Optimization of Log Logistics at the Operational Level Considering Sorting Decisions and Synchronization Requirements

by

Seyed Salar Ghotb

M.Sc., Isfahan University of Technology, 2018

B.Sc., University of Tabriz, 2015

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Examining Committee:

Dr. Taraneh Sowlati, Professor, Department of Wood Science, UBC
Supervisor

Dr. Verena Griess, Professor, Department of Environmental Systems Science, ETH Zürich
Supervisory Committee Member

Dr. Dominik Roeser, Associate Professor, Department of Wood Science, UBC
Supervisory Committee Member

Joel Mortyn, Manager, Inventory & Analysis, Western Forest Products
Supervisory Committee Member

Dr. Farrokh Sassani, Professor Emeritus, Department of Mechanical Engineering, UBC
University Examiner

Dr. Gregory Smith, Professor, Department of Wood Science, UBC
University Examiner

Abstract

Log logistics activities, such as transporting, loading/unloading, and processing of logs, are essential elements of forest operations and account for a significant portion of the total costs of delivered logs. Although previous studies investigated log logistics, they mainly emphasized on economic aspects and did not address some practical aspects of the logistics problem. The main goal of this dissertation is to optimize log logistics at the operational level incorporating practical considerations and complexities. In order to achieve this goal, a decomposition framework is employed that divides the log logistics problem into two phases. In the first phase, a bi-objective optimization model is developed in which sorting decisions, trucking contractors, and compatibility requirements at supply and demand locations are considered. The first objective of the bi-objective model is to minimize the total transportation costs, while the second objective addresses the social aspects by balancing the workload of contractors. The outputs of the first phase are used as the inputs of the second phase, for which an optimization model is developed to determine the daily routing and scheduling of heterogeneous trucks using continuous time representation. The model enables synchronization of log loaders and trucks and generates a detailed schedule of activities. In addition, a solution approach based on the simulated annealing algorithm is developed to solve the large-sized daily routing and scheduling problem. The Taguchi method is used to enhance the quality of the solutions by calibrating the input parameters of the algorithm. The framework, optimization models, and the solution approach are applied to a case study of a large Canadian forest company where logs are transported from cut blocks to sort yards for further processing. Results show that the framework can generate balanced workloads for all contractors with less than 1% increase in transportation costs and can determine the daily schedule of log trucks considering practical operational considerations. It is concluded that assigning overtime to trucks instead of dispatching a new truck can generate cost savings. The proposed

models and the solution approach can be applied to other cases and regions by modifying the input data.

Lay Summary

Log logistics activities have a significant contribution to the total log procurement costs. Despite the various complexities, operational details did not get enough attention in previous studies. This research aims to improve log logistics at the short-term planning by proposing an optimization framework for daily routing and scheduling of trucks considering practical aspects. Also, a solution approach is presented to overcome the computational burden of solving large-scaled problems. This work incorporates different complexities such as workload balance, log sorting decisions, trucking contractors, and synchronization requirements. The results of employing the framework to the case study of a Canadian forest company reveal that with a slight increase in total costs, the logistics network can be more sustainable by addressing social considerations. Also, detailed scheduling of log logistics activities can assist decision makers to utilize their resources efficiently.

Preface

All the work presented in this thesis was carried out by the author, Seyed Salar Ghotb, during his PhD program. The work was conducted under the supervision of Dr. Taraneh Sowlati at the Industrial Engineering Research Group of the University of British Columbia, Vancouver, Canada. Parts of this dissertation is presented in the following publications.

- A version of Chapter 3 is published in the following article.
    - Ghotb, S., Sowlati, T., Mortyn, J., Roeser, D., & Griess, V. C. (2022). A goal programming model for the optimization of log logistics considering sorting decisions and social objective. *Canadian Journal of Forest Research*, *52*(5), 716-726.

  I was the main author of the article. I developed the mathematical programming models and solved them, obtained the required data, conducted analysis, and prepared the manuscript. Sowlati, T. was the supervisory author who advised in defining the problem and research objectives, reviewed and approved methodologies and models, provided support in the communications and meetings with our industrial partner, and guided in manuscript preparation and revisions. Mortyn, J. was from our industrial partner who provided the data, identified the case study, verified the results, and contributed to the manuscript editing. Roeser, D. and Griess, V.C. proofread and edited the manuscript.

- A version of Chapter 4 is submitted to a peer-reviewed journal for publication and is under review.
    - Ghotb, S., Sowlati, T., Mortyn, J. (2023). An optimization model for detailed scheduling of heterogeneous fleet of log trucks considering synchronization.

I was the main author of this article. I developed the mathematical programming models and solved them, defined test problems, conducted analysis, and prepared the manuscript. Sowlati, T. was the supervisory author who advised in defining the problem, reviewed and approved methodologies and models, provided support in the communications and meetings with our industrial partner, and guided in manuscript preparation and revisions. Mortyn, J. was from our industrial partner who provided the data, identified the case study, verified the results and contributed to the manuscript editing.

- A version of Chapter 5 is submitted to a peer-reviewed journal for publication and is under review.
    - Ghotb, S., Sowlati, T., Mortyn, J. (2023). Scheduling of log logistics using a metaheuristic approach.

I was the main author of this article. I developed the solution approach and coded it, ran the algorithm to get the results, conducted analysis, and prepared the manuscript. Sowlati, T. was the supervisory author who advised in defining the problem, reviewed and approved the algorithm, provided support in the communications and meetings with our industrial partner, and guided in manuscript preparation and revisions. Mortyn, J. was from our industrial partner who provided the data, identified the case study, verified the results and contributed to the manuscript editing.

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To my family

Chapter 1: Introduction

1.1 Background

Log logistics include different activities such as loading/unloading, transporting, scaling, cutting, sorting, and storing logs. Overall, these activities comprise a large proportion of the total log procurement costs. In 2019, logistics activities including scaling, trucking, and loading accounted for 29% of the average delivered log costs in central Interior, BC (Girvan & Taylor, 2020).

In the forest covered regions, a large volume of logs is sent from forest areas to demand locations. In Sweden, for example, trucks carried 36.8 million tons of roundwood in 2012 (Swedish Forest Agency, 2014). As the capacity of trucks is limited, a significant number of truckloads is delivered from forest areas to satellite yards, mills, and other industrial centers. For example, in British Columbia, almost 1.4 million truckloads were transported in 2014 (British Columbia Forest Safety Council, 2015). Due to the high number of trips and long distances between forest areas and demand locations, log transportation has a higher contribution to the cost among the other logistics activities. In 2021, transportation accounted for more than 38% of the unit delivered cost of industrial roundwood in Finland (Natural Resources Institute Finland, 2023). Hence, improvements in log transportation could potentially generate cost savings (Palmgren et al., 2004) and consequently could increase the competitiveness of forest companies.

The log transportation planning includes decisions at different levels. While long-term and medium-term decisions are made at strategic and tactical levels, operational plans are mainly related to short-term decisions such as routing and scheduling of log trucks (Malladi & Sowlati, 2017).

The log logistics and transportation problem is subject to several challenges. For example, each cut block provides various log sorts, and different mills may require different log sorts. Thus, logs of different species and diameter classes need to be sorted and processed at cut blocks or demand locations. The fleet of log trucks carrying the logs can be either homogeneous or heterogeneous. Homogeneous fleets consist of the same type of truck, while heterogeneous fleets consist of more than one type of truck with different characteristics such as capacity and costs. Some trucks may not be suitable to carry some types of logs or travel to certain locations. Therefore, compatible trucks should be used to deliver logs to yards, mills, or other industrial sites.

In the routing and scheduling of log trucks, some important practical aspects need to be considered in the operational logistics planning. For example, the operational time of a mill/yard during which the logs should be delivered and the maximum driving time of a truck driver impact logistics planning. In addition, logs need to be transported from cut blocks in a timely manner as they may deteriorate over time. Also, log flows should be smoothly distributed over the planning horizon (Hirsch, 2011). Besides, processing/storage capacities, and maximum working time of trucks limit the delivery of truckloads. Furthermore, there are resources that must operate simultaneously to fulfill a logistics activity. Log loaders and trucks, for example, work together for loading and unloading of truckloads. By synchronizing the trucks and loaders, waiting times can be reduced, resulting in more efficient transportation planning. Hence, the above-mentioned aspects should be included in log logistics planning at the operational level.

Due to the importance of transportation, recent studies proposed different methods to improve and optimize log transportation at the operational level. In a group of studies (e.g. Vitale et al., 2021; Melchiori et al., 2022), the flows of logs between different supply and demand points were considered as decision variables of models. In other words, these flows were outputs of the proposed optimization models. This group of studies is referred to log truck scheduling problems (LTSP) in the literature (Malladi & Sowlati, 2017). In another group of papers (e.g. Zazgornik et al., 2012; Oberscheider et al., 2013), the flows of logs were either known and used as inputs or were driven from an upper-level model. As mentioned in (Malladi & Sowlati, 2017), this group is referred to timber transportation vehicle routing problem (TTVRP).

While some authors (e.g. Rey et al., 2009; Haridass et al., 2014; Melchiori et al., 2022) proposed daily logistics and transportation plans the planning horizon in other studies (e.g. Flisberg et al., 2009; Rix et al., 2015) was more than one day. In previous studies, both homogeneous and heterogeneous fleets of trucks were considered for carrying the logs from supply points to demand locations (e.g. Palmgren et al., 2004; Rey et al., 2009; El Hachemi et al., 2013). Different logistics aspects were incorporated in the log logistics literature to have a more realistic plan. For instance, multiple depots (e.g. Flisberg et al. 2009), road weight requirements (e.g. Gronalt and Hirsch 2007) and time windows (e.g. Oberscheider et al. 2013; Haridass et al. 2014) were incorporated in the routing and scheduling of log trucks.

Although the log logistics problem has evolved well in recent years, further practical details can be incorporated to have a more applicable and efficient logistics plan. The main objective of the existing models (e.g. Rey et al., 2009; Bordón et al., 2018; Vitale et al., 2021) was the economic objective, while other aspects including social ones have not been investigated enough. The harvested logs have different assortments, and the industrial sites may demand specific assortments. Therefore, sorting of logs is one of the important processing activities before log consumption. To the best of my knowledge, previous studies did not consider log sorting in their problems. Besides, in the forest operations, logs should be transported by compatible fleet of trucks. However, compatibility of logs and truck types was not considered in the log logistics literature. In addition, forest companies may contract out their logistics activities to logistics companies and contractors. These contractors and their limitations such as balancing the workload did not get enough attention in the proposed log logistics planning in the literature.

There are also other considerations in log truck scheduling that can improve the overall logistics plans. According to (Lagzi, 2016), the representation of time significantly affects the quality of solutions in the scheduling optimization problems. Time can be represented by finite discrete intervals or continuous variables. In finite discrete representation, activities are assigned to finite intervals and schedules are generated accordingly, while in continuous time representation, the schedule of activities is defined by minutes or hours. Both discrete and continuous time representations have strengths and limitations. It is easier to use discrete intervals for modelling the scheduling problem for shared resources such as loaders used for loading/unloading activities (Lee & Maravelias, 2018). The start time of each activity of the resources is assigned to the beginning of discrete intervals. However, it is challenging to define the duration of intervals, which in turn affects the accuracy of the schedules. In the continuous time representation, the schedules are more accurate because activities can happen at any time in the planning horizon. Moreover, variable processing times can be easily addressed by continuous variables (Lagzi, 2016). However, modelling the problem for shared resources is more difficult using continuous variables. Despite all aforementioned advantages and drawbacks, there is no general consensus about time representation in scheduling optimization problems (Stefansson et al., 2011). Most papers in the log transportation literature (e.g. El Hachemi et al., 2013; Melchiori et al., 2022) used discrete time representation, while less attention was given in the literature to employ continuous variables in log transportation scheduling.

