iterations; then, the temperature value is decreased to its next value. After running the algorithm for all temperatures and all iterations, the search process is terminated and the best found schedule for the week is reported.

Chapter 4 presents the results of application of the simulated annealing method to the case study and also includes discussion and conclusions.
4 Base Case Results and Discussion

The simulated annealing algorithm for wood chip truck routing and scheduling was programmed in MATLAB R2013b (The MathWorks Inc., 2013). The model was implemented with real data and it was validated by the fibre supply manager at the pulp mill. The input data, which included the number of weekly truckloads of wood chips produced in each sawmill, wood chip production schedules, and travel times were inserted into an Excel file and the MATLAB code read the file at the beginning of each run. The other input parameters related to the number of trucks, cost coefficients, penalty coefficients, high priority sawmills, driver switch point locations, maximum driver hours in a shift and in a day, and the minimum driver rest times were directly defined in the MATLAB code. After completion of each run, the results were saved to a MATLAB formatted binary file named MAT-file. In order to evaluate and use the results, the objective function values, the schedules, and other required information were retrieved from the MAT-file and saved to an Excel file.

For each MATLAB run, the number of trucks was held constant and a computer with CPU of 3.40 GHz was used. The solution time depended on the number of trucks and the number of iterations in the simulated annealing process. For the sample run, the truck routes, schedules, and the driver schedules were checked to ensure that the model met the requirements, specifications, and regulations considered for the problem.

4.1 Results

The outputs of the model included weekly truck routes, schedules, and drivers’ schedules as well as costs and penalties used to evaluate the results. The model can be updated at any time during the week to determine revised truck routes, schedules, and driver schedules until the end of the week.

Table 14 shows an example of the model’s output for one of the trucks based on 15 minute time segments. According to Table 14, truck 1 starts the week with driver 1 and the first trip assigned to the truck is sawmill 3 (CA2). The pulp mill departure time for the first trip is time segment 24 (Monday 5:45 a.m.); at the time of departure, the driver has only worked for one time segment (15 minutes for truck check). The truck arrives to the pulp mill after 3 time segments (45 minutes) on Monday 6:30 a.m., picks the load (load pick up and truck checking takes 30 minutes) and arrives to the pulp mill at time segment 32 (Monday 7:45 a.m.); since the dumper is available at Monday 7:45 a.m., the truck is unloaded and there are no waiting times involved. At the time of arrival the driver has worked for 9 time segments (2:15 hours); and after
unloading and truck weighing, he has worked for 11 time segments (2:45 hours). In the same way, the truck and the driver are assigned to the second trip, which is again to sawmill 3 (CA2). The truck comes back from the second trip at time segment 42 (Monday 10:15 am) but the dumper is busy with other trucks until time 52 (Monday 12:45 p.m.); so the loaded truck has to wait at the pulp mill for 10 time segments (2:30 hours). After unloading the wood chips, the truck goes to the third trip, which is to sawmill 1 (A2) and comes back at time 62 (3:15 p.m.) but the dumper is booked until time segment 73 (5:30 p.m.). Since the driver has already worked for 39 time units (9:45 hours), his shift is over and the shift changing takes place. Consequently, driver number 2 starts his shift by unloading a truck at the pulp mill. In the same way, the tasks are scheduled until the shift for driver 2 is over and driver number 1 starts another shift. These steps are repeated and the tasks are assigned to the trucks until the maximum weekly hours of the drivers is reached.
Table 14: Detailed weekly schedule for one truck for SA run 1

<table>
<thead>
<tr>
<th>Truck</th>
<th>Mill</th>
<th>Driver at dep.</th>
<th>Dep. at dep.</th>
<th>Driver time at dep.</th>
<th>Driver at arr.</th>
<th>Driver time at arr.</th>
<th>Unloading driver</th>
<th>Driver time after unloading</th>
<th>Loaded at pulp mill</th>
<th>Empty at pulp mill</th>
<th>Loaded at sawmill</th>
<th>Unloaded at sawmill</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
<td>1</td>
<td>24</td>
<td>1</td>
<td>27</td>
<td>32</td>
<td>1</td>
<td>9</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>1</td>
<td>34</td>
<td>11</td>
<td>37</td>
<td>42</td>
<td>1</td>
<td>19</td>
<td>1</td>
<td>31</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>54</td>
<td>31</td>
<td>57</td>
<td>62</td>
<td>1</td>
<td>39</td>
<td>2</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>75</td>
<td>3</td>
<td>78</td>
<td>83</td>
<td>2</td>
<td>11</td>
<td>2</td>
<td>23</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>2</td>
<td>95</td>
<td>23</td>
<td>102</td>
<td>111</td>
<td>2</td>
<td>39</td>
<td>2</td>
<td>45</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
<td>119</td>
<td>1</td>
<td>126</td>
<td>135</td>
<td>3</td>
<td>17</td>
<td>3</td>
<td>19</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>137</td>
<td>19</td>
<td>140</td>
<td>145</td>
<td>3</td>
<td>27</td>
<td>3</td>
<td>41</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>2</td>
<td>161</td>
<td>1</td>
<td>168</td>
<td>177</td>
<td>4</td>
<td>17</td>
<td>4</td>
<td>19</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>179</td>
<td>19</td>
<td>182</td>
<td>187</td>
<td>4</td>
<td>27</td>
<td>4</td>
<td>39</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>203</td>
<td>1</td>
<td>206</td>
<td>211</td>
<td>5</td>
<td>9</td>
<td>5</td>
<td>19</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
<td>221</td>
<td>19</td>
<td>228</td>
<td>237</td>
<td>5</td>
<td>35</td>
<td>5</td>
<td>39</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>6</td>
<td>2</td>
<td>245</td>
<td>1</td>
<td>261</td>
<td>279</td>
<td>6</td>
<td>35</td>
<td>6</td>
<td>37</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>281</td>
<td>37</td>
<td>284</td>
<td>289</td>
<td>6</td>
<td>45</td>
<td>7</td>
<td>3</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>1</td>
<td>303</td>
<td>3</td>
<td>306</td>
<td>311</td>
<td>7</td>
<td>11</td>
<td>7</td>
<td>23</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
<td>323</td>
<td>23</td>
<td>330</td>
<td>339</td>
<td>7</td>
<td>39</td>
<td>7</td>
<td>43</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>2</td>
<td>345</td>
<td>1</td>
<td>348</td>
<td>353</td>
<td>8</td>
<td>9</td>
<td>8</td>
<td>20</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>2</td>
<td>364</td>
<td>20</td>
<td>367</td>
<td>372</td>
<td>8</td>
<td>28</td>
<td>8</td>
<td>35</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>379</td>
<td>35</td>
<td>382</td>
<td>387</td>
<td>8</td>
<td>43</td>
<td>8</td>
<td>47</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>1</td>
<td>393</td>
<td>1</td>
<td>396</td>
<td>401</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>11</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>1</td>
<td>403</td>
<td>11</td>
<td>406</td>
<td>411</td>
<td>9</td>
<td>19</td>
<td>9</td>
<td>21</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
<td>413</td>
<td>21</td>
<td>420</td>
<td>429</td>
<td>9</td>
<td>37</td>
<td>9</td>
<td>39</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

The table is based on 15 minute time segments starting a 12:00 am Monday
Table 15 summarizes the results of the simulated annealing for all trucks scheduled in one week. Since the pulp mill was using 60 trucks, the same number of trucks was used in the model. In order to neutralize the effect of random solution generation in the simulated annealing, the model was repeated for 50 independent runs and the results presented in Table 15 are based on average outcomes for all 50 runs. According to the results, with 60 trucks the fleet is able to transport all wood chip loads produced during the week and the transportation delay penalty is equal to zero. The model was able to reduce the total waiting times by 7% compared to initial solutions obtained by simulation. The average solution time was 19 minutes for one run.

Table 15: Results of simulated annealing for weekly truck schedule with 60 trucks

<table>
<thead>
<tr>
<th>Total number of unmet transportation demands (loads)</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial wait times (hour)</td>
<td>4,127</td>
</tr>
<tr>
<td>Final wait times (hour)</td>
<td>3,853</td>
</tr>
<tr>
<td>Improvement form the initial solution (%)</td>
<td>7</td>
</tr>
</tbody>
</table>

Figure 7 shows the daily number of truckloads of wood chips produced in all sawmills and the number of loads transported by the entire fleet. The trucks were able to transport all loads by the end of Saturday.

![Figure 7: Number of daily wood chip loads produced and transported by a fleet of 60 trucks](image)
Table 16 shows the number of wood chip loads that were transported from each sawmill as well as the productive time spent on each load. The productive time included travel time from the pulp mill to a sawmill to pick the load, service time at the sawmill including loading time (fifteen minutes) and truck check-up time (fifteen minutes), travel time from the sawmill to the pulp mill and service time at the pulp mill including unloading time at the pulp mill (fifteen minutes; requires the dumper), and truck check-up time (fifteen minutes). The total productive time of the fleet was equal to 2,758 hours of the week. Comparing to the total wait times during the week, which was equal to 3,853 hours, it can be concluded that the efficiency of truck utilization is only 42%, showing large opportunities for improvement. The reason for this low efficiency was that there were too many trucks and on many occasions, trucks had to wait for hours before unloading.

Table 16: The number of weekly wood chip loads transported with a fleet of 60 trucks and the productive truck times spent on transportation

<table>
<thead>
<tr>
<th>Sawmill No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sawmill name</td>
<td>A2</td>
<td>A3</td>
<td>CA2</td>
<td>B9</td>
<td>B10</td>
<td>P31</td>
<td>U21</td>
<td>U41</td>
<td></td>
</tr>
<tr>
<td>Weekly loads transported</td>
<td>112</td>
<td>168</td>
<td>120</td>
<td>40</td>
<td>20</td>
<td>44</td>
<td>28</td>
<td>28</td>
<td>560</td>
</tr>
<tr>
<td>Travel time from pulp mill to sawmill (hours)</td>
<td>0:45</td>
<td>1:45</td>
<td>0:45</td>
<td>4:45</td>
<td>2:45</td>
<td>4:00</td>
<td>2:30</td>
<td>5:00</td>
<td></td>
</tr>
<tr>
<td>Travel time from sawmill to pulp mill (hours)</td>
<td>0:45</td>
<td>1:45</td>
<td>0:45</td>
<td>4:45</td>
<td>2:45</td>
<td>4:00</td>
<td>2:30</td>
<td>5:00</td>
<td></td>
</tr>
<tr>
<td>Service time at sawmill (minutes)</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td></td>
</tr>
<tr>
<td>Service time at pulp mill (minutes)</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td>0:30</td>
<td></td>
</tr>
<tr>
<td>Total service time for one load (hours)</td>
<td>2:30</td>
<td>4:30</td>
<td>2:30</td>
<td>10:30</td>
<td>6:30</td>
<td>9:00</td>
<td>6:00</td>
<td>11:00</td>
<td></td>
</tr>
<tr>
<td>Total service time for all loads (hours)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2798</td>
</tr>
</tbody>
</table>

To investigate if a smaller fleet size resulted in better efficiencies, two options were considered: (1) if one-third of trucks and (2) if two-thirds of trucks were back up trucks. Based on these two cases, 50 independent runs with a fleet size of 40 and 20 were completed; and the results were compared to the results of simulated annealing for a fleet size of 60.

According to Figure 8, with 60 and 40 trucks all loads produced in one week could be transported in the same week; however, with 20 trucks, the fleet does not have enough resources to transport all loads. Consequently, the simulated annealing focused on transportation of wood chips from high priority mills and transported the majority of loads.
produced in those mills while postponing transportation of almost all loads from low priority sawmills to the following week.

Figure 8: The number of weekly wood chip loads production at each sawmill and the number of weekly wood chip load transportation with a fleet size of 20, 40 and 60

Figure 9 shows the number of loads transported each day. While the transportation network did not need to work on Sundays with 60 trucks, it did need to work on all days with 20 and 40 trucks.

Figure 9: Number of daily wood chip load production and transportation by a fleet of 20, 40 and 60 trucks
Table 17 summarizes the results of the simulated annealing model for the case study when the numbers of active trucks were 20, 40, and 60. According to the results, as the number of trucks increased, the solution time required by the model increased as well. With 20 trucks, transportation delays were inevitable; while 40 and 60 trucks could transport all loads. Consequently, it was concluded that 40 trucks could provide sufficient capacity for the case study. The results also showed that reducing the active trucks by one-third or two-thirds could significantly reduce the truck waiting times. With 20 and 40 trucks, the savings in waiting times were 87% and 72%, respectively. The calculation of the total transportation penalty (summation of transportation delay penalty and truck waiting penalty) showed that the attainable improvements with 20 and 40 trucks were 44% and 72%, respectively.

Table 17: Results of simulated annealing for weekly truck schedules with 20, 40, and 60 trucks

<table>
<thead>
<tr>
<th>Fleet size (number of trucks)</th>
<th>60</th>
<th>40</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solution time (mm:ss)</td>
<td>19:00</td>
<td>15:49</td>
<td>9:25</td>
</tr>
<tr>
<td>Transportation delay penalty ($)</td>
<td>0</td>
<td>0</td>
<td>190,022</td>
</tr>
<tr>
<td>Improvement (%)</td>
<td>0</td>
<td>-100</td>
<td></td>
</tr>
<tr>
<td>Truck wait penalty ($)</td>
<td>444,171</td>
<td>123,689</td>
<td>58,879</td>
</tr>
<tr>
<td>Improvement (%)</td>
<td>72</td>
<td>87</td>
<td></td>
</tr>
<tr>
<td>Total transportation penalty ($)</td>
<td>444,171</td>
<td>123,689</td>
<td>248,901</td>
</tr>
<tr>
<td>Improvement (%)</td>
<td>72</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>Final truck efficiency (%)</td>
<td>42</td>
<td>72</td>
<td>71</td>
</tr>
</tbody>
</table>

In all cases, the SA was able to build a feasible weekly transportation plan and improve the total transportation penalty through a number of iterations. However, the best results were attainable when 40 trucks were utilized. The final truck efficiencies with 20 and 40 trucks were 71% and 72% respectively. As a result, it was concluded that the pulp mill needed to use 40 trucks to transport all weekly wood chips under the logic that this fleet size fulfills all transportation demands, reduces truck wait times and improves the efficiency of truck utilization; meaning that the fleet size can be decreased by 33%.

4.2 Discussion and Conclusions

In this study, a mathematical programming model was developed for weekly truck routing and scheduling for transportation of wood chips from a number of sawmills to a pulp mill with limited truck unloading capacity. Consequently, a simulated annealing metaheuristic was developed to produce an initial weekly transportation plan and then successively improve it. In literature, the available studies in the area of truck transportation for wood chips and biomass delivery are
limited to three studies introduced in Section 2.4.2. Väätäinen et al. (2005) studied peat and woodchips transportation from a fuel storage area to a bio-power plant with two unloading facility. The planning horizon in the study was one week but the transportation network included only one supply point and one demand point. Acuna et al. (2012) studied truck transportation of wood chips from a number of locations with in-field chipping operations to a port with limited truck unloading capacity. Their study did not consider wood chips storage; instead, it had a constraint that would allow chipping operation to proceed only if a truck was available to be loaded. Their study did not consider transportation delays or service priorities. Moreover the time span of transportation planning was limited to one working shift based on working hours of the harvest areas or the port. The study by Han & Murphy (2012) considered truck scheduling for biomass transportation from multiple sawmills to multiple demand points (pulp mills, bio-energy plants, or export harbours). They considered four products (wood chips, hog fuel, sawdust, and shavings) and six truck-trailer configurations. However, their study did not consider transportation delays, service priorities or limited truck unloading capacity. Moreover, truck scheduling and driver scheduling in their study was on a daily basis, and their model did not account for driver shift changing, rest times, switch points and multiple shifts. The transportation environment and constraints in these three studies are different from the transportation problem studied in this thesis and so, the results cannot be compared with each other.

In this thesis, the simulated annealing model, which was programmed and implemented in MATLAB consisted of an initiation phase that used a simulation to build an initial solution and an improvement phase that performed a neighbourhood search to find an alternative solution. The attributes of the simulated annealing including the initial temperature value, the cooling schedule, the number of iterations for each temperature value, and the stopping criteria were determined by using the results of test runs.

The results of implementation of the simulated annealing model to solve the case study indicated that it was able to reduce the total penalty for waiting times and unmet transportation demands compared to initial solutions generated by simulation. The model and its results were validated by the pulp mill’s fibre supply manager. It is also worth mentioning that if some input parameters change or an unexpected event takes place, and make the schedule unattainable, the model can be executed again mid-week to update the truck routes and schedules for the rest of the week. This simulated annealing model provides an operational level tool that can
help the dispatcher at a pulp mill find an improved transportation plan and also to evaluate and compare the efficiency of different transportation plans.

The results also showed that the fleet size of 60 used by the pulp mill was larger than required. With 60 trucks, all transportation demands were met and the simulated annealing was able to reduce the waiting times by 7 percent compared to an initial solution but the truck efficiency was as low as 42% meaning that the fleet time was mostly spent in line-ups. To investigate the performance of the transportation network with fewer trucks, two additional cases were considered when one-third and two-thirds of the fleet were back up trucks based in the pulp mill yard.

The fleet size could be reduced by one-third and the pulp mill could still transport all wood chip loads before the end of the week. With 40 trucks, the truck network was able to fulfil all weekly transportation demands and at the same time, the best obtained waiting times were 25% of the best obtained waiting times with 60 trucks. With 20 trucks, there were not enough resources to meet all transportation demands and the truck network was only able to transport 66% of all loads produced. Consequently, the simulated annealing focused on providing a better service level for high priority sawmills at the cost of delaying transportation of wood chips produced in the other sawmills. To sum up, it was concluded that using 40 active trucks produced the best results compared to the other two cases and with a fleet size of 60 trucks, the pulp mill should actively use two-thirds of the trucks and maintain the remaining third as backup.

The model and the study presented in this chapter have some limitations. The model was built under assumptions explained in section 4.2 and it may not capture all constraints and conditions in the real life wood chip transportation network, such as transportation delays, truck breakdowns, and drivers’ route preferences, etc. Consequently, in practice the pulp mill may need more than 40 trucks. However, the assumptions, the model, and its results were validated by the pulp mill’s fibre supply manager which indicates that the model is a close representation of the real condition.

In this chapter, it was assumed that the fleet size was fixed and only three variations between active trucks and backup trucks were considered. In the next chapter, a more extensive sensitivity analysis and scenario analysis is performed to determine the optimum number of trucks required for the case problem. Moreover, the effect of changes in some other structural parameters on the transportation costs and penalty function is evaluated. The results can be used by the pulp mill manager to improve the design of the transportation network.
5  Transportation Structure Improvement

In this chapter, sensitivity and scenario analyses are used in combination with the simulated annealing model developed in Chapter 4 in order to explore the effects of changing various structural parameters of the transportation network. Specifically, the parameters explored in the analysis include: 1) number of trucks (fleet size); 2) number of truck dumpers at the pulp mill (one or two); 3) truck types (regular or self-unloading); and 4) switch point locations for truck drivers. The results of sensitivity and scenario analysis was used to determine the optimal fleet size, estimate benefits of adding an additional dumper, identify the optimal number of self-unloading trucks, and decide on the best switch point locations for truck drivers.

5.1  Fleet Size

In the base case, it was assumed that a truck fleet of 60 trucks (actual number used in the case study) was available to transport a total of 560 truckloads of wood chips from 8 sawmills. In this section, the impact of transportation fleet size on the total transportation penalty and trucking cost is analyzed.

Running too few trucks has disadvantages. First, with too few trucks, the transportation service level to sawmills is compromised. In high priority sawmills, the lack of enough trucks results in lost loads and in low priority sawmills, it triggers inventory-holding. Moreover, it is important for the pulp mill to maintain a reliable standing with the sawmills for future contracts. Secondly, with too few trucks in the system, the working pressure on available trucks increases. This increased working pressure can negatively impact the willingness of truck drivers to continue working in the forest sector. The industry is already struggling with hiring and maintaining experienced drivers familiar with the roads who are able to operate heavy trucks under diverse road and weather situations. Third, with an insufficient number of trucks, the dumper utilization decreases. Considering the high wood chip consumption rate at the pulp mill, the dumper should be utilized as much as possible when it is available.

Conversely, running too many trucks is inefficient. First, it is obvious that as the number trucks increase, the hiring costs of drivers and trucks increase. Second, with more trucks, the sawmills are visited more frequently, which results in increased truck arrival traffic at the pulp mill. If the truck arrival rate exceeds the truck unloading rate of the dumper, trucks need to form a line-up and wait for dumper service. Third, if the wood chip gathering capacity of the truck network
exceeds the wood chip production rate at sawmills, from one trip to the next, the trucks have to wait at the pulp mill or at a sawmill before a new truckload of wood chips becomes available.