Having detailed and accurate schedules is more important in synchronization of log loaders and trucks to calculate the waiting times for loading/unloading because inaccurate waiting times may violate time windows (i.e., operational time of a mill) and impact the efficiency of the entire schedule. However, only a few papers addressed synchronization of log loaders and trucks and determined detailed schedules. In (El Hachemi et al., 2011, 2013, 2015; Melchiori et al., 2022), discrete time slots were used to facilitate synchronization of log loaders and homogeneous trucks. However, defining time slots can be more challenging when there is more than one type of truck and loading/unloading times depend on the type of the truck. Additionally, to synchronize log loaders and trucks efficiently, the discrete intervals need to be granulated enough which results in more binary and integer variables and makes the problem more difficult to solve compared with the continuous time variables. Soares et al. (2019) used continuous times in synchronization of different machines including trucks, lorries, and loaders in the biomass transportation problem. However, they had the synchronization only at the delivery points, where loaders with lorries and trucks with loaders needed to be synchronized. Moreover, trucks can be assigned overtime by the trucking contractors to fulfill the transportation tasks. Working overtime usually has a higher cost rate compared to that of the regular working time. Depending on the contract, there is a maximum limit for assigning overtime to each truck. Incorporating overtime in log transportation planning is useful for decision makers as it gives them an understanding of the trade-off between assigning overtime and dispatching a new truck to deliver the truckloads.

It is noteworthy that the log logistics problem is a variant of pickup and delivery problem (Audy et al., 2022). Hence, the problem is NP-Hard, which means that the large-sized problem cannot be solved using commercial solvers. Commercial software packages can be used to solve log logistics optimization models only for small and medium-sized problems. Therefore, non-exact solution approaches are required to solve real-world large-sized problems in a reasonable time.

1.2 Research objectives

The main goal of this research is to optimize the log logistics planning at the operational level (1-month planning horizon) considering real-world complexities and to apply it to the real case of a forest company in British Columbia, Canada. The goal is achieved through the following research objectives.

1) Optimize monthly flows of logs with minimum transportation costs and balanced workloads for trucking contractors by developing a bi-objective model. The proposed model will determine the daily flows of logs between different supply (cut blocks) and demand (sort yards) locations considering various practical aspects and complexities such as sorting decisions, social aspects, trucking contractors, a heterogeneous fleet of trucks, and truck compatibility requirements.
2) Optimize daily routing and scheduling of a heterogeneous fleet of trucks by introducing an optimization model. The model will synchronize log loaders and trucks at both pickup (cut blocks) and delivery (sort yards) locations, generate detailed schedules for trucks, and include operational decisions for trucking contractors.
3) Develop a non-exact solution approach to solve the large-sized daily routing and scheduling problem in a reasonable time considering the complexities of the real case.
4) Apply the models and solution approach to a real case study.

These objectives are linked to each other through a decomposition approach, in which the problem is divided into two phases. Objectives 1 and 2 correspond to the first and the second phase, respectively. The first phase determines the daily allocation of logs between supply and demand locations with minimum costs and smooth workload for the trucking contractors. In the second phase, detailed schedules of trucks are generated considering synchronization of trucks and loaders at both supply and demand locations. It is noteworthy that the number of truckloads obtained from the first phase is the input of the second phase of the decomposition approach. Then, the third objective overcomes the computational complexities of the model developed in the second phase by proposing a solution approach. Finally, the fourth objective is achieved by applying the proposed models and solution approach to a real case study.

1.3 Case study

In this research, the logistics problem of a large forest company is investigated. The company is one of the leading forestry companies in Canada. It is an integrated forest company that generated more than $1.3 billion revenue in 2022. It has sawmills and remanufacturing facilities in Canada and the US. The company predominantly manages Crown tenures with an annual harvesting of roughly 6 million m^3 of logs for its mills' consumption and other external markets. The forest company procures different species such as Western Hemlock (Tsuga heterophylla) and Douglas Fir (Pseudotsuga menziesii) with different log diameter classes.

To procure logs from cut blocks and deliver them to the sawmills, the company has different harvesting phases such as falling trees for building roads, road construction, falling, yarding, and transporting. The company has operations in different regions. According to the company's request, the focus of this study is on logistics and transportation of logs in one of the regions where the company has more than 100 cut blocks, and truckloads are sent to three sort yards for processing.

Each month, roughly 20 to 25 cut blocks are harvested. Then, the harvested logs are stored at the roadside. The company aims to maintain the level of stored logs at roadside as low as possible. The monthly volume of supply and demand is known in advance from a high level-planning model, which is developed internally at the company, considering the scheduling of other harvesting phases. The harvested logs are either sorted or unsorted. In total, there are over 40 log sorts, which are identified by their species and diameter classes. Table 1-1 presents the minimum, average, and maximum volume of each type of logs harvested in the cut blocks.

Table 1-1. The minimum, average, and maximum volume of logs at cut blocks (provided by the forest company)

	Sorted logs	**Unsorted logs**
Minimum (m^3)	0	0
Average (m^3)	100	230
Maximum (m^3)	3156	6418

Both sorted and unsorted logs are transported to 3 sort yards for further processing. The sort yards are located next to the water to facilitate the water transportation to mills. In each sort yard, there are operators and machines for processing of delivered truckloads. Sort yards have different space and processing capacities (Table 1-2). The second and the third columns of Table 1-2 list the processing capacities for sorted and unsorted logs, respectively. Also, the total volume of processed logs (both sorted and unsorted) should be less than the total processing capacity of the sort yards (fourth column of Table 1-2). Most of the daily delivered logs need to be kept in the water, and only a limited volume of logs can be stored in the sort yards (fifth column of Table 1-2).

Table 1-2. The daily processing and storage capacities of sort yards (provided by the forest company)

Sort yards	**Processing capacity (m^3/day)**			**Space capacity (m^3)**
	Sorted logs	**Unsorted logs**	**Total**	
Sort yard 1	400	810	810	200
Sort yard 2	1030	2400	2400	200
Sort yard 3	1200	820	1400	200

Depending on the type of logs in a truckload, the processing activities are different. As shown in Figure 1-1, unsorted logs arriving at the sort yards are first unloaded by a loader. The unloaded logs, then, are measured, scaled, and sorted by operators. After sorting, log piles are placed into a bunk. Finally, logs are bundled and dumped into the water using a bandit and a loader. For the sorted logs, however, operators do not need to measure and sort them as they are already sorted. When the sorted truckloads are delivered to the sort yards, the logs are placed into the bunk immediately after getting unloaded. Similarly, bundling and dumping the logs into the water are done using the bandit and the loader. Finally, all the stored logs in the water are transported using tugboats and barges to mills and other manufacturing facilities. The schedule of the tugboats is determined by the company, and these tugboats usually tow the logs at least twice a month.

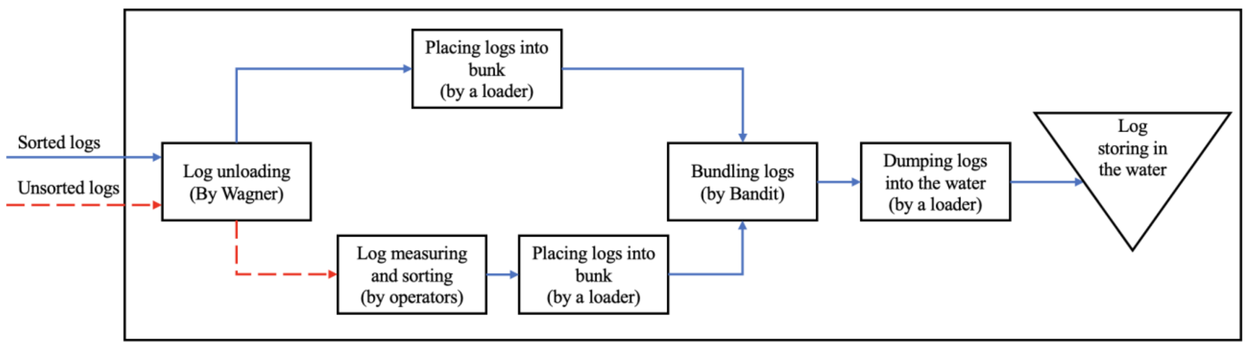

Figure 1-1. The logistics processes of delivered logs at sort yards

It should be noted that the transportation and processing planning in this work covers the activities from the roadsides till the logs are dumped into the water at sort yards. If the transportation planning was from the forest roadsides to the mills, then the water transportation had to be considered as well. If the truckloads were required to be directly delivered to sawmills, the processing activities had to be done at roadside of cut blocks because the sawmills have demands for specific log sorts. In addition, more trucks would be needed to deliver the truckloads to the mills, leading to more transportation costs. However, the company can take advantage of water transportation, resulting in less transportation costs. Moreover, in the case study, the processing activities cannot be done at cut blocks because of space limitations of forest areas.

For delivering the truckloads from the cut blocks to the sort yards, the forest company has contracted out the transportation activities to trucking contractors, who employ a heterogeneous fleet of trucks to fulfill the transportation activities. These contractors can serve only in certain cut blocks and have different numbers of trucks (Table 1-3). It should be mentioned that the third column of Table 1-3 shows the total number of trucks that each contractor owns, and these trucks can be used for other regions where the contractor has operations. Based on the communication with the forest company, it is important to generate a balanced and smooth workload for the contractors over the planning horizon as an unbalanced workload leads to contractors' dissatisfaction.

Table 1-3. Information of trucking contractors (provided by the forest company)

Contractors	**No. of cut blocks**	**No. of trucks**
Contractor 1	8	1
Contractor 2	18	12
Contractor 3	2	12
Contractor 4	8	8
Contractor 5	18	10
Contractor 6	18	4
Contractor 7	8	7
Contractor 8	22	22

On each day, trucks are dispatched from a central depot to cut blocks to get loaded. Then, they move the truckload to a sort yard for unloading. A truck works for 8.5 hours and can have 2 to 3 trips per day. The contractors can also assign up to 150 minutes of overtime to each truck. The heterogeneous trucks are either highway or off-highway trucks that have different compatibility requirements (Figure 1-2).

(a) (b)

Figure 1-2. Log trucks (a) off-highway (b) highway (photo taken by Seyed Salar Ghotb)

Due to transportation regulations, off-highway trucks are not allowed on highways, while highway trucks can be used on all road types. Highway trucks can deliver both sorted and unsorted logs, while off-highway trucks do not carry sorted logs because the capacity of these trucks is greater than the capacity of the lifts at the sawmills to bring them out of the water. Additionally, the larger capacity of off-highway trucks compared to that of highway trucks leads to a longer loading time by loaders. However, the unloading time for both types of truck is the same as a loader called "Wagner" unloads both types at once (See Table 1-4).

Table 1-4. Characteristics of highway and off-highway trucks (provided by the forest company)

Truck type	**Compatible truckload**	**Capacity (m^3)**	**Loading time (min.)**	**Unloading time (min.)**
Highway	Sorted and unsorted truckload	43	15	8
Off-highway	Unsorted truckload	95	20	8

Currently, the company does not use any decision-making tool for logistics planning at the operational level. The company aims to have a logistics planning tool for a 1-month planning horizon. The tool should assist the company to generate balanced workload for the contractors and to determine: 1) the daily volume and number of both sorted and unsorted truckloads from each cut block to each sort yard to meet the demands, 2) the daily volume of logs that is sorted in each sort yard, 3) the daily number of trucks of each type that is dispatched by contractors, and 4) routing and detailed scheduling of trucks including the arrival time, waiting time and start time. This research aims to address the problem by developing optimization models and a suitable solution approach to solve large-scale problems.

1.4 Outline of the thesis

In addition to the current chapter, the thesis has the following chapters.

Chapter 2 reviews the proposed methodologies, models, and solution approaches in the log logistics literature as well as studies related to logistics of other forest products.

In chapter 3, a bi-objective mixed integer programming (MIP) model is introduced to determine the flows of logs, the volume of processed and stored logs, and the workload of trucking contractors. The results are analyzed, and a sensitivity analysis is conducted to identify the most sensitive parameters.

Chapter 4 includes an MIP model for routing and scheduling of the heterogeneous fleet of trucks considering synchronization of log trucks and loaders. The results of the suggested model for several test problems from the case study are presented.

A metaheuristic algorithm is developed as a solution approach in Chapter 5 to solve the routing and scheduling of trucks for large-sized problems. The algorithm is then applied to the case study, and the results are provided and analyzed.

Finally, Chapter 6 concludes the research work and includes strengths, limitations, and directions for future research.

Chapter 2: Literature review

2.1 Synopsis

Log logistics comprise of a variety of different activities including transportation and account for a considerable portion of total delivered costs. In different countries, delivering logs to mills can contribute to more than 45% of the operational costs (Audy et al., 2012). Therefore, various studies have been conducted in recent years to optimize log logistics and address different challenges. This chapter explains the log logistics and provides a review of previous studies. The studies are categorized into two groups: 1) Integrated optimization approach, and 2) Decomposition optimization approach. The main features and limitations of each group are described. Additionally, the papers on logistics and transportation of other forest products are reviewed.

2.2 Log logistics and main features

Log logistics include sorting, processing, transportation, and storage of logs. In sorting and processing, logs of different species are sorted into distinct sorts and diameters, while during the transportation phase logs are carried from forest areas to different demand locations including satellite yards, mills, and other industrial sites using the same or different types of trucks. It is important to note that full truckloads are often used for log transportation (Audy et al., 2012), which means a truck is fully loaded at a supply point and delivers the load to only one demand location. Due to the large volume of logs, each supply and demand point is usually visited more than once per day.

The main decisions of log logistics and transportation at the operational level include the determination of log flows between supply and demand locations, the volume of stored logs, and routing and scheduling of trucks (Malladi & Sowlati, 2017). Routing of a log truck involves the determination of the sequence of locations that the truck should visit, while in the scheduling of trucks, times are assigned to each transportation activity. In log logistics, machines may work together to perform an activity. Log trucks and loaders, for instance, work simultaneously for loading/unloading of logs. Thus, synchronization of different machines is an important aspect in logistics planning as it leads to more detailed scheduling and efficient plans.

In recent years, optimization models have been introduced to address the complexities and make log logistics planning more practical. Previous studies can be classified into two main groups: 1) Integrated optimization approach, and 2) Decomposition optimization approach.

2.2.1 Integrated optimization approach

In this approach, an optimization model is developed to address the problem. The advantage of this method is to integrate various decisions in a single optimization model. However, it increases the complexities, leading to more computational expenses in optimization problems (e.g. Vacca et al., 2010).

In this class, a group of studies considered a homogeneous fleet of trucks for delivering the logs. In (Murphy, 2003; Bordón et al., 2018; Melchiori et al., 2022, 2023), the authors employed commercial solvers to solve their problems. Murphy (2003) suggested that it was more efficient to have forest owners rather than purchasers to transport logs from supply points to demand points. The author proposed an integer programming (IP) model for the daily routing of homogeneous trucks to minimize the total costs for two case studies with different sizes in New Zealand. In addition to the demand and supply constraints, each truck could operate only for a limited amount of time. It was concluded that the application of the model could result in cost savings for both cases. Bordón et al. (2018) introduced an MIP model that could integrate the log flow decisions into the routing decisions to minimize the total costs. In their problem, the homogeneous trucks were assigned to routes for delivering the truckloads from harvest areas to plants. The authors applied their suggested model to two case studies and evaluated the performance of their model using different scenarios. An MIP model integrating the log allocation decisions along with routing and scheduling of homogeneous trucks was presented by (Melchiori et al., 2022). The main decisions of their model included raw material allocation, routing, and the arrival time of trucks at supply and demand locations. For scheduling, the time was discretized into shifts for loading and unloading activities to synchronize log loaders and trucks. The proposed model was applied to several examples from the Argentinian forest industry. The same authors extended their work in (Melchiori et al., 2023) by incorporating the synchronization of multiple resources. An integer linear programming (ILP) model was developed for allocation, routing, and scheduling of homogeneous trucks. They introduced valid inequalities and symmetry-breaking constraints to improve solving large-sized problems, and a heuristic method to obtain good initial feasible solutions.

For complex problems, other papers developed non-exact methods to get good solutions with a reasonable optimality gap. Zazgornik et al. (2012) investigated the daily routing and scheduling of single truck type with stackable and foldable containers to deliver predetermined orders to customers with minimum total working time. The trips of the problem were classified into three groups, namely full-container trips, empty-container trips, and empty trips. Full-container trips were considered as transport orders and empty-container trips were those movements for relocations of empty containers at forest sites and sawmills. The authors developed an MIP model and implemented the Tabu[1] search-based approach to solve the problem and get the

[1] Tabu search: It is one of the effective metaheuristic algorithms. In the Tabu search, already visited solutions are kept in the Tabu list, through which trapping in local optimum solutions is avoided (Gendreau & Potvin, 2019).

solution in a reasonable time. To evaluate the performance of their algorithm, generated data were used, and three scenarios were defined. A computational study was conducted by Derigs et al. (2012) for routing and scheduling of delivering predetermined truckloads from forest areas to plants using a heterogeneous fleet of trucks dispatched from multiple depots. The trucks had a maximum tour length and could not be assigned to some routes because of road weight requirements. The performance of the proposed heuristics was evaluated using test problems. Daily routing and scheduling of homogeneous trucks were developed by Haridass et al. (2014) to minimize the total unloaded traveled distance per day. The simulated annealing (SA) algorithm was used to solve their problem. The authors tested their proposed algorithm on a small-sized problem with four trucks, two mills, and three loggers and the algorithm could find the optimal solution in less than two minutes. Moreover, the algorithm was also implemented for a company in Mississippi with 68 trucks, 13 mills, and 22 loggers. Based on the results, the unloaded traveled distance was decreased by 28% for the company. The synchronization of trucks and loaders was not considered in the problem.

There have been few studies incorporating a heterogeneous fleet of trucks in the integrated models for log logistics planning. Non-exact methods were used in these papers to solve the routing and scheduling of trucks. Column generation based approaches were employed in (Rey et al., 2009; Rix et al., 2015). Rey et al. (2009) developed a column generation-based IP model for LTSP with a 1-day planning horizon to determine the number of employed trucks, the schedule of trucks, and the daily volume of pickups and deliveries with minimum costs. Rix et al. (2015) introduced a problem with a 1-year planning horizon, which was divided into working days. In the study, flows of logs and routing and scheduling of trucks were integrated through an MIP model that minimized the total hauling and storage costs. The authors considered the inventory between different periods, deterioration of logs in the supply points, different truck types, smooth workload between different periods, and synchronization of loaders and trucks. The column generation method was employed to solve the problem. The model, then, was applied to four different case studies in Quebec and British Columbia. Hirsch (2011) was another author who modeled the log transportation problem with predetermined flows as a multi-depot vehicle routing problem with pickup and delivery and time windows where trucks were heterogeneous and weight limits of routes had to be met. The solution approach included heuristics and variants of the Tabu Search (TS) algorithm. To illustrate the suggested method, the approach was applied to two test problems, concluding that the algorithm could find proper solutions for real problems.

2.2.2 Decomposition optimization approach

In the decomposition hierarchy methods, a complex problem is decomposed into smaller and simpler sub-problems to reduce the computational complexity and to make the problem more tractable (Schneeweiss, 1999). In (Palmgren et al., 2003), a two-phase method was employed for addressing the log truck scheduling problem with homogeneous trucks considering multiple log assortments. It was assumed that the logs of different assortments would not be mixed, and each truck had a trailer with three blocks where each block could include only one assortment. In the first phase, the routes were generated, while the second phase determined the scheduling decisions using the branch and price method. The routes had to satisfy the time window and truck capacity constraints. Palmgren et al. (2004) extended their previous research by proposing the column generation approach and the shortest path to solve the routing and scheduling of a homogeneous fleet of trucks. A two-stage approach was employed by El Hachemi et al. (2011). In each forest area and wood product mill, there was a loader for loading and unloading of trucks, and the home base of the homogeneous trucks was at the wood product mills. In the problem, it was assumed that different log types were combined as a single product and the goal was routing and scheduling of trucks delivering predetermined full truckloads between forest areas and the wood product mills with the minimum total unloaded driving time and waiting time. The authors developed a constraint programming (CP) model for routing and scheduling decisions considering synchronization of trucks and loaders, and an IP model to minimize the empty driving time. The two models were linked together through global constraints. The models were applied to a Canadian case study. In (Vitale et al., 2021), homogeneous trucks, dispatched from a depot, were considered to carry different types of raw material from harvest areas to mills. The authors introduced a column generation algorithm to determine log allocation, routing decisions, and the number of dispatched trucks considering the maximum travelling time. Their approach was applied to test problems and a real case in Argentina.

In (El Hachemi et al., 2013, 2015; Amrouss et al., 2017), a two-phase decomposition method was used for routing and scheduling of homogeneous log trucks with a one-week planning horizon in Canadian forest companies. In this method, the daily flows of logs were determined in the first phase, and the second phase tackled the daily routing and scheduling problem. In the study conducted by El Hachemi et al. (2013) synchronization of homogeneous trucks and loaders, multiple products, and inventory stock were considered. The authors introduced two different heuristic approaches to schedule daily activities with the minimum waiting time. Their study was tested on two different case studies in Canada. In (El Hachemi et al., 2015), daily flows between demand and supply points were determined through an IP model. Then, an IP flow-based model considering lunch breaks and synchronization of trucks and loaders was introduced. A branching strategy was introduced to minimize the empty driving time and waiting time for loaders and trucks delivering full truckloads of different log assortments. In the network flow model, each activity such as deadhead, loading, loaded travel, and unloading was modeled as an arc, and time was discretized into time slices of a fixed duration. The authors applied their model to two different case studies. In a study conducted by Amrouss et al. (2017), unforeseen events disrupting transportation activities in the daily routing and scheduling of trucks were considered. Uncertainty and unforeseen events were addressed through a time-space network model. The authors listed some common unforeseen events such as delays, demand and supply variations, and closure of forest sites, mills, and roads, and explained the consequences of each of these events. In their approach, after the occurrence of unforeseen events, the space network and parameters were adjusted, and the updated network was re-optimized. This model was used as the second phase of a 2-phase decomposition approach, in which the flow-based model developed by El Hachemi et al. (2015) determined the daily flows of logs in the first phase. The model was applied to six Canadian case studies with a 6-week planning horizon and a simulation procedure was used to generate unforeseen events. The results showed that their approach performed well compared to a case in which all events were known in advance. Bordón et al. (2020) introduced a two-phase decomposition approach for daily log allocation, routing, and scheduling of homogeneous trucks considering route limitations and the maximum operating time for the trucks. In the first phase, an MIP model was developed for log allocation and routing of the trucks, while the second phase used the results of the first phase and addressed the scheduling decisions through an MIP model. The proposed methodology was tested on two cases to show the applicability of the models.

For heterogeneous truck fleets, there have been few studies using decomposition methods. Rummukainen et al. (2009) investigated timber transportation in Finland. They described that the planning had three stages, namely load collection, load assignment, and truck routing. For each stage, they defined the problem and explained the objectives and constraints. In the load collection problem, batches were classified based on their assortments and diameters. In the load assignment problem, an MIP was presented to assign each load to a destination and a delivery date with minimum transport and penalty costs. The load assignment problem was constrained by long-term transport and harvest plans. Finally, a heuristic method was used for the routing and scheduling problem to find the optimal routes and schedules for each day with the minimum total transportation costs. The transportation problem contained different types of nodes, which were start nodes, collection nodes, delivery nodes, crane pick-up nodes, driver change nodes, and stoppage nodes. The authors suggested the TS algorithm to solve the three problems.

A two-phase decomposition approach was introduced by (Flisberg et al., 2009). In the first phase, the authors proposed a linear programming (LP) model to determine flows between supply and demand points, and then, they suggested two methods, i.e., heuristics approach and mathematical programming, to create transport nodes. In the second phase, they employed a standard TS for having near-optimal routing and scheduling decisions. To evaluate their methodology, the authors applied their problem to different Swedish forest companies, concluding that their approach was efficient in solving case studies with different sizes.

Table 2-1 summarizes the log logistics literature.