Figure 10 shows the conceptual relationships between the number of trucks in the network and different cost, time, utilization, and satisfaction parameters. A positive relationship means that more trucks increase the related parameter and a negative relationship means that more trucks decrease the related parameter.

![Diagram showing relationships between number of trucks and various parameters](image)

**Figure 10: Relationships between number of trucks and time, cost, utilization, and satisfaction levels**

In order to determine the optimum number of trucks, a sensitivity analysis was performed in which the size of the transportation fleet was changed by an increment of one truck at a time. For each number of trucks, the simulated annealing method was repeated for 10 independent runs to find the average change in the total cost and penalty function. For a fixed number of trucks, the objective function was calculated as a summation of the truck waiting penalty and the transportation delay penalty for unmet transportation demands according to Equation (22).

The number of trucks affected the truck waiting penalty and the transportation delay penalty. Figure 11 shows the truck waiting penalty and the transportation delay penalty for the initial solution of the simulated annealing model, which was obtained by the simulation model described in Section 4.3.1. According to the results, with the range of 15 to 27 trucks, the truck waiting penalty was minor, indicating that with this range of fleet size, the arrival rate of trucks to the pulp mill was less than the unloading capacity of the dumper. As a result, the trucks were used very efficiently. As the number of trucks increased, in the range of 28 to 40 trucks, the truck waiting penalty increased accordingly. The reason for this condition was the high rate of wood chip transportation and the high truck arrival traffic at the pulp mill; which resulted in truck waiting. According to the results for the transportation delay penalty, as the number of trucks
increased, there was a reduction in the transportation delay penalty, indicating that more loads were transported.

Figure 11: The truck waiting penalty and the transportation delay penalty for the initial solution obtained by simulation

Figure 12 shows the final waiting penalty and the final transportation delay penalty obtained by the simulated annealing compared to the initial values. The results showed that the model was able to significantly decrease the transportation delay penalty. With a minimum of 22 trucks, the transportation delay penalty was insignificant because the transportation network had enough vehicles to transport all the weekly wood chip loads from the high priority sawmills. The results showed that with 34 trucks or less, the final truck waiting penalty was worse than the initial waiting penalty. The reason for this trend was that with 34 trucks or less, the transportation delay penalty was much higher than the truck waiting penalty and the solution method focused on reducing transportation delays from high priority sawmills even at the cost of deteriorating the truck waiting times. This was done in order to improve the total objective function (Equation (22)). However, with a minimum of 22 trucks, the fleet was able to transport all weekly loads from high priority sawmills and the level of truck waiting penalty deterioration decreased, which was the reason for the reduction in the final wait penalty from 22 trucks to 24 trucks. With 34 trucks or more, the initial wait penalty was more than the initial delay penalty; consequently, the simulated annealing was able to reduce the waiting penalty as well.
Figure 12: The truck waiting penalty and the transportation delay penalty for the initial solution obtained by simulation and the final solution obtained by the simulated annealing model.

Figure 13 shows the average transportation penalty (Equation (22)) for the best solution obtained by the simulated annealing for 10 repetitions compared to the penalty of initial solutions obtained by the simulation for each repetition. The average transportation penalty is calculated as the summation of truck waiting penalty and transportation delay penalty. The results showed that the simulated annealing model was consistently able to improve the transportation penalty compared to an initial solution that was obtained by simulation.

As the number of trucks is altered, the fixed and variable costs related to the fleet should also be considered in the evaluation of costs and benefits. These cost components include hiring costs of tractors and trailers as well as the operating costs for drivers, fuel consumption, lube and oil consumption, tire consumption, repair, and maintenance, which are directly related to the number of trucks. Moreover, with a different number of trucks, the transportation capacity of the fleet changes and consequently, it is important to include costs related to travel times, service time at sawmills or at the pulp mill in the assessment of costs and benefits.
The total cost and penalty function utilized to determine the optimal fleet size was calculated according to Equation (25) and included three components: 1) trucking costs; 2) penalties for truck waiting times; and 3) penalties for transportation delays.

\[
\text{Total Cost and Penalty} = \text{Trucking Cost} + \text{Truck Waiting Penalty} + \text{Transportation Delay Penalty}
\]  

The cost and penalty components were calculated in Appendix A and their formulas are repeated below:

- **Trucking Cost for each truck ($/week)** = Fixed cost + Variable cost
  
  \[ = 2,388 + 93.56 \times \text{Weekly working hours} \]

- **Truck waiting penalty for each truck ($/week)**
  
  \[ = 115.27 \times \text{total truck waiting hours in a week} \]

- **Transportation Delay Penalty ($/week)**
  
  \[ = 6,645 \times \text{Number of delayed truckloads from mills A2, A3, CA2} \]
The impact of the number of trucks on transportation costs and penalties was used to determine the minimum required number of trucks. Figure 14 shows the variation in the transportation penalty (summation of the truck waiting penalty and the transportation delay penalty), the trucking costs, and the total penalties and costs for a range of fleet sizes assigned to the transportation tasks explained in Section 4.4. As the results show, the minimum required number of trucks was 24 trucks.

![Graph showing transportation penalty and costs](image)

**Figure 14: The total transportation penalty and trucking cost for different number of trucks**

With the minimum required number of trucks, the summation of weekly transportation costs and penalties was minimized. However, the transportation network failed to fulfill many of the transportation demands. Figure 15 shows the number of wood chips truckloads with transportation delays segmented by high priority sawmills, low priority sawmills, and all sawmills. According to the results, with 24 trucks, all the wood chips produced in high priority sawmill were transported on-time but the transportation delay penalty for low priority sawmills was equal to 134 truckloads which accounted for 84% of the total wood chip supply from those sawmills.
Figure 15: The number of weekly truckloads of wood chips with transportation delays

Figure 16 shows the number of delayed truckloads relative to the entire weekly transportation tasks. According to the results, the following was concluded:

- With 21 trucks or less, the truck network had very limited transportation capacity and was not able to completely serve high priority sawmills even if all transportation orders from other sawmills were ignored;
- With 22 to 30 trucks, the truck network was able to transport all high priority loads and a portion of loads from the other sawmills;
- With 31 to 33 trucks, the truck network could transport all loads from high priority sawmill and at least 90% of weekly loads from all sawmills;
- With 34 to 35 trucks, the trucks were adequate to transports all wood chip loads from high priority sawmills and 90% of the loads from the other sawmills;
- With 36 trucks or more, the trucks were able to fulfill all weekly wood chip transportation demands within the planning week.
In summary, in an exceptional truck shortage condition, the pulp mill needed to utilize at least 24 trucks to fulfill transportation demands from the high priority mills, but under normal conditions, the pulp mill needed to utilize 36 trucks. The pulp mill did not want to lose any loads even from the low priority sawmills. Transportation delays for low priority sawmills increased the inventory level at those sawmills. However, the pulp mill had to provide transportation resources for those loads at some time. With more than 36 trucks, the trucking cost and truck waiting times increased but the transportation service levels were same. As a result, the optimum number of trucks was equal to 24 in a temporary truck shortage condition and 36 for normal conditions.

5.2 An Additional Dumper

This section evaluates the impact of using an additional truck dumper on the costs and penalties. Truck dumpers have significant capital costs and as a result, in many pulp mills the number of dumpers is limited. In the case study pulp mill, the pulp mill owns and operates one truck dumper. The dumper has a lifting capacity of 127 tonnes and for every truck, the dumping process takes about fifteen minutes. According to pulp mill managers interviewed for this study, the truck dumper is the main source of truck line-ups and transportation inefficiencies.

The simulated annealing algorithm also identified truck dumper’s limited unloading capacity as the main source of truck efficiencies. Figure 17 shows the ratio of each of the four types of truck
waiting times to the total truck waiting time for a range of fleet sizes. The results showed that independent from the number of trucks, more than 90% of the waiting times were because of the dumper and with 24 trucks or more, the waiting of loaded trucks at the pulp mill accounted for 97% of the total truck waiting times.

Figure 17: The ratio of each type of truck waiting times to the total truck waiting times

In order to examine the effect of an additional truck dumper, a sensitivity analysis was conducted in which the truck unloading capacity at the pulp mill was increased to two trucks at a time. Once more, a range of 15 to 40 trucks were considered for the fleet size and for each fleet size, the simulated annealing model was repeated 10 times to find the average changes in the transportation delay penalty and the truck waiting penalty. Figure 18 shows the truck waiting penalty and the transportation delay penalty obtained by the simulated annealing for the pulp mill when using one truck dumper compared to two truck dumpers.

The results showed that two dumpers could improve both the truck waiting penalty and the transportation delay penalty. Figure 18 shows the variations in the penalty functions for different number of trucks when the pulp mill used one truck dumper or two truck dumpers. With two dumpers, for the range of 24 trucks or more, the truck waiting penalty was negligible (less than two hours per truck per week), showing that an additional truck dumper could reduce the waiting penalty significantly. For 23 trucks or less, the truck waiting penalty was notable but still better than the truck waiting penalty with one dumper. The reason for the notable waiting penalty was
that with 23 trucks or less, the pulp mill reserved the limited transportation resources for high priority sawmills, which resulted in increased waiting times at high priority sawmills before loads were produced, picked up, and transported. The results showed that by using two truck dumpers the transportation delay penalty could be decreased. This means that the reduced truck waiting time reduced the transportation delay penalty as well. The reason was that with the same number of trucks and two dumpers, the savings that were made in truck waiting times could be used to transport more loads, which consequently reduced the transportation delay penalty.

![Figure 18: The truck waiting penalty and the transportation delay penalty with one truck dumper and two truck dumpers](image)

Using two dumpers also resulted in better truck efficiencies. Figure 19 shows truck utilization when the pulp mill used one dumper versus two dumpers. With very few trucks in the system (less than 22 and one dumper or less than 20 and two dumpers), as the number of trucks increased the truck efficiency decreased. The reason is that with those fleet sizes, the transportation resources were not sufficient to respond to all demands from high priority sawmills. As a result, the trucks were allowed to serve only the high priority sawmills and as the number of trucks increased, more trucks were assigned to those sawmills. From time to time, the wood chip pick up rate at high priority sawmills exceeded the production rate, causing waiting times before the production of a load. With 21 trucks or more and two dumpers (23
trucks or more and one dumper), all the transportation demands from the high priority sawmills were met and the trucks were allowed to also visit the other sawmills, which resulted in more flexibility, less waiting times, and improved efficiency. With 24 trucks or more and one dumper, once more, more trucks resulted in a decrease in truck efficiency. Because, with more trucks, the wood chip loads were picked faster and so, the truck arrival rate to the pulp mill and the truck waiting time at the pulp mill increased. Conversely, with 24 trucks or more and two dumpers, as the number of trucks increased, the truck efficiency remained the same (about 98%). The reason for this is that two dumpers were able to serve the chip trucks almost instantly upon their arrival and with two dumpers the truck waiting times were minor.