Table 2-1. The summary of log logistics papers

Classification	Author (year)	Planning horizon	Flow decisions	Routing decisions	Scheduling decisions	Methodology	Homogeneous	Heterogeneous	Cost objective	Social objective	Environmental	Processing	Synchronization	Exact solution	Non-exact solution	Case study
Integrated	Murphy (2003)	Daily		•	•	IP[2]	•		•					•		•
	Rey et al. (2009)	Daily		•	•	IP/heuristic		•	•						•	
	Hirsch (2011)	Daily		•	•	Metaheuristic		•	•						•	•
	Derigs et al. (2012)	Daily		•	•	Metaheuristic		•	•						•	
	Zazgornik et al. (2012)	Daily		•	•	MIP[3]/ Metaheuristic	•		•						•	
	Oberscheider et al. (2013)	Daily		•	•	MIP/heuristic	•		•		•				•	•
	Haridass et al. (2014)	Daily		•	•	LP[4]/ Metaheuristic	•		•						•	•

[2] IP: Integer programming
[3] MIP: Mixed integer programming
[4] LP: Linear programming

Classification	Author (year)	Planning horizon	Flow decisions	Routing decisions	Scheduling decisions	Methodology	Homogeneous	Heterogeneous	Cost objective	Social objective	Environmental	Processing	Synchronization	Exact solution	Non-exact solution	Case study
	Rix et al. (2015)	Yearly		•	•	MIP/heuristic		•	•				•		•	•
	Bordón et al. (2018)	Daily	•	•		MIP	•		•					•		
	Vitale et al. (2021)	Daily	•	•		IP	•		•						•	•
	Melchiori et al. (2022)	Daily	•	•	•	MIP	•		•				•	•		
	Melchiori et al. (2023)	Daily	•	•	•	ILP/heuristic	•		•				•	•		
Decomposition	Palmgren et al. (2003)	Daily		•	•	IP/heuristic	•		•						•	•
	Palmgren et al. (2004)	Daily		•	•	IP/heuristic	•		•						•	•
	Rummukainen et al. (2009)		•	•	•	MIP/ heuristic		•	•						•	•
	Flisberg et al. (2009)	Weekly	•	•	•	LP/ Metaheuristic		•	•						•	•
	El Hachemi et al. (2011)	Daily		•	•	CP[5]/IP	•		•				•		•	•

[5] CP: Constraint programming

Classification	Author (year)	Planning horizon	Flow decisions	Routing decisions	Scheduling decisions	Methodology	Homogeneous	Heterogeneous	Cost objective	Social objective	Environmental	Processing	Synchronization	Exact solution	Non-exact solution	Case study
	El Hachemi et al. (2013)	Weekly	•	•	•	MIP/heuristic	•		•				•		•	•
	El Hachemi et al. (2015)	Weekly	•	•	•	MIP/IP	•		•				•	•		•
	Amrouss et al. (2017)	Weekly	•	•	•	MIP/IP	•		•				•	•		•
	Bordón et al. (2020)	Daily	•	•	•	MIP/MIP	•		•				•	•		

2.3 Logistics and transportation of other forest products

Rantala et al. (2003) focused on long-distance transportation of different types of seedlings to nurseries at the tactical level. To optimize the annual transportation, an LP model was presented in which loading and unloading costs, and fixed and variable costs for each vehicle were considered. The authors compared the centralized with decentralized transportation strategy for different production allocation strategies, concluding that a centralized strategy led to cost savings for nurseries. Another research for seedling transportation was conducted by Rantala (2004) that considered unit transportation costs per vehicle load rather than per seedling. To address the problem, the author presented an MIP model in which the objective function included terminal costs and transportation costs. To estimate the transportation cost for each vehicle between given supply and demand points, a linear equation was proposed that considered fixed and variable costs. Finally, the MIP and LP models in (Rantala et al., 2003) were compared. The author concluded that the results of the MIP were more accurate compared with those of the LP model, but in practice, the LP model was sufficient for companies.

Scheduling of woody biomass trucks in western Oregon was described in (Han & Murphy, 2012). The authors proposed an IP model to schedule different types of trucks carrying pre-determined orders of biomass from 45 sawmills to 20 conversion facilities with minimum transportation costs and total working time for a whole day. Their problem was subject to a number of constraints such as assignment constraints, time limitation constraints, and demand satisfaction constraints. To solve the problem, the authors employed the SA algorithm.

Agricultural-based biomass transportation was addressed by Gracia et al. (2014). In the study, different obstacles in the collection, handling, and transportation of agricultural-based biomass were identified. To address the transportation problem, the authors developed an IP model to minimize the total cost of transporting biomass from orchards to biomass storage facilities. For solving the problem, Gracia et al. (2014) proposed a hybrid approach based on the genetic algorithm and local search methods. To show the applicability of the suggested model, they applied the model to a case study in Spain, in which the network contained 18 supply points and biomass storages.

Wood chips transportation was studied by Nadimi et al. (2015). In the problem, homogeneous trucks delivered wood chips from a set of sawmills to a demand point. The goal was to schedule the trucks with minimum waiting times on a weekly basis. In the proposed methodology, an IP model was introduced to assign loads to each truck. Then, another IP model was developed for scheduling decisions. These two models were related to each other, and the output of the first model was used as the input of the second model. The models were solved iteratively, and in each iteration, inputs of the models were adjusted. For the solution approach, the authors implemented the SA algorithm, and the suggested model was applied to a case study in British Columbia. Results revealed that the fleet size was reduced by one-third compared to the base case scenario. Malladi et al. (2018) considered a large biomass logistics company in British Columbia where the suppliers provided different types of biomass using heterogeneous trucks. A group of trucks was not compatible with some locations and biomass types. Some types of biomass could be delivered directly from suppliers to customers, while other types of biomass required processing. To address this problem, the authors developed optimization models using the decomposition approach to minimize total costs. Initially, a transshipment model was introduced by which the number of truckloads between demand and supply points, the quantity of biomass to be comminuted, and the required truck types for each day of a week were determined. Then, the authors developed a routing model to find the optimal daily routes. The output of the transshipment model was the input of the routing model. The scheduling of activities, however, was not addressed in their study.

2.4 Transportation of forest products using other modes

In addition to trucks, other transportation modes such as vessels and trains can be used to transport forest products. As mentioned by Kogler & Rauch (2018) , multimodal transportation is suitable for large volumes and long distances, and it leads to robustness of wood supply chains. In the wood supply chain literature, logistics of forest products with other transportation modes have been investigated using simulation models.

A group of studies considered water transportation modes such as vessels to deliver forest products. Asikainen (2001) conducted a simulation study to analyze vessel transportation delivering wood from islands to a mill in Finland. The authors concluded that in their case study, it was more beneficial to utilize a barge system including a pusher boat and three barges. In another simulation study conducted by Karttunen et al. (2012), the cost efficiency of waterway transportation was compared with that of truck transportation for forest chips in a region in Finland. They found that waterway transportation was cost-competitive to the trucking for distances more than 100-150 km.

Rail is another mode of transportation in forest products supply chains. Gronalt & Rauch (2018) focused on transportation of logs using railway by developing a discrete event simulation model. Different simulation experiments with several terminals and industrial sites were conducted to improve the scheduling of railway operations. The study recommended to replace a single wagon load by a shuttle system. Karttunen et al. (2013) investigated the cost-efficiency of combined truck and railway transportation of wood chips. In their study, a simulation model was introduced and applied to the case of central Finland. The authors considered three scenarios, and concluded that the cost of traditional supply chains was 5-19% more than that of the multi-modal scenarios.

2.5 Conclusions

In previous years, researchers have developed optimization models, heuristics approaches and solution methods to improve log logistics planning. A group of studies (e.g. Melchiori et al., 2022; Rix et al., 2015) integrated logistics decisions. Although the integrated method ensures the feasibility of plans, it adds to the complexities particularly for large-sized problems. To overcome the computational burdens, other studies employed (e.g. Bordón et al., 2020; Flisberg et al., 2009) decomposition methods, in which decisions are determined in different stages. The main objective of papers in both methods was economic related, for example minimization of costs, time, and unloaded traveled distance. However, other objectives, specifically social objectives, have not been considered enough in log logistics planning.

Some researchers (e.g. Derigs et al., 2012; Oberscheider et al., 2013) assumed that the flows of logs were given as inputs or determined from an upper-level plan, and the main decisions of their model included routing and scheduling of trucks. Other studies (e.g. Flisberg et al., 2009; Vitale et al., 2021) determined flows of logs along with routing and scheduling of trucks. These studies had one day (e.g. Melchiori et al., 2022; Rey et al., 2009) or longer planning horizons (e.g. El Hachemi et al., 2013; Rix et al., 2015). Inventory decisions were usually used to link different periods when the planning horizon was more than a day. The daily processing decisions, however, were not incorporated in the literature.

In the literature, papers have included details to address the practical aspects of the logistics planning. Both homogeneous and heterogeneous fleets of trucks, time windows, and maximum driving time have been addressed in previous studies (e.g. Murphy, 2003; Flisberg et al., 2009;

Zazgornik et al., 2012). Additionally, road weight limitations were considered in previous works to ensure that appropriate trucks were dispatched for delivering logs. However, other real-world complexities received less attentions in the literature. In previous studies, it was assumed that each truck could carry only one type of logs, and all logs were already sorted. However, in the actual operations, logs need to be sorted based on their species, quality and diameter. There are also other considerations for dispatching trucks. For instance, some trucks might not be suitable for delivering some logs. The compatibility requirements of trucks need to be incorporated in the log logistics planning. Also, forest companies usually employ trucking contractors to fulfill transportation activities. These contractors and their considerations were not investigated in the existing literature.

For the scheduling of log trucks, most papers considered discretized time slots, meaning that activities were scheduled by assigning them to these slots with predetermined start and finish times. However, few studies used continuous time representation for modeling of log truck scheduling. Using continuous time representation can avoid unnecessary waiting times and leads to more accurate schedules compared to discretized time representation.

As the log logistics and transportation problem is NP-Hard, appropriate solution approaches are required to solve the problem in a reasonable time. In the literature, different methods such as column generation-based approaches (e.g. Palmgren et al., 2004; Rix et al., 2015) and metaheuristics (e.g. Flisberg et al., 2009; Haridass et al., 2014) were developed to solve the problem. However, less attention was given to include operational details including trucking contractors and synchronization of heterogeneous trucks at both pickup and delivery locations.

Therefore, future studies need to incorporate these details to have more realistic and practical logistics plans.

Chapter 3: Optimization of monthly flows of logs

3.1 Synopsis

Log logistics include sorting, processing, and transportation of logs from their place of harvest to demand locations. These activities account for a significant portion of the total log procurement costs; therefore, attempts were made in previous studies to optimize some aspects of log logistics. This chapter achieves the first objective of this dissertation by proposing a bi-objective mixed-integer programming model to minimize the logistics costs and to provide a balanced workload for trucking contractors. The goal programming approach is employed to solve the bi-objective model. The proposed model addresses the research gaps by incorporating operational details, such as sorting decisions, truck compatibility requirements, and social objectives, leading to more realistic and applicable results. The model is applied to a large Canadian forest company, where trucking contractors use a heterogeneous fleet of trucks to carry various log sorts from cut blocks to sort yards. The planning horizon is one month with daily decisions.

3.2 Problem definition

The majority of previous log logistics studies focused on economic objectives. Real-world complexities such as log sorting were less investigated. In this chapter, a bi-objective optimization model is developed for the determination of log flows considering real-world complexities. The first objective of the model is to minimize the total costs of log logistics considering sorting decisions, a heterogeneous fleet of trucks, compatibility requirements, and multiple log assortments. The second objective balances the workload for log trucking contractors.

It is noteworthy that our approach in balancing the workload is different from previous studies. While Hirsch and Gronalt (2013) balanced the workload for carriers after determining the transport orders in a separate optimization model, in our model, workload balancing is integrated into the truckload optimization model. Unlike Rix et al. (2015), who added a constraint for balancing the workload into their optimization model, a second objective function is added in our model to balance the workload of contractors. This will allow the model to optimize the log logistics based on costs and social objective. The social objective minimizes the summation of maximum difference between truckload numbers and the desired number of truckloads for each contractor. Hence, the workload for all contractors is balanced in our work as opposed to minimizing the maximum working hours which was done in (Ramos et al. 2014). Compared to the log logistics literature, the novelty of this research is in incorporating truck/log-type/location compatibility requirements, log sorting decisions, different contractors, and the social objective into the mathematical programming model.

3.3 Bi-objective optimization model

The developed mathematical programming model is a bi-objective MIP model for optimizing the logistics problem. The inventory volume and the flows of logs between cut blocks and sort yards, and the volume of processed logs at sort yards are the decisions of the model, while the main inputs of the model include costs parameters, yard capacities, and compatibility requirements. The main outputs of the model are: (1) The daily number of truckloads of each type of truck transported from each cut block to each sort yard by each contractor, (2) The daily volume of unsorted logs that is sorted at each sort yard, (3) The inventory decisions at each sort yard, and (4) The workload of the trucking contractors over the planning horizon. The notations of the model are shown in Table 3-1.

Table 3-1. The notations of the monthly flow optimization model

Indices	**Description**
B	Set of cut blocks $b \in \{1, \dots, B\}$
Y	Set of yards $y \in \{1, \dots, Y\}$
S	Set of log sorts $s \in \{1, \dots, S\}$

Indices	Description
R	Set of truck types $r \in \{1, \dots, R\}$
O	Set of contractors $o \in \{1, \dots, O\}$
T	Set of time periods $t \in \{1, \dots, T\}$
Parameters	**Description**
TT_{byr}	Travelling time from cut block b to yard y by truck type r (including back and forth trips, loading and unloading times) (hour)
TC_r	Transportation cost of truck type r per hour ($/hour)
SW_{bs}	Supply volume of log sort s in sorted logs (m^3)
SC_{bs}	Supply volume of log sort s in unsorted logs (m^3)
Q_r	Capacity of truck type r (m^3)
α_{bo}	If contractor o can serve cut block b 1; otherwise, 0
β_{ro}	If contractor o has truck type r 1; otherwise, 0
N_{ro}	The number of truck type r that contractor o owns
ϕ_o	Desired number of truckloads that each contractor prefers to carry on each day
γ_r	If truck type r can carry sorted logs 1; otherwise, 0
ε_r	If truck type r can carry unsorted logs 1; otherwise, 0
M	A large number that is used in compatibility constraints to ensure that appropriate contractors and trucks are used
D_{ys}^{t}	The demand volume of log sort s at yard y on each day (m^3)
SC_y	Space capacity of yard y for unsorted logs (m^3)
CW_y	Daily processing capacity of yard y for sorted logs (m^3)
CC_y	Daily processing capacity of yard y for unsorted logs (m^3)
CY_y	Daily total processing capacity of yard y (m^3)
T_{max}	Maximum driving time of trucks on each day (hour)
P	Penalty for having inventory at cut blocks at the end of the planning horizon ($/$m^3$)

Decision variables	Description
ibw_{bs}	Stored volume of log sort s in sorted logs at cut block b at the end of planning horizon (m^3)
ibc_{bs}	Stored volume of log sort s in unsorted logs at cut block b at the end of planning horizon (m^3)
vw_{bysro}^{t}	The volume of log sort s in sorted logs transported by contractor o using truck type r between cut block b and yard y on each day (m^3)
vc_{bysro}^{t}	The volume of log sort s in unsorted logs transported by contractor o using truck type r between cut block b and yard y on each day (m^3)
nw_{bysro}^{t}	The number of truckloads of log sort s transported between cut block b and yard y by contractor o using truck type r on each day
nc_{byro}^{t}	The number of truckloads for unsorted logs transported between cut block b and yard y by contractor o using truck type r on each day
iw_{ys}^{t}	Inventory of log sort s at the water in yard y at the end of each day (m^3)
ic_{ys}^{t}	Inventory of log sort s in unsorted logs in yard y at the end of each day (m^3)
pv_{ys}^{t}	Volume of unsorted logs for sort s that is sorted (processed) in yard y at the end of each day (m^3)
u_o	Maximum difference between the daily number of truckloads and the desired number for contractor o

3.3.1 Objective function

The first objective function of this model, shown in equation (3-1), is to minimize the total costs associated with the logistics network. The first term represents the total monthly transportation costs, which include the fixed cost of using trucks and variable costs such as the drivers' pay. The second term calculates the penalty costs for storing sorted and unsorted logs at the cut blocks.

$$\mathrm{Min.}\, Z_1 = \sum_{t\in T}\sum_{b\in B}\sum_{y\in Y}\sum_{r\in R}\sum_{o\in O}\left(\sum_{s\in S} nw_{bysro}^{t} + nc_{byro}^{t}\right).\, TC_r.\, TT_{byr} + \sum_{b\in B}\sum_{s\in S} P * (ibw_{bs} + ibc_{bs}) \qquad (3\text{-}1)$$

As explained in (Malladi et al., 2018), because the volume of supply and demand is greater than the volume of trucks, and multiple truckloads are needed to fulfill the transport orders between supply and demand points, the travelling time includes back-and-forth trips and loading and unloading times.

The second objective function, shown in equation (3-2), is the social objective to balance contractors' workload by minimizing the summation of the maximum difference between the daily number of truckloads and the desired number of truckloads for each contractor. This leads to less variation in the daily number of truckloads that the contractors transport over the planning horizon. Hence, the workload of all contractors will be more balanced, which is assumed to result in the overall satisfaction of the contractors.

$$\text{Min } Z_2 = \sum_{o \in O} u_o \tag{3-2}$$

3.3.2 Constraints

Constraint set (3-3) indicates that the total volume of sorted logs sent from the roadside of each cut block plus the stored volume of the sorted logs at the cut block is equal to the available volume of sorted logs at that cut block over the entire planning horizon. Similarly, constraints (3-4) imply that at the roadside of each cut block, the total stored volume of unsorted logs and volume of unsorted logs sent from the roadside of the cut block during the planning horizon is equal to the available unsorted logs.

$$\sum_{t \in T} \sum_{o \in O} \sum_{r \in R} \sum_{y \in Y} vw^t_{bysro} + ibw_{bs} = SW_{bs} \qquad \forall b \in B, s \in S \tag{3-3}$$

$$\sum_{t \in T} \sum_{o \in O} \sum_{r \in R} \sum_{y \in Y} vc^t_{bysro} + ibc_{bs} = SC_{bs} \qquad \forall b \in B, s \in S \tag{3-4}$$

Some contractors cannot fulfill transport orders from some cut blocks. Additionally, some trucks cannot be used for transporting some types of logs. Hence, the number of truckloads between supply and demand points depends on the truck type. It means that the number of truckloads delivered by incompatible truck types should be zero. Constraint set (3-5) ensures that appropriate contractors and truck types are used for transporting loads containing sorted logs. Constraint set (3-6) guarantees that compatible trucks and contractors transport unsorted logs.

$$\sum_{t \in T} \sum_{y \in Y} nw_{bysro}^{t} \leq M.\alpha_{bo}.\beta_{ro}.\gamma_{r}\,, \qquad \forall b \in B, s \in S, o \in O, r \in R, \tag{3-5}$$

$$\sum_{t \in T} \sum_{y \in Y} nc_{byro}^{t} \leq M.\alpha_{bo}.\beta_{ro}.\varepsilon_{r}\,, \qquad \forall b \in B, o \in O, r \in R, \tag{3-6}$$

The daily number of truckloads of sorted and unsorted logs between cut blocks and sort yards is calculated using constraint sets (3-7) and (3-8), respectively. Constraint set (3-7) asserts that each sorted truckload has only one log sort, while constraints (3-8) imply that each unsorted truckload can include more than one log sort.

$$\left(nw_{bysro}^{t} - 1\right)Q_{r} \leq vw_{bysro}^{t} \leq nw_{bysro}^{t}Q_{r}\,, \qquad \forall b \in B, y \in Y, s \in S, o \in O, r \in R, t \in T \tag{3-7}$$

$$\left(nc_{byro}^{t} - 1\right)Q_{r} \leq \sum_{s \in S} vc_{bysro}^{t} \leq nc_{byro}^{t}Q_{r}\,, \qquad \forall b \in B, y \in Y, o \in O, r \in R, t \in T \tag{3-8}$$

Constraint set (3-9) ensures that for each contractor, the daily difference between the total number of truckloads and the desired number cannot exceed the maximum value.

$$\left|\left(\sum_{b \in B} \sum_{y \in Y} \sum_{r \in R} \left(nc_{byro}^{t} + \sum_{s \in S} nw_{bysro}^{t}\right)\right) - \phi_{o}\right| \leq u_{o}\,, \qquad \forall o \in O, t \in T \tag{3-9}$$

Constraints set (3-10) calculates the daily inventory of stored unsorted logs for each sort at the sort yards, which is equal to the total inventory of the sort on the previous day and the volume of the sort in unsorted logs delivered on that day minus the volume of the sort obtained from sorting the unsorted logs. The daily inventory of each sort in the water is determined using constraint set (3-11), where the volume of the sort coming out of unsorted logs is added to the total inventory of the sort on the previous day and the volume of sorted logs delivered on that day. Also, the daily demand of each sort is deducted from the inventory of the sort in the water.

$$ic_{ys}^{t} = ic_{ys}^{t-1} + \sum_{b \in B} \sum_{o \in O} \sum_{r \in R} vc_{bysro}^{t} - pv_{ys}^{t}, \qquad \forall y \in Y, s \in S, t \in T \qquad (3\text{-}10)$$

$$iw_{ys}^{t} = iw_{ys}^{t-1} + \sum_{b \in B} \sum_{o \in O} \sum_{r \in R} vw_{bysro}^{t} + pv_{ys}^{t} - D_{ys}^{t}, \qquad \forall y \in Y, s \in S, t \in T \qquad (3\text{-}11)$$

At each sort yard, there is a limited space available for storing unsorted logs. As shown in constraint set (3-12), the daily inventory of unsorted logs in each yard cannot exceed the storage capacity of the yard.

$$\sum_{s \in S} ic_{ys}^{t} \leq SC_{y}, \qquad \forall t \in T, y \in Y, \qquad (3\text{-}12)$$

Each sort yard has a limited daily capacity for processing sorted and unsorted logs. Constraint set (3-13) ensures that on each day, each sort yard cannot process sorted logs more than its capacity. Constraint set (3-14) implies that the daily volume of unsorted logs that is sorted at each sort yard should be less than the capacity of the sort yard.

$$\sum_{r \in R} \sum_{o \in O} \sum_{b \in B} \sum_{s \in S} vw_{bysro}^{t} \leq CW_{y}, \qquad \forall t \in T, y \in Y \qquad (3\text{-}13)$$

$$\sum_{s \in S} pv_{ys}^{t} \leq CC_{y}, \qquad \forall t \in T, y \in Y, \qquad (3\text{-}14)$$

There is a maximum capacity for each sort yard for processing both sorted and unsorted logs. Constraint set (3-15) guarantees that the total daily volume of sorted and unsorted logs that is processed in each sort yard cannot exceed the total processing capacity of the sort yard.

$$\sum_{R\in R}\sum_{o\in O}\sum_{b\in B}\sum_{s\in S} vw_{bysro}^{t} + \sum_{s\in S} pv_{ys}^{t} \leq CY_{y}\,, \qquad \forall t \in T, y \in Y \qquad (3\text{-}15)$$

Constraint set (3-16) ensures that contractors have sufficient trucks of each type to deliver both sorted and unsorted truckloads from cut blocks to sort yards on each day.

$$\sum_{b\in B}\sum_{y\in Y}\left(\sum_{s\in S} nw_{bysro}^{t} + nc_{byro}^{t}\right) TT_{byr} \leq N_{ro} * T_{max} \qquad \forall o \in O, r \in R, t \in T \qquad (3\text{-}16)$$

Finally, constraint sets (3-17) and (3-18) control the sign and the domain of the variables.

$$vw_{bysro}^{t} \geq 0, vc_{bysro}^{t} \geq 0, ibw_{bs} \geq 0, ibc_{bs} \geq 0, iw_{ys}^{t} \geq 0\,, ic_{ys}^{t} \geq 0, pv_{ys}^{t} \geq 0\,, \qquad \forall b \in B, y \in Y, s \in S, r \in R, o \in O\ t \in T, \qquad (3\text{-}17)$$

$$nw_{bysro}^{t} \in \mathbb{Z}\,, nc_{byro}^{t} \in \mathbb{Z}\,, u_{o} \in \mathbb{Z}\,, \qquad \forall b \in B, y \in Y, s \in S, r \in R, o \in O\ t \in T. \qquad (3\text{-}18)$$

3.4 Goal programming model

To solve the proposed bi-objective model, the goal programming method is employed. In this approach, a goal is defined for each objective function and deviations from the goals are minimized (readers are referred to (Jones, 2010) for a comprehensive explanation on goal programming). In order to determine the goals, one approach is to solve the single objective models and use the values of single objective functions as the goals. Another approach is to use decision makers' defined goals (Colapinto et al., 2017). Additional notations for the goal programming model are shown in Table 3-2.