![Graph showing truck efficiencies with one truck dumper and two truck dumpers](image19)

**Figure 19: Truck efficiencies with one truck dumper and two truck dumpers**

However, an extra dumper brings about additional costs and in order to justify investing in a new dumper, the associated costs and benefits need to be analyzed together. The costs of a new truck dumper can be categorized as the fixed costs required for purchasing the machinery and variable cost required for operating it. Since, in this study, the weekly transportation tasks were known and fixed, the total number of dumper operating hours was also fixed. With one dumper, the working hours are forced on one dumper, while with two dumpers, the costs are shared between the two facilities. However, the total working hours and dumper variable costs was fixed and was thus eliminated from the cost analysis. According to the fibre supply manager interviewed for the case study, the capital cost required for purchasing a new truck dumper was
$6,000,000. However, with regular maintenance and proper repair services a truck dumper can be used for a very long time. The existing truck dumper at the pulp mill was installed in 1968 when the pulp mill started up, and has been used ever since. It is still in such a good condition and works full time. However, the economic life time of a new dumper was considered 25 years based on literature (RISI, 2014).

In order to translate the capital cost of a new dumper to annual and weekly cost, the annuity concept and the time value of money was considered. To calculate the annual cost of the new dumper, Equation (26) was used (Brown, 2007).

\[
A = P \times \left[ \frac{i(1 + i)^n}{(1 + i)^n - 1} \right]
\]

(26)

In Equation (26), \(A\) was the annual fixed cost that the pulp mill undertakes for the new dumper, \(P\) was the present capital cost of the new dumper \((P = \$ 6,000,000)\), \(n\) was the expected life of the new dumper \((n = 25)\) and \(i\) was the annual interest rate. An interest rate of 6% was considered for equipment financing \((i = 0.06)\) (Williams & Larson, 1993). With these values, the annual dumper price was $469,360. Assuming that the annual maintenance cost is 20% of the annual capital cost, the annual ownership cost of the dumper was estimated to be $563,232. Assuming the same time value of money over a year and that the new dumper is utilized 48 weeks per year, the weekly ownership cost of a new truck dumper is estimated to be $11,734.

The total cost and penalty function considered for the transportation network with two dumpers included four components: 1) trucking costs; 2) penalties for truck waiting times; 3) penalties for transportation delays; and 4) ownership costs of a new truck dumper. Figure 20 shows the variations in the transportation penalty (summation of truck waiting penalties and transportation delay penalties), the trucking costs, and the total penalties and costs for a range of fleet sizes assigned to the transportation tasks.
Figure 20: The total transportation penalty and trucking cost for different number of trucks and two dumpers

Figure 21 shows the total cost and penalty function for the transportation network with two dumpers compared to the base case with one dumper. The results suggested a new dumper was able to improve the performance of the transportation network and reduce the minimum required number of trucks from 24 to 21.

Figure 21: The total cost and penalty function with one truck dumper and two truck dumpers
Using an additional dumper made it possible to reduce the required number of trucks in a week. Figure 22 shows relationship between the number of trucks and the ratio of tasks with transportation delays to the entire weekly transportation tasks. The results showed that:

- With 20 trucks or less, the truck network had very limited transportation capacity and was not able to completely serve high priority sawmills even if all other transportation orders were ignored;
- With 21 to 26 trucks, the truck network was able to transport all high priority loads and a portion of loads from the other sawmills;
- With 27 or 28 trucks, the truck network was able to transport all loads from high priority sawmill and at least 90% of weekly loads from all sawmills;
- With 29 or 30 trucks, the trucks were able to transport all wood chip loads from high priority sawmills and 90% of loads from the other sawmills;
- With 31 trucks or more, the trucks were able to fulfill all weekly wood chip transportation demands within the planning week.

Figure 22: The percentage of weekly truckloads of wood chips with transportation delays when using two truck dumpers

In summary, the pulp mill could benefit from an additional truck dumper. An additional dumper could help the pulp mill reduce both truck waiting times and transportation delays. An additional truck dumper was also able to reduce the truck waiting time penalties and transportation delay
penalties by an average of 77% and 59%, respectively compared to the initial case study. The results also indicated that an extra dumper could reduce the minimum required number of trucks from 24 to 21 and the required number of trucks in normal conditions can be reduced from 36 to 31. The fibre supply manager at the case study pulp mill suspected that the addition of a secondary dumper could improve the efficiency of the truck transportation network and this analysis provides evidence to support this claim and convince the management team to invest in a new dumper.

5.3 Truck Types

This section investigates the impact of truck types (regular or self-unloading) on transportation costs and penalties. According to the pulp mill manager, the industry identifies two main solutions to increase the pulp mill’s dumping capacity: 1) investing in an additional truck dumper or 2) the use of self-unloading trucks. Section 5.2 explored the differences an additional truck dumper can make and this section studies the impact of using self-unloading trucks.

There are two types of self-unloading trucks: trucks that have trailers with dump boxes and trucks that have trailers with walking floors (Jokay & Pavel, 2013b). Self-unloading trucks with dump boxes may possess a trailer that can be unloaded from one side or from the end. In self-unloading trucks with walking floors, the floor of the trailer is equipped with moveable slats that can move wood chips to the front or the back of the trailer.

The ability to self-unload comes at an extra cost, since the truck and trailer must be equipped with a hydraulic system that unloads the truck. According to experts, when a regular truck-trailer combination costs $120 per hour, an end dump truck-trailer combination costs $130, which shows an 8% increase in the costs (Jokay & Pavel, 2014). Consequently, in this study the renting cost and the operating cost of a self-dumping truck was assumed to be 10% higher than a regular truck.

In order to test the influence of using self-unloading trucks, a number of scenarios with different combinations of regular trucks and self-unloading trucks were developed. For all scenarios it was assumed that the weekly transportation tasks were the same as the base scenario investigated in Section 5.1 and the pulp mill was utilizing one truck dumper. It was also assumed that the unloading time of a self-unloading truck was fifteen minutes per load. For each scenario, the simulated annealing model was executed 10 times considering a fleet size of...
15 to 40 trucks. In order to study the impact of self-unloading trucks, the following five scenarios were examined:

1- All the trucks are regular trucks (base scenario)
2- 90% of the trucks are regular trucks and 10% of the trucks are self-unloading
3- 50% of the trucks are regular trucks and 50% of the trucks are self-unloading
4- 20% of the trucks are regular trucks and 80% of the trucks are self-unloading
5- All the trucks are self-unloading trucks

Using self-unloading trucks can improve both the truck waiting penalty and transportation penalty. Figure 23 compares the truck waiting penalties and the transportation delay penalties of the base scenario with the other four scenarios developed to assess the impact of truck types. For the scenarios when 10%, 50%, 80%, or 100% of the trucks were self-unloading, the simulated annealing model was able to improve the average truck waiting times by 41%, 82%, 86%, and 86% respectively; and it was able to enhance the average delay penalty for unmet transportation demands by 7%, 20%, 22%, and 22% respectively.
(a) Scenario 2, 10% of the trucks are self-unloading

(b) Scenario 3, 50% of the trucks are self-unloading

(c) Scenario 4, 80% of the trucks are self-unloading

(d) Scenario 5, all trucks are self-unloading

Figure 23: The truck waiting penalty and the transportation delay penalty of the base scenario compared with the four scenarios developed to assess the impact of truck types
Figure 24 shows the total cost and penalty function for the base scenario compared with the other four scenarios based on the number of trucks and truck types. As before, the function included fixed and variable trucking costs, truck waiting penalties, and delay penalties for unmet transportation demands. The results suggested that self-unloading trucks could reduce transportation costs and penalties. However, the average potential savings were almost the same when 50%, 80%, or 100% of the trucks were self-unloading. Hence, it was sufficient to use a truck network in which half of the trucks were regular trucks and half were self-unloading.

Replacing half of the fleet with self-unloading trucks resulted in a reduction in weekly truck requirements. Figure 25 shows the relationship between the number of trucks and the ratio of tasks with transportation delays to the entire weekly transportation tasks when half of the trucks were considered to be self-unloading. The results showed that:

- With 20 trucks or less, the truck network had very limited transportation capacity and was not able to completely serve high priority sawmills even if it ignored all transportation orders from other sawmills;
- With 21 to 26 trucks, the truck network was able to transport all high priority loads and a portion of loads from the other sawmills;
• With 27 or 28 trucks, the truck network could transport all loads from high priority sawmill and at least 90% of weekly loads from all sawmills;
• With 29 or 30 trucks, the trucks were adequate to transports all loads from high priority sawmills and 90% of loads from the other sawmills;
• With 31 trucks or more, the trucks were able to fulfill all weekly wood chip transportation demands within the planning week.

![Graph showing weekly truckloads with transportation delays](image)

**Figure 25:** The percentage of weekly truckloads of wood chips with transportation delays when half of the trucks were self-unloading

When half of the trucks were self-unloading, the required number of trucks was the same as the required number of trucks when another truck dumper was added to the pulp mill. So, now the question was if purchasing another truck dumper brought about more cost savings or replacing half of the fleet with self-unloading trucks. Figure 26 compares the total cost and penalty function for the base scenario with the two other cases. The graph indicates that the trucking cost and penalty is almost the same for both structural changes.
In summary, replacing a part of the truck fleet with self-unloading trucks could result in cost savings. Self-unloading trucks are more expensive to rent and operate compared to regular trucks but the results of scenario analysis showed that the obtained cost savings were more than the additional fixed and variable costs of these trucks. Self-unloading trucks were able to reduce truck waiting times as well as transportation delays. For the same number of trucks, if 10%, 50%, 80%, or 100% of the trucks were self-unloading, the truck waiting penalties were reduced by 41%, 82%, 86%, and 86% and the transportation delay penalties were reduced by 7%, 20%, 22%, and 22% compared to the base scenario where all the trucks were regular trucks. The results for the total cost and penalty function indicated that if 10%, 50%, 80%, or 100% of the trucks were self-unloading, improvements of 9%, 18%, 18%, and 17% were attainable. Consequently, it was concluded that as the ratio of self-unloading trucks to fleet size increase from 50% to 80% or 100%, the variations in the potential cost savings were insignificant. So, because of limited availability of self-unloading trucks, it was sufficient to replace half of the regular trucks with self-unloading trucks. The results also indicated that self-unloading trucks could reduce the required number of trucks; with replacing half of the fleet with self-unloading trucks, the minimum number of trucks in truck shortage condition could be reduced from 24 to 21 and the required number of trucks in normal condition could be reduced from 36 to 31.
5.4 Switch Point Locations

The purpose of this section is to explore the impact of switch point locations. In the case study, the trucks were hired from a trucking company and it was assumed that each truck was operated by two drivers working in shifts. Each truck can work 24/7 but for each driver there are working hour regulations that must be respected in shift assignments. In Canada, the normal shift length is ten to twelve hours, the maximum allowed driving time is fourteen hours, and each working shift should follow ten consecutive hours off duty. The drivers are allowed to work 55 hours per week followed by 34 or more consecutive hours off duty (Ministry of Transportation and Infrastructure, 2011).