Table 3-2. Notations of the goal programming model

Parameters	Description
w_1	The weight for goal 1
w_2	The weight for goal 2
$Goal_1$	Goal for the first objective
$Goal_2$	Goal for the second objective
Decision variables	**Description**
dev_1^+	Positive deviation of objective function 1 from Goal 1
dev_2^+	Positive deviation of objective function 2 from Goal 2

As underachievement of goals is desired, only positive deviations of objectives from their goals should be minimized. Objective function (3-19) minimizes the weighted summation of positive deviations where the weights reflect the importance of the goals.

$$\text{Min } Z = w_1 . dev_1^+ + w_2 . dev_2^+, \tag{3-19}$$

As the objectives do not have the same scale, the deviations from the goals are normalized. The model has the same constraints as shown for the bi-objective model (Constraint sets (3-3) to (3-18)).

Constraint sets (3-20) and (3-21) are added in the goal programming model to link the first and the second objective functions to their goals.

$$\sum_{t \in T} \sum_{b \in B} \sum_{y \in Y} \sum_{r \in R} \sum_{o \in O} \left(\sum_{s \in S} nw_{bysro}^t + nc_{byro}^t \right) . TC_r . TT_{byr} + \sum_{b \in B} \sum_{s \in S} P * (ibw_{bs} + ibc_{bs}) - dev_1^+ \leq Goal_1 \tag{3-20}$$

$$\sum_{o \in O} u_o - dev_2^+ \leq Goal_2 \tag{3-21}$$

The sign and the domain of the decision variables are illustrated by constraints (3-22) and (3-23).

$$\mathrm{dev}_1^+ \geq 0 \tag{3-22}$$

$$\mathrm{dev}_2^+ \in \mathbb{Z} \tag{3-23}$$

3.5 Execution of the model

As we were in contact with the forest company, and not with their contractors, we used the single objective model to estimate the desired number of truckloads for the contractors. If we were in contact with the contractors, we would just use the number of truckloads they would propose. In general, the desired number of truckloads can be given as a parameter to the model, and the goal programming model can generate workloads with small deviation from the desired number.

First, the single-objective cost model (excluding the second objective function, equation (3-2), and constraint set (3-9)) is solved. Then, the minimum total cost from the single-objective model is considered as the cost goal. The daily number of truckloads for each contractor is determined by the model and is used to calculate the average number of truckloads (desired number) for each contractor. Next, the second goal, i.e., the summation of the maximum difference between daily number of truckloads and the desired levels, is set to zero, corresponding to the ideal case in which all contractors have even workloads over the planning horizon. Finally, the goal programming model with different weights for goals are solved.

The proposed model for the case study has a 1-month planning horizon (20 working days) with 8.5 working hours per day. It is assumed that tugboats tow the logs from sort yards at the end of day 10 and day 20. The developed goal programming model for the case study had 3,080,403 decision variables, among which 1,037,569 were binary and integer decisions. The model included 2,105,195 constraints. Using CPLEX solver of AIMMS software package (*CPLEX — AIMMS*, 2022) on a desktop computer with Intel® Core™ i7-6700 CPU, 3.40 GHz processor, and 16 GB RAM, led to a processing time of 8 hours.

3.6 Results

3.6.1 Single-objective cost minimization model

Table 3-3 summarizes the minimum, the average, and the maximum number of daily truckloads and also the maximum difference between daily truckload numbers and the average value for each contractor obtained from the single-objective optimization model. The total logistics cost obtained from the single objective model is $1,093,953.

Table 3-3. Information regarding number of daily truckloads for each contractor (single objective model)

Contractors	Min. number of truckloads	Average number of truckloads	Max. number of truckloads	Maximum difference between daily truckload numbers and the average value
Contractor 1	1	1	2	1
Contractor 2	4	20	33	16
Contractor 3	2	5	22	17
Contractor 4	1	4	12	8
Contractor 5	3	16	28	13
Contractor 6	3	4	6	2
Contractor 7	1	5	11	6
Contractor 8	13	30	50	20
Total		**85**		**83**

The number of each truckload type delivered to the sort yards and the volume of unsorted logs that is sorted are shown in Table 3-4. As Yard 2 has more processing capacity, it receives more truckloads and larger volume of unsorted logs are sorted there compared to the other yards.

Table 3-4. Number of delivered truckloads and the volume of logs sorted in the sort yards (single objective model)

Sort yards	# of sorted truckloads	# of unsorted truckloads	Total number of truckloads	Volume of unsorted logs that is sorted (m^3)
Yard 1	29	112	141	7,296
Yard 2	205	691	896	31,104
Yard 3	255	388	643	16,400

Figure 3-1 shows the inventory of stored logs in the water for each sort yard over the planning horizon. As more truckloads are delivered and processed at the sort yards, the inventory of logs in the water increases until the tugboats tow the logs. The tugboats are assumed to tow the logs on day 10 and day 20. Therefore, the log inventory at the water is reduced on these days.

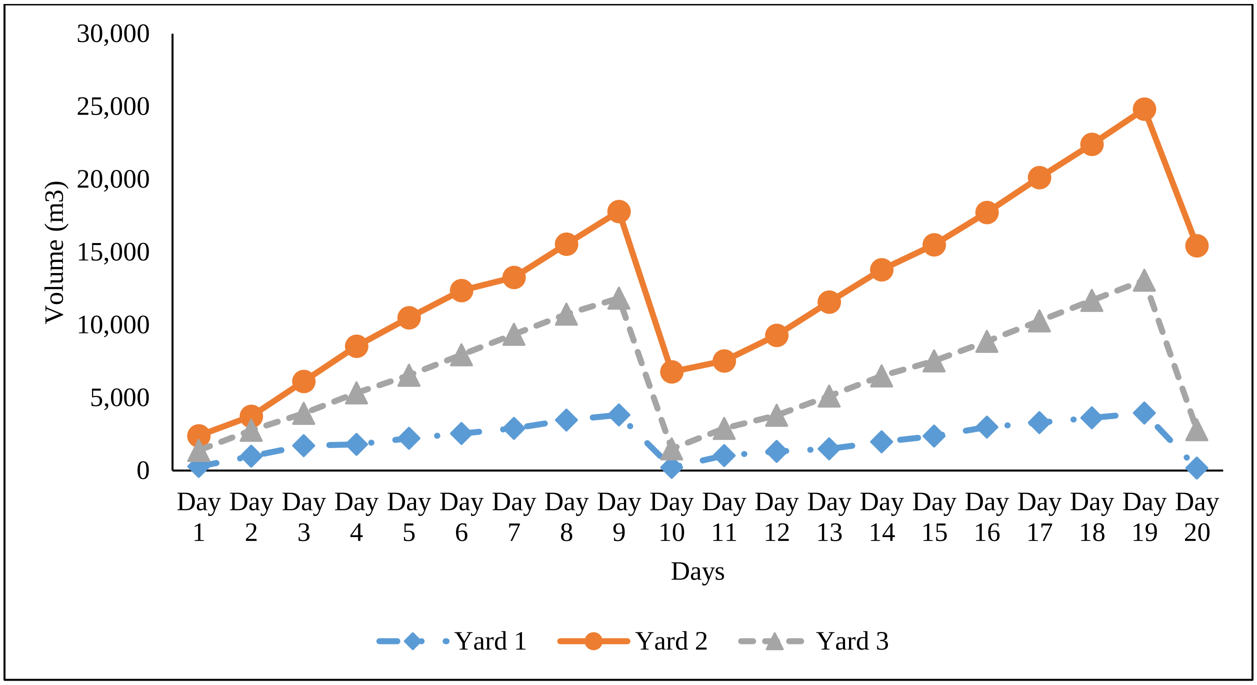

Figure 3-1. The inventory of logs in the water at each yard over the planning horizon

The single objective model does not generate a balanced workload for the contractors. Figure 3-2 shows the daily number of both sorted and unsorted truckloads delivered by each contractor on each day. The total number of truckloads delivered by contractors varies over the planning horizon. Contractors prefer less workload variations among working days to avoid operation disruption in other regions. However, the variations for some contractors are significantly high. For instance, as shown in Figure 3-2, contractor 8 carries 14 truckloads on day 15 and 50 truckloads on day 17.

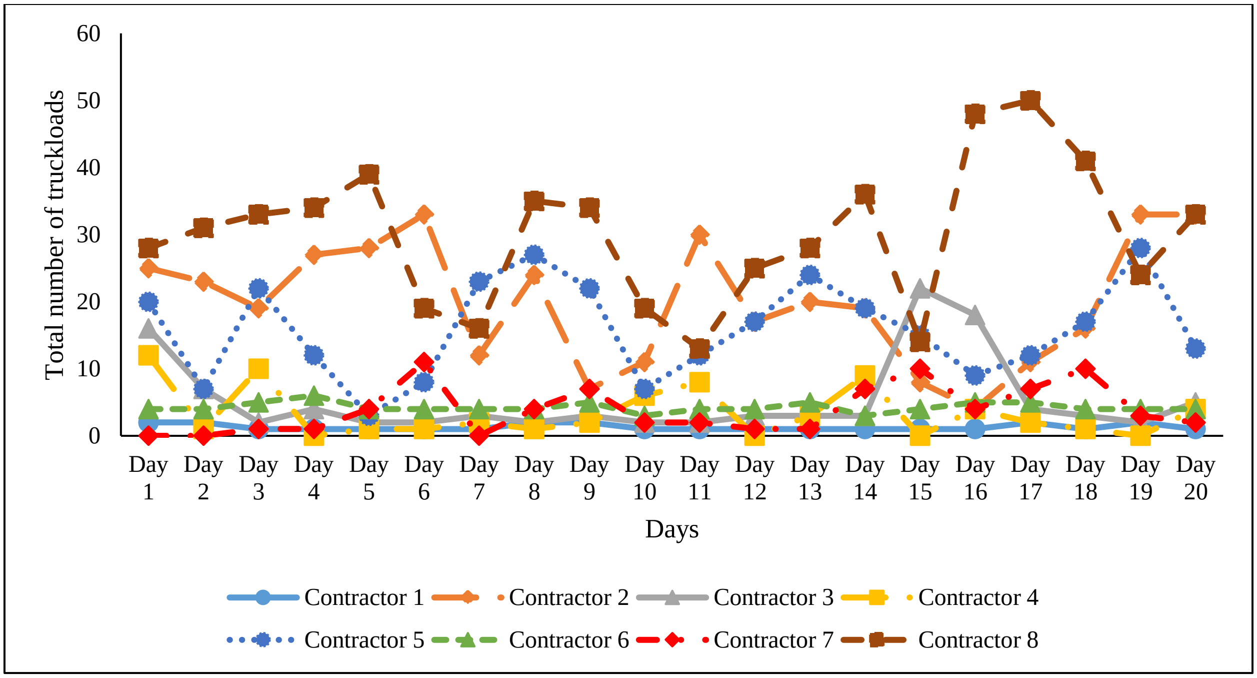

Figure 3-2. Daily total number of truckloads for each contractor over the planning horizon (single objective model)

3.6.2 Goal programming model

The forest company indicated that the contractors prefer balanced workloads and they asked to consider that in the modeling. As shown earlier, the single objective model cannot generate smooth and balanced workloads. Even adding constraints to the single objective model in order to limit the variations of truckloads between consecutive days to the specified low values would lead to high variations over the planning horizon and that model had been tested. Therefore, the goal programming is used to balance the workload of contractors by minimizing the deviations from the total cost goal and deviations of daily number of truckloads from the desired number.

In the goal programming model, the importance of goals is expressed by the value of their weights. Greater weights reflect more importance, while equal weights indicate the same importance. When the goal programming model with the same weight ($w_1 = w_2 = 0.5$) is solved, the model generates balanced workloads with only 0.4% increase in the total cost (Figure 3-3).

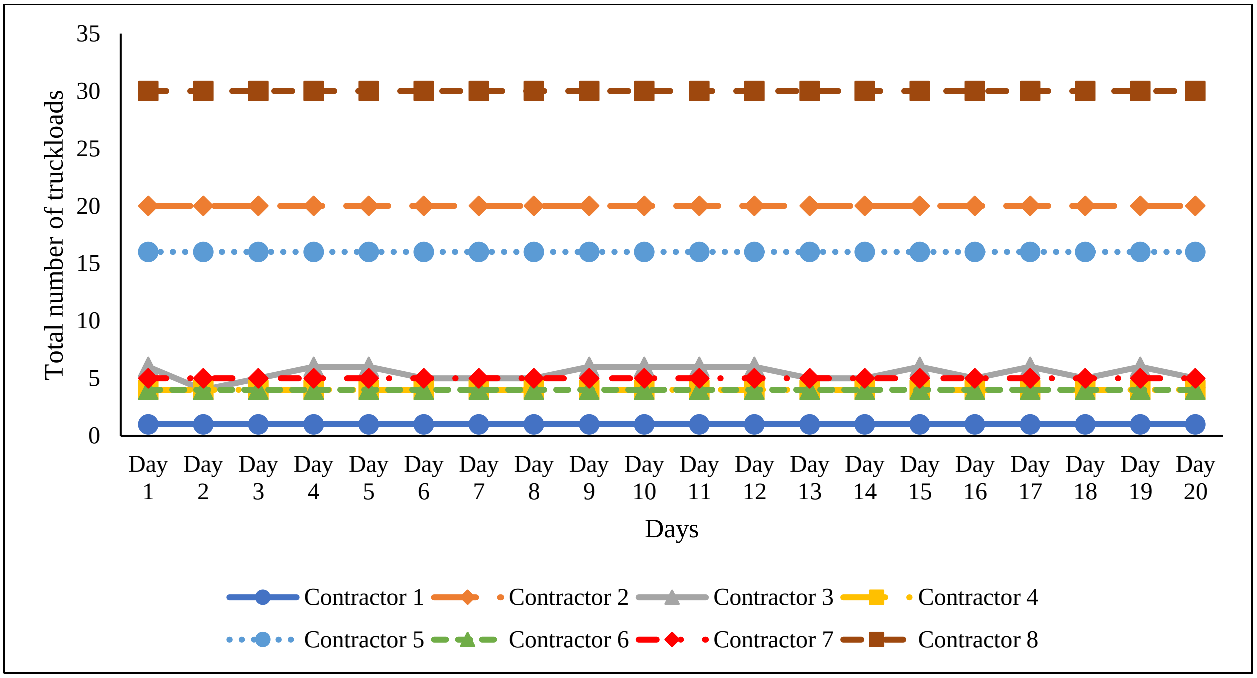

Figure 3-3. Daily workload of contractors (goal programming model when w_1=w_2=0.5)

When the objectives have the same weights ($w_1 = w_2 = 0.5$), the contractors transport 1,709 truckloads over the planning horizon, while 1,680 truckloads are carried to sort yards in the solutions obtained from the single-objective model. Table 3-5 depicts the total number of truckloads for each contractor resulted from the single objective and goal programming models.

Table 3-5. The total number of truckloads carried by each contractor

Contractor	**Total number of truckloads**	
	Single objective model	**Goal programming model ($w_1 = w_2 = 0.5$)**
Contractor 1	26	20
Contractor 2	400	400
Contractor 3	108	109
Contractor 4	67	80
Contractor 5	317	320
Contractor 6	85	80
Contractor 7	77	100
Contractor 8	600	600
Total	**1680**	**1709**

The number of truckloads delivered to each sort yard and the volume of processed unsorted logs at the sort yards from the goal programming model are shown in Table 3-6. The third and the fifth columns of Table 3-6 present the percentage of change in the number of truckloads compared to the solution from the single-objective model for sorted and unsorted truckloads, respectively.

Table 3-6. Number of delivered truckloads and volume of logs sorted in the sort yards (goal programming model when w_1=w_2=0.5)

Yards	**Sorted truckloads**		**Unsorted truckloads**		
	Number	**Change compared to single-objective model**	**Number**	**Change compared to single-objective model**	**Volume of unsorted logs that is sorted (m^3)**
Yard 1	35	21%	119	6%	7,001
Yard 2	243	19%	665	-4%	31,174
Yard 3	270	6%	377	-3%	16,400

The percentage of used and unused processing capacities are shown in Figure 3-4. It can be observed that Yard 3 is using 93% of its total processing capacity, while Yard 1 utilizes almost half of its capacity.

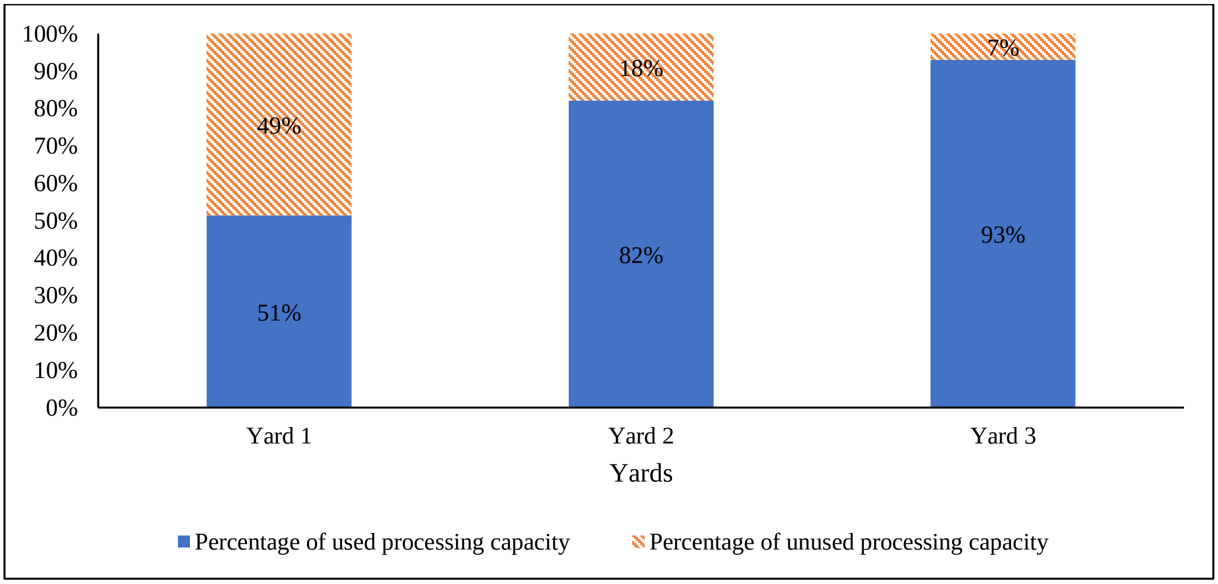

Figure 3-4. Percentage of average processed volume when w_1=w_2=0.5

3.6.3 Sensitivity analysis

In this section, two types of sensitivity analysis are conducted on the goal programming model to evaluate the impact of changes in parameters on the outputs of the model.

In the first type of sensitivity analysis, different values are assigned to the weight of each goal to evaluate the changes in the total costs and the total maximum difference of truckload numbers from the desired value for the contractors (Table 3-7). In Table 3-7, the first and the second columns indicate the weights, which represent the importance of each goal, and the third and fourth columns show the value of objective functions. As it is shown, there is a trade-off between the two objectives, and increasing the weight of the second goal leads to a more balanced workload for the contractors. When the weight of the second goal is 0.9, the workload is fully balanced for all contractors over the planning horizon.

Table 3-7. Sensitivity analysis of the goal programming model based on different weights

Weight of the cost goal (w_1)	**Weight of the workload balancing goal (w_2)**	**Cost objective (Z_1)**	**Workload balancing objective (Z_2)**
0.1	0.9	$1,103,494	0
0.5	0.5	$1,097,767	1
0.9	0.1	$1,095,768	2

The second type of sensitivity analysis is performed on the goal programming model for equal weights (when $w_1 = w_2 = 0.5$) to evaluate the impact of changes in the value of parameters on the achievement of the defined goals. The same approach as presented in (Chang, 2011) is applied for the second type of sensitivity analysis. As mentioned earlier, the cost goal is $1,093,953, while the second goal is set to be zero. The effect of changes in six parameters (space and processing capacities, transportation costs, supply, demand, the desired number of daily truckloads, and the penalty cost) is investigated. Similar to Vancas (2003), the parameters are changed by ±20%. The achievement of each goal and the total deviation resulting from changes in input parameters are summarized in Table 3-8.

Table 3-8. Sensitivity analysis of the goal programming model (w_1=w_2=0.5) based on variations in parameters

Parameter (variation percentage)	**Goal 1 achievement**	**Goal 2 achievement**	**Total deviation from the goals**
Transportation cost (-20%)	100%	100%	0
Demand (-20%)	100%	100%	0
Yards capacity (+20%)	100%	100%	0
Penalty cost (-20%)	99.8%	99%	0.004
Penalty cost (+20%)	99%	99%	0.0043
Desired number of truckloads (+20%)	96%	94%	0.0048
Transportation cost (+20%)	80%	14%	0.51
Supply (+20%)	0%	0%	1.22
Desired number of truckloads (-20%)	90%	0%	4.94
Yards capacity (-20%)	Infeasible	Infeasible	Infeasible
Demand (+20%)	Infeasible	Infeasible	Infeasible
Supply (-20%)	Infeasible	Infeasible	Infeasible

According to Table 3-8, decreasing hourly transportation cost and demand results in lower total transportation costs, and both goals are fully achieved by the goal programming model. Also, when capacities of yards increase, both goals are achieved as the model becomes more flexible to generate balanced workloads and reduce total costs. However, when supply increases, none of the goals are met because more logs need to be delivered to yards. As a result, the variation of workload from contractors' desired value increases. In addition, when the daily desired number of truckloads decreases, the generated workload by the model would not be balanced and the cost goal would be achieved by 90%.

It should be mentioned that the problem becomes infeasible when supply decreases or demand increases by 20%, as these changes cause supply shortage. Also, when the capacity of yards decreases by 20%, the problem becomes infeasible because the yards would not have enough capacity to process the delivered logs.

3.7 Discussion

In the case study, the contractors (not drivers) are hired by the company to perform the transportation of logs, therefore, the company aims to address the contractors' concerns. In the communication with the forest company, it was told that high variations in daily number of truckloads would not be acceptable by the trucking contractors. Therefore, the results of the single cost objective model were not acceptable because of high variations of daily truckload numbers over the planning horizon (Figure 3-2). In fact, a model was needed in order to balance the daily workload for the trucking contractors.

According to previous studies (e.g. Matl et al. 2019; Vidal et al. 2020), more attention has been given to balancing the workload in logistics and supply chain networks. Balanced workloads result in reduced overtime costs, improved customer service, better utilization of resources, and stakeholder and employee satisfaction. It is noteworthy that there is no specific definition of workload (Mancini et al., 2021). Most studies considered tour length for balancing the workloads, while other important aspects such as the amount of delivered loads were often disregarded (Matl et al., 2019; Mancini et al., 2021). In our study, the daily number of truckloads is considered as a determinant of workload balancing. According to the forest company, balanced truckload numbers over the planning horizon would satisfy the trucking contractors. Because each contractor in the case study operates in cut blocks that are geographically close to each other, and each truck delivers 2 to 3 truckloads each day, balancing the number of truckloads for contractors translates to having a balanced number of trucks and consequently to a balanced workload for each truck driver over the planning horizon. The proposed bi-objective model introduced a separate objective function that minimizes the summation of the maximum difference between the daily number of truckloads and the desired number of truckloads for each contractor. This separate objective achieves contractors' satisfaction and indirectly drivers' satisfaction.

As mentioned above, employee/stakeholder satisfaction is one of the consequences of the workload balancing. Employee satisfaction is identified as one of the social aspects in previous studies (e.g. Banasik et al. 2018; Sherafati et al. 2020; Moghdani et al. 2021). For example, Banasik et al. (2018) considered stakeholder satisfaction along with other factors such as number of created jobs as social indicators in supply chain networks. As the generated workloads are accepted by the forest company and can lead to contractors' satisfaction according to the forest company, the second objective function is called the "social objective" in this work.