After each shift, the truck driver leaves the truck at the pulp mill or one of the acceptable switch point sawmills. In the case study, the average shift length is ten hours and it is acceptable to vary the length of a shift by two hours from one day to the next. Until now, it was assumed that the switch points where the drivers can meet and take over a shift included the pulp mill, sawmill A2, sawmill CA2, and sawmill B10. These switch point locations are currently used and they were selected based on technical constraints and the experience of the pulp mill manager, the truck dispatcher, and the drivers.

Five scenarios were developed to explore the effect of switch point locations on the transportation costs and penalties. In each scenario, the allowed switch point locations were altered while the weekly transportation tasks and all other assumptions were kept the same as the base scenario. For each scenario, a fleet size of 15 to 40 trucks was considered and for each fleet size, the simulated annealing model was executed 10 times. The following five scenarios were modelled:

1- The pulp mill and sawmills A2, CA2, and B10 are switch points (base scenario);
2- Only the pulp mill is a switch point;
3- The pulp mill and the four closest sawmills (A2, A3, CA2, and U21) are switch points;
4- The pulp mill and the four farthest sawmills (B9, B10, P31, and U41) are switch points;
5- The pulp mill and all the sawmills are switch points.

Figure 27 displays the truck waiting penalty and the transportation delay penalty for the base scenario compared with the other four switch point scenarios. For scenario 2 (shift changes allowed only at the pulp mill) and scenario 3 (shift changes allowed at the pulp mill and at the closest sawmills), the average truck wait times decreased by 3% and 4%. For scenario 4 (shift
changes allowed at the pulp mill and at the farthest sawmills) and scenario 5 (shift changes allowed at all sawmills), the average truck wait times increased by 26% and 39%. In scenarios 4 and 5, when there were very few trucks in the system (22 or less), the transportation fleet only served the high priority sawmills and the wait penalty was almost the same as the base scenario. With a range of 23 to 35 trucks, both scenarios showed a worse level of truck wait times compared to the base scenario. In both scenarios when the farthest sawmills were allowed to be driver switch points, there ended up being uneven shift length between successive drivers worked on the same truck and increased truck wait times (either loaded or unloaded) at the sawmills. With 36 trucks or more, the system was able to transport all the loads from all the sawmills and it had enough flexibility to avoid sending trucks to trips with long waiting times at the sawmills. Consequently, the wait times were again almost the same as the base scenario. For all the scenarios, the average delay penalty for unmet transportation demands was worse than the base scenario. The average transportation penalty for scenarios 1, 2, 3, and 4 was, respectively 6%, 3%, 35%, and 40% worse than the base scenario.
(a) Scenario 2, only the pulp mill is a switch point

(b) Scenario 3, the pulp mill and the four closest sawmills are switch points

(c) Scenario 4, the pulp mill and the four farthest sawmills are switch points

(d) Scenario 5, the pulp mill and all the sawmills are switch points

Figure 27: The truck waiting penalty and the transportation delay penalty of the base scenario compared with the four scenarios developed to assess the impact of switch point locations
Figure 28 shows how the total costs and penalties changed as the switch point locations changed. As before, the total costs and penalties was calculated as the summation of fixed and variable trucking costs, truck waiting penalties, and delay penalty for unmet transportation demands. The results suggested that the existing switch points in the base scenario represented the best possible switch point locations. In all the other scenarios, the average transportation costs and penalties were higher than the base scenario. Scenarios 2, 3, 4, and 5 increased the total transportation costs and penalties by an average of 2%, 1%, 14%, and 17%, respectively compared to the base scenario.

In summary, changing the switch point locations could not improve the performance of the transportation network in terms of associated costs and penalties. The existing switch point locations were selected based on the experience of pulp mill manager, the truck dispatcher, and the truck drivers and the computational results support them as the best shift changing locations. Considering scenarios 2, 3, 4, and 5 for the switch point locations, the truck waiting penalties changed by 3%, 4%, -26%, and -39% and the transportation delay penalties changed by -6%, -3%, -35%, and -40% compared to the base scenario. The results for the total cost and penalty function indicated that scenarios 2, 3, 4, and 5 resulted in transportation plans, which were 2%, 1%, 14%, and 17% worse than the base scenario. Since the base scenario was more
flexible than scenario 2, it was able to obtain better transportation plans. For scenarios 2, 3, and 5, the results indicated that increasing the switch point locations resulted in a decline in the performance of the truck network. Besides, facilitating more switch point locations also brings about others costs that need to be added to the total transportation costs and penalties. In order to change shift at new locations, the pulp mill needs to provide transportation services that take the truck drivers to the switch point locations. Moreover, the drivers may have to spend long hours to access the farthest switch point locations to start work or to go to home at the end of a working shift. It is most likely that the pulp mill needs to consider those extra travel times as working hours for the drivers. Based on the results, it can be concluded that the existing switch point locations provide the best results. Given that there are no additional costs to change the switch point locations, the results justified switching to scenarios 2 or 3 because the transportation costs and penalties for these scenarios were slightly more than the base scenario. However, the results were strongly against scenarios 4 and 5 because those scenarios increased the transportation costs and penalties significantly.

5.5 Discussion and Conclusions

This chapter investigated if the transportation costs and penalties could be improved by changing the structure of the transportation network. Sensitivity analysis and scenario analysis were used in combination with the simulated annealing model to examine the effect of changes in the number of trucks in the system (fleet size), the number of truck dumpers (one or two), the type of trucks (regular or self-unloading), and the location of switch points for truck drivers.

The sensitivity analysis on the number of trucks indicated that the pulp mill could reduce its fleet size to improve truck efficiency. The case study presented here showed that 36 trucks would be able to transport all the weekly wood chip loads provided by all sawmills and the number of trucks could be reduced by 40% compared to the number of trucks that the pulp mill actually used in the study week (60 trucks). The model provided an improved transportation plan for wood chip transportation during the week and suggested better truck routes and schedules, which were able to reduce the number of trucks. This also reduces pressure on the hauling companies, which are presently experiencing significant labour shortages. The model was also able to help the pulp mill to determine the minimum number of trucks required by the pulp mill during temporary truck shortage conditions. In exceptional conditions, the pulp mill needed to utilize at least 24 trucks to fulfill transportation demands from the high priority mills, which was 60% lower than the actual number of trucks (60 trucks) and 30% lower than the optimum number of trucks suggested by the model (36 trucks).
The results supported a decision on investing in an additional truck dumper. A new dumper would be able to reduce truck waiting time penalties and transportation delay penalties by an average of 77% and 59%, respectively. In order to consider the additional costs needed to invest in a new dumper, the capital cost was broken down into weekly ownership costs for the expected lifetime of the proposed dumper. The total costs and penalties considered to evaluate the performance of the transportation network with two dumpers included four components: trucking costs, penalties for truck waiting times, penalties for transportation delays, and ownership costs of a new truck dumper. An additional dumper was also able to reduce the required fleet size during normal operating conditions from 36 to 31 trucks (a 14% improvement) and the minimum required number of trucks during exceptional truck shortage conditions from 24 to 21 trucks (a 13% improvement). The results showed that the total transportation costs and penalties with two dumpers and 31 trucks was 31% better than the total transportation cost and penalty with one dumper and 36 trucks.

To assess the impact of using self-unloading trucks the base scenario and four other scenarios were assessed. The first scenario was the base scenario that assumed that all trucks were regular trucks and needed the truck dumper to unload. Scenarios 2, 3, 4, and 5 assumed that 10%, 50%, 80%, or 100% of the trucks had self-unloading capabilities. If 10%, 50%, 80%, or 100% of the trucks were self-unloading, the truck waiting penalties were reduced by 41%, 82%, 86%, and 86%, respectively and the transportation delay penalties were reduced by 7%, 20%, 22%, and 22% compared to the base scenario. The results also indicated that the variations in the cost savings were insignificant between scenarios 3, 4 and 5 and so, scenario 3 was identified as the best change to adopt because it required the least change in the transportation fleet. Scenario 3 was able to reduce the required number of trucks during normal operating conditions from 36 to 31 (a 14% improvement) and the minimum required number of trucks during exceptional truck shortage conditions from 24 to 21 (13% improvement). The results showed that the total transportation costs and penalties for scenario 3 with 31 trucks was 29% better than the total transportation costs and penalties for the base scenario with 36 trucks. A comparison between the conditions when half of the trucks were self-unloading and when the pulp mill was utilizing two truck dumpers (no self-unloading trucks) showed that in both cases, the cost savings were approximately the same. However, according to the fibre supply manager of the pulp mill, the ratio of the self-unloading trucks to all trucks that the trucking company can provide is about 10%. Even if the trucking company was willing to substitute half of the fleet with self-unloading trucks or the pulp mill could switch to another trucking company that owned more
self-unloading trucks, the increased unloading capacity would be the property of the trucking company. Since using two dumpers can guarantee the increased unloading capacity of the pulp mill for many years, it was concluded that the pulp mill manager should invest in another truck dumper rather than replacing half of the fleet with self-unloading trucks.

To study the effect of changing drivers’ switch point locations the base scenario and four other scenarios were investigated. Once again, the first scenario was the base scenario which assumed that truck drivers were allowed to change shifts at the pulp mill or sawmills A2, CA2, and B10. Switch point locations for Scenario 2 assumed only the pulp mill, scenario 3 assumed the pulp mill and the four closest sawmills, scenario 4 assumed the pulp mill and the four farthest sawmills, and scenario 5 allowed the truck drivers to switch at the pulp mill or at any of the sawmills. The results indicated that the existing switch point locations were the best available options. Changing the switch point locations according to scenarios 2 and 3, decreased the average truck waiting times by 3% and for 4% respectively, while changing them based on scenarios 4 and 5, increased the truck waiting times by 26% and 39% respectively compared to the base scenario. Altering the switch point locations based on scenarios 2, 3, 4, and, 5 increased the transportation delay penalties by 6%, 3%, 35%, and 40%. Moreover, scenarios 2, 3, 4, and 5, increased the total transportation costs and penalties by an average of 2%, 1%, 14%, and 17% compared to the base scenario. The base scenario was more flexible than scenario 2 and consequently, it was able to obtain better transportation plans. The base scenario was also better than scenarios 2, 3, and 5, because it was able to avoid wait times more efficiently. Assuming that there were no additional costs to change the switch point locations, the results still allow switching to scenarios 2 or 3 because the transportation costs and penalties for these scenarios were close to the base scenario. However, scenarios 4 and 5 had a significant negative effect on the transportation costs and penalties even if it was assumed that there were no additional costs to facilitate driver shift changing at the farthest sawmills.

This Chapter addressed the second objective indicated in Section 1.2. It provided an analysis on the impact of structural changes in the wood chip transportation network. The results of this chapter can help the management team at the pulp mill and the investors to make more informed decisions and increase the competitiveness of the pulp mill by improving the transportation activities required to supply wood chips to the pulp mill.
6 Summary, Conclusions, Strengths, Limitations and Future Work

6.1 Summary

Despite the pulp and paper industry’s important role in the Canadian forest industry, the majority of research on transportation planning has focused on log trucking. The main reason for the lack of research on wood chip transportation planning is that until recent years, the wood chips required by pulp mills were an abundant by-product of other logging operations, which could be supplied from local sawmills or by pulp log chipping; consequently, there was no impetus to demonstrate efficiency for wood chip supply and transportation.

However, in recent years, traditional pulp and paper producers – especially in North America - have faced new challenges. These new challenges include: 1) limitations in availability of sawmill wood chips which resulted from declines in lumber production after the downturns in Canadian and American housing markets (Statistics Canada, 2013) 2) emerging pulp producers in tropical and subtropical regions with lower fibre costs, lower labor costs, and high technology plants (Bajpai, 2013); 3) decreasing paper production and consumption for some grades of paper in North America and its increasing dependence on the competitive export market (FAO, 2012); 4) growing global market for wood chips and pulp logs (Goetzl, 2008); 5) increasing competition for wood chip supply between pulp mills and bioenergy plants (Uronen, 2010); 6) expanding the competition of available land between wood plantations and food production; and 7) increasing limitations on wood harvest as a result of environmental and societal pressures. Consequently, fibre sources required for the pulp and paper industry are becoming more expensive and scarce.

Transporting wood chips to pulp mills is distinct from log truck transportation in several ways. Because of the high capital cost, pulp mills work continuously, which results in a very high frequency of transportation. Wood chip truck routing and scheduling problems need to be analyzed weekly in contrast to log transportation that are done on daily basis. The need for a continuous supply of wood chips to pulp mills requires complicated crew scheduling. Scheduling must account for drivers’ shift starting and ending times, shift changing times, changeover locations, rest times, and the number of weekly shifts for each truck and each driver. In addition, because of high capital cost of truck dumpers, the unloading capacity at pulp mills is usually limited to one truck at a time, which introduces a very strict unloading capacity compared to a log transportation models. Finally, pulp mills usually need to consider additional constraints to
provide a better transportation service for their major and permanent suppliers, such as transportation priorities for the main suppliers. A wood chip truck routing and scheduling problem with these constraints has not been considered in any of the previous studies and was the subject of this thesis.

The overall goal of this research was to improve the weekly truck transportation activities for wood chip transportation to a pulp mill with a limited truck unloading capacity. A simulated annealing model developed and presented in Chapter 4 along with the sensitivity analysis and scenario analysis presented in Chapter 5 was used to meet this objective. The simulated annealing method was able to model the truck routing and scheduling problem for wood chip transportation to a pulp mill and improve the weekly transportation plans that fulfilled the first objective of this study. The sensitivity and scenario analyses were able to evaluate the impact of changes in the structure of the transportation network and suggest the most promising changes that should be adapted by the pulp mill, which achieved the second objective of this study.

6.2 Conclusions

The solution approach based on simulated annealing was able to solve the daily and weekly truck transportation problem regarding the routes and schedules for a fleet of vehicles serving a large number of transportation demands from various suppliers. The simulated annealing model could help the truck dispatchers of pulp mills to make better decisions. For each truck, the decisions are which sawmills to visit, the sequence of visits to take, the pulp mill departure time, wood chip pickup time, pulp mill arrival time, wood chip unload time, driver shift change time, and driver shift change location. The model provides the opportunity to produce, evaluate, and improve the whole weekly schedule for the transportation network in a few minutes. It also gives the truck dispatchers the opportunity to easily and quickly analyze and compare alternative weekly transportation plans.

The simulated annealing model integrated several components of the wood chip supply and transportation problem, including: 1) wood chip production rate at sawmills; 2) inventory levels at sawmills; 3) transportation by trucks; 4) and unloading at the pulp mill over a weekly planning horizon. The results of this model are helpful to the truck dispatchers at pulp mills and pulp mill managers because with manual transportation planning, it is impossible to quickly generate, evaluate, and improve the weekly transportation plans. In the case featured in this study, transportation decisions are made based on the experience of the truck dispatchers. Specifically, whenever a truck is ready to go to its next trip, the dispatcher decides about its
destination based on the wood chip inventory level at the sawmills, the travel distances, and the number of hours the driver can work before his shift ends. Consequently, each transportation decision is made by evaluating a single trip for a single truck without considering the integrated weekly plan. The model developed here could be applied to produce an integrated weekly transportation plan for all the trucks, evaluate it, and improve it with each use.

Sensitivity and scenario analyses were used to evaluate the impact of changes in the structure of the transportation network on the performance and the costs of the transportation network. Sensitivity analysis was used to analyze the impact of changing the number of trucks utilized for transportation and the impact of an additional truck dumper. Scenario analysis was used to compare the impacts of different switch point locations for truck drivers and different combinations of regular trucks and self-dumping trucks.

The sensitivity analysis on the fleet size showed that variations in the transportation delay penalties, truck waiting penalties, and transportation costs were based on the number of trucks assigned to the same transportation tasks. The results could be used to determine the optimum number of trucks required to fulfill all the transportation demands and the minimum number of trucks required to provide an acceptable transportation service to high priority sawmills during temporary truck shortage conditions.

The sensitivity analysis on the number of truck dumpers (one or two) indicated that the performance could be improved by using an additional truck dumper. Investment in new truck dumper requires a high capital cost but it can guarantee an increased truck dumping capacity for many decades. The computational results showed that increasing the available truck dumpers from one to two could decrease the truck waiting times, the transportation delays, and the total weekly costs and penalties associated with the transportation network. A new dumper was also able to reduce the number of trucks required in the wood chip delivery network. The results supported investment in a new truck dumper because of the level of weekly cost savings it could return was more than the weekly ownership expenditures.

The scenario analysis on the impact of self-unloading trucks concluded that using self-unloading trucks improved the truck wait times, the transportation service level provided for the sawmills, and the total trucking costs and penalties. However, when half of the fleet was self-unloading trucks, adding more self-unloading trucks could not really improve the cost savings. Consequently, it was concluded that it was sufficient to substitute half of the trucks with self-unloading trucks. The results also showed the cost savings obtained from an additional truck
dumper was almost the same as using self-unloading trucks. However, a new dumper increases the unloading capacity of the pulp mill but self-unloading trucks increase the unloading capacity of the trucking company. Consequently, given the opportunity, it seems that investment in an additional truck dumper is more secure than investment in using self-unloading trucks.

The scenario analysis on the effect of changing drivers’ switch point locations concluded that the existing switch point locations provided the best combination. It was concluded that if only the pulp mill or the closest sawmills were switch point locations, the weekly transportation costs and penalties would increase. However, the level of deterioration was not significant and if required, the pulp mill manager could allow changing switch point locations according to those scenarios. It was also concluded that if all the sawmills were switch point locations or if the farthest sawmills were switch point locations, the weekly transportation costs and penalties would increase significantly.

In summary, this study addressed the rarely studied truck routing and scheduling problem for wood chip transportation from multiple sawmills to a central pulp mill. A solution method based on simulated annealing was developed, which was successful in modeling the transportation network and improving its performance. The results could help the truck dispatchers to decrease truck waiting times and increase transportation service level provided for the suppliers. The sensitivity and scenario analysis in conjunction with the simulated annealing method indicated that the structure of the transportation network could be improved. The results of this research can help the management team at the pulp mill and associated investors to strengthen the competitiveness of the pulp mill by improving the transportation network required to transport wood chip from sawmills to the pulp mill.

6.3 Benefits and Limitations

The benefits of this thesis can be summarized as follows: 1) a solution method was developed to model and improve truck routing and scheduling for wood chip transportation to a pulp mill with limited truck unloading capacity, 2) the model was applied to a real case study; and 3) the effect of changes in the structure of the transportation network were evaluated.

The primary benefit of this study was its detailed examination of truck routing and scheduling for wood chip transportation to a pulp mill. This study considered all the constraints related to the sawmill-to-pulp mill wood chip supply, including sawmills with different production plans located at various geographical distances from the pulp mill, sawmill priorities, available truck networks, drivers’ working hour regulations, and truck unloading facilities at the recipient pulp mill. Taking
all of these parameters into consideration produced a model that was an accurate representation of the complex problem of wood chip truck routing and scheduling. The solution method, which was based on a simulated annealing algorithm was able to produce detailed weekly truck routes and schedules for the entire truck fleet and all truck drivers within a few minutes. The model gives the decision makers – truck dispatchers in this case – practical opportunities to easily and quickly produce a set of weekly transportation plans, from which it is possible to analyze and select the most appropriate plan.

Another benefit of this study is that it utilized industry case study data. The case study presented here is based on a pulp mill operating in British Columbia, its supplier sawmills, and the truck network that facilitates transportation of wood chips from the sawmills to the pulp mill. Having access to real data and applying the model to it, is a strength point of this research. The fibre supply manager of the pulp mill also validated the model, its assumptions, and its results. This confirms that the model is a good representation of the problem under study and meets the needs of a pulp mill that has limited truck unloading capacity and seeks to improve its transportation plans.

The last benefit of this research is that a series of sensitivity and scenario analyses were designed to determine if the pulp mill could improve the structure of the transportation network and the truck unloading facilities. The potential changes considered in this study were the ones that the pulp mill had the authority to adjust, and for each change, the required additional costs and the potential obtainable cost savings were analyzed and reported. The results of the sensitivity and scenario analyses can help the pulp mill management team and investors to identify and adopt the most profitable changes and improve the competitiveness of their pulp mill.

The main limitations of this study are: 1) the model has a number of simplifying assumptions, 2) it did not consider uncertainties, and 3) it did not consider environmental or social issues. The model was built under assumptions explained in section 4.2 and it may not capture all constraints and conditions in the real life wood chip transportation network, such as transportation delays, truck breakdowns, and drivers’ route preferences, etc. The model also assumed that the truck loads were constant and there was one species of wood chips. However, in practice different truck loads may have different weight and volumes; and the pulp mill may use more than one species of wood chips. These variations can affect the value of different truck loads and the truck unloading times. Another assumption in this study was that all
the trucks were company trucks run by two drivers; but, in real life, a pulp mill may use a combination of company trucks and owner operated trucks that are run by one driver. Moreover, the model deemed that all drivers could visit all sawmills. In real life, some drivers may not be permitted to visit some sawmills. For examples, in the case study, since the pulp mill is in Canada and some of the sawmills are in the United States, some truck drivers may not have the transit documents that allow them to visit those sawmills. Additionally, this study assumed that there are no limitations on wood chips storage time and as long as a sawmill allows it, the wood chips can be stored in the yards from a few minutes to up to two month. This is true in summer and good weather condition but cannot be practiced in winter and cold weather condition. The reason is that in winter after a few hours of storage, the wood chips in the bins can freeze and usually if only bin storage is available, the wood chips needs to be transported in less than two hours after its production. Nevertheless, if stockpile storage is available, it can store wood chips for up to two month even in winter condition. In spite of all the simplifying assumptions, the model and its results were validated by the pulp mill’s fibre supply manager which indicates that the model is a close representation of the real condition.

This study did not consider uncertainties while developing the model or analyzing the results. It was assumed that truck travel time between each sawmill and the pulp mill, wood chip production rate at the sawmills, the truck loading times, and truck unloading times were constant numbers. In this thesis, estimated average values of these parameters were considered. A consideration of uncertainties can provide a more accurate view of the problem and the performance of the transportation network under uncertain conditions. Adding uncertainties make the truck routing and scheduling problem further complicated and it requires historical data on uncertain distribution of mentioned parameters. To mitigate the potential issues that arise from ignoring uncertainties, the simulated annealing model can be executed again with updated input data to produce an adjusted transportation plan for the remainder of the week.

Another limitation of this study is that it focused on economic objectives and did not consider environmental or social objectives. In this study, the improvements in the transportation plans and the structure of the transportation network were all based on financial interest of the pulp mill. Wood chip transportation to pulp mills produce social and environmental impacts on local job market, truck drivers, and greenhouse gas emissions, which were not considered in this study. The improvements made in transportation efficiency usually can be translated into reduction of greenhouse gas emissions and more efficient transportation plans usually result in better working environment for truck drivers. However, a more detailed analysis is required to
evaluate the social and environmental impacts of wood chip truck transportation. Social and environmental issues are generally addressed at the time of pulp mill design and can be found in feasibility studies conducted during this process. Incorporating these issues into the model was unfortunately beyond the scope of this research.

6.4 Future Work

The current study can be further developed to capture and incorporate more constraints into the transportation model, such as truck drivers’ route preferences, the home location of the truck drivers, and hog fuel transportation for energy production. One of the key issues in truck transportation is the availability and maintenance of experienced truck drivers. In order to increase the convenience of work environment for the existing drivers, the study may go a step further to assign drivers to their favourite routes. Another database that could be incorporated in the model is the home location of the truck drivers. In this way, the impact of switch point locations could be investigated more accurately. Moreover, this study can be expanded to consider transportation of hog fuel as well as wood chips. The hog fuel transported to the pulp mill is used for energy production.

An additional area for future work is the incorporation of uncertainties into the truck transportation model. There are many stochastic parameters that may affect the results of a deterministic model; and an interesting area for future research could be developing models that explicitly include variations in average values of parameters such as truck travel times, truck loading times, and dumper unloading times. Incorporation of these uncertain parameters requires a reliable historical database, which could be used to understand the uncertain nature of the associated parameters. The uncertainty also could be considered at higher levels such as uncertainties about the availability of suppliers in future. For example, in the case where one of the major suppliers closes down a sawmill or new sawmills and wood chip suppliers arise in future.

Another possibility for future research is considering environmental and social objectives along with economic objectives in the analysis of costs and benefits. The study of social and environmental impacts of economics are becoming increasingly critical, and considering them can provide broader results that also address issues such as the impacts of wood chip truck transportation on emissions, the local job market, pulp mill employers, truck drivers, local industries, and the communities residing in the neighbourhood area.
References


Appendix A: Calculation of Cost Coefficients for Trucking and Penalties

Trucking cost: The trucking cost was estimated based on fixed and variable costs for each tractor-trailer combination. In order to estimate the cost, the information obtained from Jokay and Pavel (2013) was used, deriving estimates based on information from vehicle manuals designed for 2000 scheduled hours of truck work per year (Table 18). In the case study problem, drivers worked an average of 55 hours/week for 46 weeks a year (taking into consideration the 6 weeks taken off for vacation and/or medical leave). Consequently, the working hours were about $55 \times 46 \times 2 \approx 5000$ hours per year with two drivers.

Equations (27) and (28) show how the fixed and variable cost for a tractor-trailer combination was calculated. Equation (29) calculates the weekly trucking cost given that a truck was on duty for 110 hours per week. When a truck is hired for a week, the weekly fixed cost was charged on it but the variable cost was only charged for the actual working hours.

\[
\text{Fixed tractor & trailer cost} \quad (27) \\
= \left( \frac{16.07}{\text{tractor ownership cost}} + \frac{3.67}{\text{trailer ownership cost}} \right) \times \frac{1.10}{\text{Profit and risk added}} \\
= 21.71 \$/h
\]

\[
\text{Variable tractor & trailer cost} \quad (28) \\
= \left( \frac{83.39}{\text{tractor operating cost}} + \frac{1.66}{\text{trailer operating cost}} \right) \times \frac{1.10}{\text{Profit and risk added}} \\
= 93.56 \$/h
\]

\[
\text{Trucking Cost for each truck ($/week) = Fixed cost} + \text{Variable cost} \quad (29) \\
= 21.76 \times 110 + 93.56 \times \text{Weekly working hours} \\
= 2,388 + 93.56 \times \text{Weekly working hours}
\]
Table 18: Fixed and variable costs for wood chips truck and trailer

<table>
<thead>
<tr>
<th>Ownership Costs</th>
<th>Costs based on 2000 h/y</th>
<th>Costs based on 5000 h/y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total purchase price (P)</td>
<td>$170,000</td>
<td>$170,000</td>
</tr>
<tr>
<td>Expected life (Y) y</td>
<td>5.00</td>
<td>10.00</td>
</tr>
<tr>
<td>Expected life (H) h</td>
<td>1000.00</td>
<td>2000.00</td>
</tr>
<tr>
<td>Scheduled hours/year (h)= (H/Y) h</td>
<td>2000.00</td>
<td>2000.00</td>
</tr>
<tr>
<td>Salvage value as % of P (s) %</td>
<td>30.00</td>
<td>15.00</td>
</tr>
<tr>
<td>Interest rate (Int) %</td>
<td>8.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Registration and Insurance Cost $/yr</td>
<td>$12,000.00</td>
<td>-</td>
</tr>
<tr>
<td>Salvage value ($S= (P-S)/100) $</td>
<td>$51,000.00</td>
<td>$10,650.00</td>
</tr>
<tr>
<td>Average investment (AVI)=((P+S)/2) $</td>
<td>$110,500.00</td>
<td>$40,825.00</td>
</tr>
<tr>
<td>Loss in resale value (P-S)/H $/h</td>
<td>$11.90</td>
<td>$3.02</td>
</tr>
<tr>
<td>Interest ((Int+AVI)/h) $/h</td>
<td>$4.42</td>
<td>$1.63</td>
</tr>
<tr>
<td>Insurance ((Ins×AVI)/h) $/hr</td>
<td>$6.00</td>
<td>$2.40</td>
</tr>
<tr>
<td>Total ownership costs (OW) $/h</td>
<td>$22.32</td>
<td>$16.07</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Operating Costs</th>
<th>Costs based on 2000 h/y</th>
<th>Costs based on 5000 h/y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel consumption (F) L/h</td>
<td>30.00</td>
<td>30.00</td>
</tr>
<tr>
<td>Fuel (tc) $/L for unmarked diesel</td>
<td>$1.32</td>
<td>$1.32</td>
</tr>
<tr>
<td>Lube &amp; oil $/yr</td>
<td>$2,250.00</td>
<td>$2,250.00</td>
</tr>
<tr>
<td>Annual tire consumption (t) -Steer</td>
<td>2.00</td>
<td>2.00</td>
</tr>
<tr>
<td>-Drives</td>
<td>$12.00</td>
<td>$12.00</td>
</tr>
<tr>
<td>-Trailers</td>
<td>$9.00</td>
<td>$9.00</td>
</tr>
<tr>
<td>Tire replacement (tc) $</td>
<td>$800.00</td>
<td>$800.00</td>
</tr>
<tr>
<td>-Steer</td>
<td>$550.00</td>
<td>$550.00</td>
</tr>
<tr>
<td>-Drives</td>
<td></td>
<td>$450.00</td>
</tr>
<tr>
<td>-Trailers</td>
<td>$450.00</td>
<td>$450.00</td>
</tr>
<tr>
<td>Tire repairs and rotations (trt) $</td>
<td>$500.00</td>
<td>$500.00</td>
</tr>
<tr>
<td>Annual operating supplies (OC) $</td>
<td>$500.00</td>
<td>$500.00</td>
</tr>
<tr>
<td>Annual repair &amp; maintenance (Rp) $</td>
<td>$20,000.00</td>
<td>$20,000.00</td>
</tr>
<tr>
<td>Shift length (sl) h</td>
<td>12.00</td>
<td>12.00</td>
</tr>
<tr>
<td>Wages (W) $/h</td>
<td>30.00</td>
<td>30.00</td>
</tr>
<tr>
<td>Wage benefit loading (WBL) %</td>
<td>25.00</td>
<td>25.00</td>
</tr>
<tr>
<td>Tire costs (t+tc)+(trt) $/yr</td>
<td>$8,200.00</td>
<td>$8,200.00</td>
</tr>
<tr>
<td>Fuel (F+tc) $/h</td>
<td>$39.60</td>
<td>$39.60</td>
</tr>
<tr>
<td>Lube &amp; oil ((tp/100)×(1+tc)) $/h</td>
<td>$1.12</td>
<td>$0.45</td>
</tr>
<tr>
<td>Tires ((htc)/h) $/h</td>
<td>$4.10</td>
<td>$2.02</td>
</tr>
<tr>
<td>Tire repairs and rotations $/h</td>
<td>$0.25</td>
<td>$0.25</td>
</tr>
<tr>
<td>Operating supplies (Ocpp) $/h</td>
<td>$0.25</td>
<td>$0.25</td>
</tr>
<tr>
<td>Repair &amp; maintenance (Rp/h) $/h</td>
<td>$10.00</td>
<td>$4.00</td>
</tr>
<tr>
<td>Wages &amp; benefits (W×1+1×WBL/100) $/hr</td>
<td>$37.50</td>
<td>$37.50</td>
</tr>
<tr>
<td>Total operating costs (OP) $/h</td>
<td>$92.02</td>
<td>$83.39</td>
</tr>
<tr>
<td>Total Ownership and Operating Costs</td>
<td>$115.14</td>
<td>$99.46</td>
</tr>
<tr>
<td>Profit and risk 10%</td>
<td>$120.00</td>
<td>$109.41</td>
</tr>
<tr>
<td></td>
<td>$10.92</td>
<td>$5.33</td>
</tr>
</tbody>
</table>


**Truck waiting penalty:** The truck waiting penalty was calculated based on trucking cost and non-productive truck times (truck waiting times). The truck waiting times were categorized into four different types: 1) Loaded truck at the pulp mill, which happened if a truck arrived at the pulp mill and the dumper was not available; 2) Unloaded truck at the pulp mill, which happened if the load planned to be picked up next was not ready or if the driver’s shift had ended but the next driver had not arrived; 3) Unloaded truck at a sawmill, which happened if the sawmill was a
shift changing location and when the driver got to the sawmill, his shift was over but the next driver was not yet there; 4) Loaded truck at a sawmill, which was similar to unloaded truck waiting at a sawmill where the only difference was that the driver had enough time to load the truck before his shift expired.

The truck waiting times show inefficiency in truck utilization and should be minimized. The penalty for truck waiting times was considered to be equal to the summation of fixed and variable costs for both tractor and trailer, which is equal to $109.41 + 5.86 = 115.27$ dollar per hour. Equation (30) displays the weekly waiting penalty for each truck in the fleet:

\[
\text{Truck waiting penalty ($/week) = 115.27 \times total\ truck\ waiting\ hours\ in\ a\ week}
\]  

(30)

**Transportation delay penalty:** The transportation delay penalty was calculated based on the number of truckloads of wood chips that were supposed to be transported to the pulp mill during the planning week but because of the limited number of trucks and drivers, the truck fleet was unable to transport them and delayed the transportation task to the following week. The penalty for unit price of transportation delay was different for high priority sawmills and low priority sawmills and was based on what sawmills do to a wood chip load after its transportation is postponed to a following week.

In a low priority sawmill, if the transportation of a load was delayed until the following week, the sawmill stored it and charged the weekly storage cost. The storage cost for a truckload of wood chips was calculated according to equation (31) and is a function of the weight of the load and the storage cost per unit of weight. Wood chip inventory adds approximately $2/BDT to the cost of producing kraft pulp for each 30 days of wood chip storage (Quillin, 1994); and in the case study, the average wood chip load weight carried in each trip was approximately 20 bone dry tonnes. Consequently, the transportation delay penalty for low priority mills was equal to $9 per one truckload per week.

\[
\text{Storage Cost} = \frac{\text{average load weight} \times \text{storage cost}}{\text{BDT/load} \times \text{BDT of woodchips}}
\]

\[
= 20 \times 2\sim40\ per\ month\ or\ 9\ per\ week
\]  

(31)

In a high priority sawmill, if the transportation of a load was postponed to the next week, the sawmill sold it to another customer; in that case, the transportation delay penalty was equal to the profit the pulp mill lost by not picking up the load and consequently is a function of wood chip load weight, pulp yield, and pulp mills' profit per unit of pulp (32). The average wood chip
weight per truckload in the case study was 20 bone dry tonnes \((load\ weight = 20)\). According to Biermann (1996), in the kraft (sulphate) process, the pulp yield for fir, larch, spruce, pine and balsam (the main species used at the case study site) is approximately 48 percent of oven-dry weight of pulp per oven-dry weight of the wood chips \((pulp\ yield = 0.48)\); and, according to Natural Resources Canada (2013), from November 2012 to November 2013, the average price for northern bleached softwood kraft (NBSK) pulp was $921 per metric tonne of pulp \((pulp\ price = 921)\).

To calculate the pulping cost, it was assumed that wood costs typically account for at 40-50\% of pulp production costs and the pulping cost was calculated according to Equation (33) based on wood chip price and its transportation cost.

\[
Pulp\ cost = \frac{(Chips\ cost + Chips\ hauling\ cost)}{0.40}
\]  

(33)

The wood chip price was assumed to be $60 per bone dry tonne (Culbertson, 2013; McCallum, 1997; Sinclair, Berlyn, and Manning, 1985) and the average wood chip hauling cost was calculated based on average travel time according to Equation (34). In order to calculate the average travel time, the information about annual production plan and travel times for the case study in year 2012 was used. Table 19 shows the sawmills, the total bone dry tonnes of wood chips they agreed to supply in one year, the number of truckloads of wood chips they provided, travel time between the pulp mill and each sawmill, service time at sawmills (including truck loading and pre-trip check-ups), service time at the pulp mill (including truck unloading and pre-trip check-ups), and total travel time for one truckload. Based on this information, the average travel time was equal to 5 hours and 27 minutes, or 5.46 hours.

\[
Average\ travel\ time = \frac{\sum_{i=1}^{n} (Travel\ time\ for\ a\ load\ from\ mill\ i \times Annual\ number\ of\ loads\ from\ mill\ i)}{\sum_{i=1}^{n} Annual\ number\ of\ loads\ from\ mill\ i}
\]  

(34)

\[
= 5:27\ (h:mm) = 5.46\ hours
\]
Table 19: Annual supply plan and travel times

<table>
<thead>
<tr>
<th>Mill</th>
<th>BDT per year</th>
<th>Truckload per year</th>
<th>One-way travel time (h:mm)</th>
<th>Service time at sawmill (h:mm)</th>
<th>Service time at pulp mill (h:mm)</th>
<th>Total travel time per load (h:mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A2</td>
<td>99,700</td>
<td>4,985</td>
<td>0:45</td>
<td>0:30</td>
<td>0:30</td>
<td>2:30</td>
</tr>
<tr>
<td>A3</td>
<td>114,853</td>
<td>5,742</td>
<td>1:45</td>
<td>0:30</td>
<td>0:30</td>
<td>4:30</td>
</tr>
<tr>
<td>CA2</td>
<td>15,102</td>
<td>755</td>
<td>0:45</td>
<td>0:30</td>
<td>0:30</td>
<td>2:30</td>
</tr>
<tr>
<td>B9</td>
<td>43,000</td>
<td>2,150</td>
<td>4:45</td>
<td>0:30</td>
<td>0:30</td>
<td>10:30</td>
</tr>
<tr>
<td>B10</td>
<td>40,000</td>
<td>2,000</td>
<td>2:45</td>
<td>0:30</td>
<td>0:30</td>
<td>6:30</td>
</tr>
<tr>
<td>P31</td>
<td>27,620</td>
<td>1,381</td>
<td>4:00</td>
<td>0:30</td>
<td>0:30</td>
<td>9:00</td>
</tr>
<tr>
<td>U21</td>
<td>14,000</td>
<td>700</td>
<td>2:30</td>
<td>0:30</td>
<td>0:30</td>
<td>6:00</td>
</tr>
<tr>
<td>U41</td>
<td>13,396</td>
<td>669</td>
<td>5:00</td>
<td>0:30</td>
<td>0:30</td>
<td>11:00</td>
</tr>
<tr>
<td>B1</td>
<td>92,942</td>
<td>4,647</td>
<td>1:30</td>
<td>0:30</td>
<td>0:30</td>
<td>4:00</td>
</tr>
<tr>
<td>B13</td>
<td>11,920</td>
<td>596</td>
<td>5:00</td>
<td>0:30</td>
<td>0:30</td>
<td>11:00</td>
</tr>
<tr>
<td>Sum</td>
<td>472,533</td>
<td>23,625</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

According to these calculations and the trucking costs from Table 18, the wood chip hauling cost is calculated based on Equation (35) and was equal to $31.49 per BDT of wood chips. Using Equations (33) and (32), the pulp cost and value of one lost load were equal to $228.73 per BDT and $6,645 per truckload respectively.

\[
\text{Chips hauling cost} = \frac{\text{Average travel time}}{\text{hour/truckload}} \times \frac{\text{Trucking cost}}{\text{$/hour}} = 5.46 \times (109.41 + 5.86) = \frac{629.85}{\text{$/truckload}} = 31.49 \frac{\text{$/bdt}}{\text{$/load}}
\]

\[
\text{Pulp cost} = \frac{60 + 31.49}{0.40} = 228.73 \frac{\text{$/bdt}}{\text{$/load}}
\]

\[
\text{Value of one lost load} = 20 \times 0.48 \times (921 - 228.73) \approx 6,645 \frac{\text{$/load}}{\text{$/load}}
\]

In the case study, sawmills A2, A3, and CA2 are high priority mills and the rest of the mills are low priority mills. In the planning week considered in this study, these three sawmills were the major suppliers and could not hold wood chips in inventory at the end of the week. However, the other sawmills were more flexible and if any transportation delays happened, they stored the wood chips and allowed transportation in the following week.
Transportation Delay Penalty for each mill

\[ \text{Transportation Delay Penalty} = 6,645 \times \text{Number of delayed truckloads from mills A2, A3, CA2} \]

\[ + 9 \times \text{Number of delayed truckloads from mills B9, B10, P31, U21, U41} \]