One of the advantages of balancing workloads in the form of a separate objective and employing the goal programming is that the workloads are balanced over the planning horizon. It may seem that if constraints were added to the single objective model to limit the workload difference between consecutive days, the solution would generate balanced truckload numbers during the planning horizon. However, that approach was tested, and the results showed high variations in the number of truckloads for contractors over the planning horizon. For instance, limiting the maximum difference of truckloads between consecutive days to 3 resulted in 48 truckloads difference between day 1 and day 20 for one of the contractors. Besides, the goal programming model generates feasible solutions with the least deviation from contractors' workload preferences. A single objective model with the workload balancing constraints might produce infeasible solutions as the preferred workload of contractors sometimes are not feasible. For example, if the difference of truckloads between the consecutive days is limited to less than 2, the model cannot satisfy other constraints, which leads to infeasibility of the problem. According to Figure 3-3, incorporating the second objective for balancing the workload along with the cost objective can considerably reduce the variations.

As shown in Table 3-3, the summation of the maximum difference between daily number of truckloads and the average value obtained from the single objective model ($w_1 = 1$, $w_2 = 0$) was 83. However, considering even a small weight for the second objective led to a substantial reduction in the total maximum difference between the daily number of truckloads and the desired number of truckloads for the contractors (workload balancing objective, Z_2, fourth column in Table 3-7). Compared to the single objective model (total cost = \$1,093,953), implementing the goal programming model increased the total cost (total cost = 1,097,767) by almost 0.4% because in order to balance the workload for the contractors, the demand of some sort yards has to be met using other contractors that serve different cut blocks with longer travelling times than the ones in the solution obtained from the single-objective model. It should be mentioned that the proposed approach was applied to different planning horizons, and the model could generate balanced workload for all of them. However, the level of workload for each contractor may not be the same in different months as the supply volume varies throughout a year.

Based on the sensitivity analysis, there was a trade-off between the cost objective and the workload balancing objective. Additionally, decreasing the hourly transportation cost, decreasing demand, and increasing yards' capacities by 20% led to the full achievement of both goals.

The proposed models are flexible and can be applied to other cases and problems. For example, in this case, the fleet of trucks consisted of only highway and off-highway trucks differentiated by their capacity and compatibility requirements. However, more truck types with different compatibility requirements can be considered. Also, contractors and their working areas and number of trucks are input parameters, and they can be adjusted in case there are changes to the contractors.

3.8 Conclusions

The focus of this chapter was on the log logistics problem. There have been several research papers addressing the log logistics problem in the literature, however, previous studies did not consider sorting decisions, compatibility requirements of assigned trucks, multiple trucking contractors, and balancing the workload for contractors. These gaps were addressed in this chapter. A bi-objective mixed integer programming model was developed and solved using the goal programming approach. The first objective of the model was to minimize the logistics costs. The second objective was to balance the workload for all contractors. Balancing the workload of contractors was done by minimizing the summation of the maximum difference between the daily number of truckloads and the desired number of truckloads for each contractor. The model was applied to a case study of a large forest company in British Columbia, Canada. The results of the goal programming model generated balanced workload for the contractors with less than 0.4% increase in the total cost compared to that of the single objective model. Sensitivity analysis conducted on the weights indicated a trade-off between the two objectives, while sensitivity analysis on input parameters showed that decreasing hourly transportation cost, decreasing demand, and increasing yard capacities by 20% would result in full achievement of both goals.

In this chapter, the first objective of the thesis was achieved through the development of a bi-objective optimization model incorporating practical considerations. The proposed model can be modified and applied to the case of other forest companies to help managers in their decision-making.

Chapter 4: Daily routing and scheduling optimization model

4.1 Synopsis

In this chapter, the second research objective of this study is achieved by developing an optimization model for daily routing and scheduling of heterogeneous trucks considering synchronization constraints. The daily log volumes and truckload numbers between each pair of cut blocks and sort yards are allocated in the upper-level plan generated from the mathematical model described in Chapter 3. Continuous time representation is used for modelling the problem to generate accurate schedules and to synchronize the trucks and loaders at cut blocks and sort yards. Compatibility requirements, overtime, and decisions related to the trucking contractors are incorporated in the model. The outputs of the model include: 1) the number of trucks utilized by each contractor, 2) the arrival times and waiting times of trucks at each location, 3) the detailed schedule of loaders, and 4) the amount of overtime assigned to the trucks. To validate the model, it is applied to test problems from a case of a Canadian forest company, where transportation activities are contracted out.

4.2 Problem definition

In this section, the developed optimization model for the daily routing and scheduling of a heterogeneous fleet of log trucks is presented. The number of truckloads between each pair of cut blocks and sort yards is determined by an upper-level model, developed in Chapter 3. The generated truckloads from the upper-level model ensures a daily balanced workload for the trucking contractors. Hence, the pickup (cut blocks) and delivery (sort yards) locations, the responsible contractor, and the truck type for each truckload are the inputs of the current model. It is assumed that there is a loader at each cut block and each sort yard for loading and unloading activities. The loaders and trucks need to be synchronized. It means that when a truck arrives at a location, it has to wait until the loader becomes idle to load/unload the logs. The goal is to assign the truckloads to available compatible trucks and to find the detailed scheduling of delivering them at the sort yards with minimum costs.

4.3 Network representation

The scheduling problem is defined on a network where P and D are pickup (cut blocks) and delivery (sort yards) nodes, respectively. In this network, each truckload is represented by a pair of pickup and delivery nodes. It is noteworthy that as cut blocks (sort yards) can send (receive) more than one truckload, each cut block (each sort yard) can have one or several nodes. The approach adopted in this study to model the problem has similarities with the one employed in (Soares et al., 2019). In both studies network models are used to model the scheduling problem. Unlike (Soares et al., 2019), this chapter synchronizes log loaders and trucks at both pickup and delivery nodes and incorporates decisions related to the trucking contractors.

For modelling purposes, the problem is divided into three sub-problems. Figure 4-1 represents the network for the first sub-problem at the pickup (cut block) nodes. To model the problem, a virtual depot including two nodes is added to the network. The first node (c^+) is the start node and the second node (c^-) is the sink node. Therefore, the directed graph, shown in Figure 4-1, can be defined as $G_1 = (N_1, A_1)$, where $N_1 = c^+ \cup c^- \cup P$ and the nodes are connected by arcs (A_1). This problem can be considered as a vehicle routing problem (VRP), where each node must be exactly visited once, by only one loader. These loaders start their trip from the start node and finish their work by visiting the sink node. In the directed graph, φ_{il}^+ and φ_{il}^- show the sets of nodes that succeed and precede node i by loader l, respectively. A simple example is shown in Figure 4-2, where nodes $c^-$and $P3$ succeed node $P2$ by loader l (i.e. $\varphi_{P2l}^+ \in \{c^-, P3\}$), and nodes c^+, $P1$, and $P4$ precede node $P2$ by loader l (i.e. $\varphi_{P2l}^- \in \{c^+, P1, P4\}$).

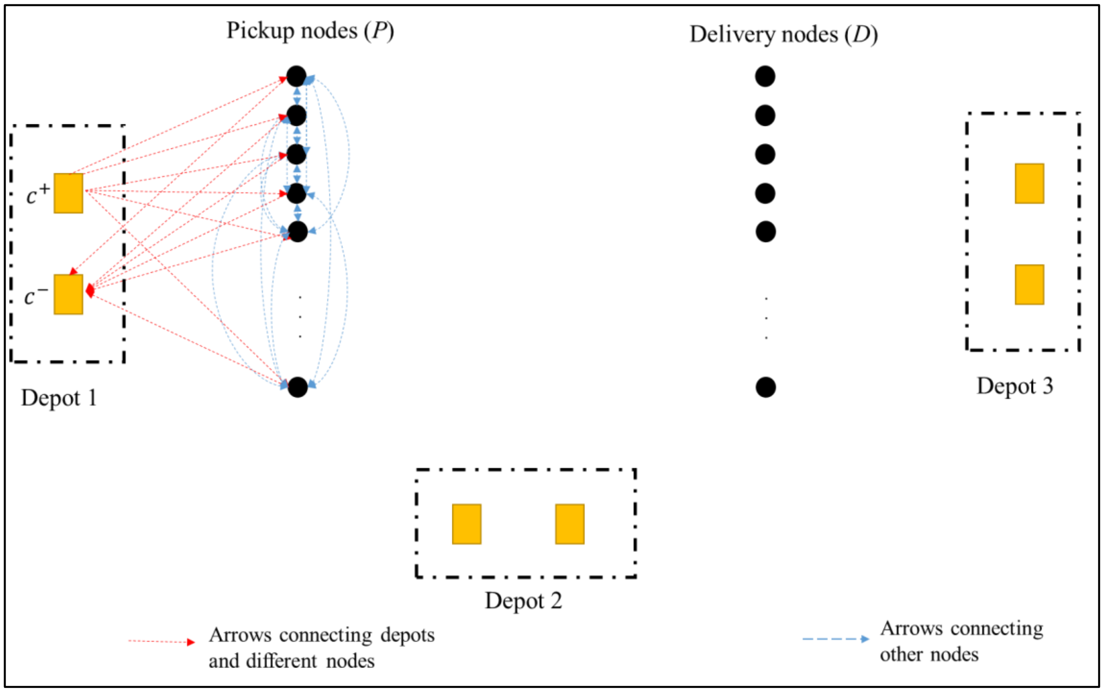

Figure 4-1. The sub-network for loaders at cut blocks (pickup network)

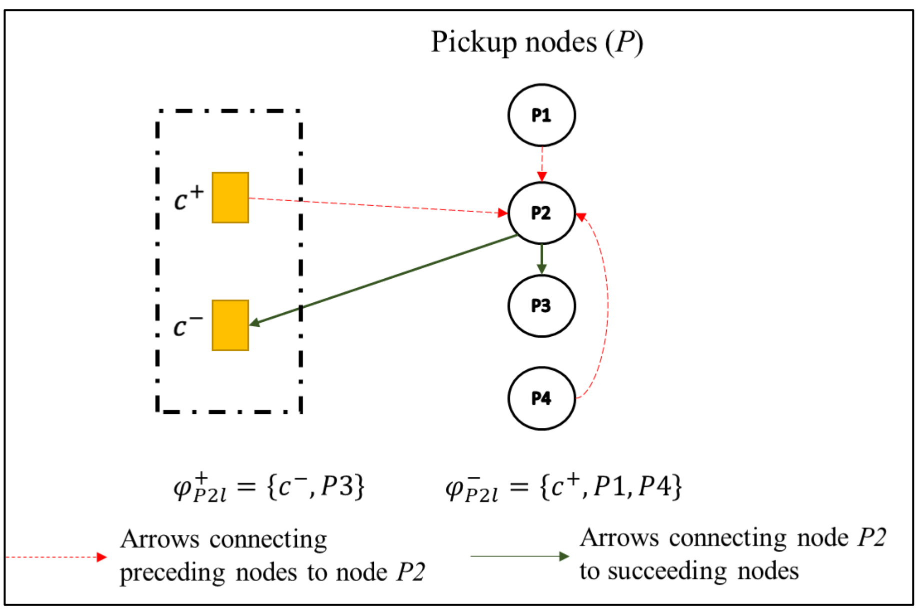

Figure 4-2. Set of succeeding and preceding nodes in the directed graph

The second sub-problem associated with the trucks is a pickup and delivery network (Figure 4-3). The network is presented by $G_2 = (N_2, A_2)$, where $N_2 = f^+ \cup f^- \cup P \cup D$ and arcs A_2 are connecting the nodes. Unlike the first sub-problem, the depot is a real depot in the second sub-problem. Each pickup and delivery node must be visited only once by one truck. If a truck is used, it should start the work from the start node (f^+) and return to the sink node (f^-). In the directed graph displayed in Figure 4-3, solid arrows show the truckloads for which the pickup and delivery nodes, responsible contractor, and the required truck type are known from the upper-level model. The dotted arrows, however, are the possible paths that each truck can choose to traverse an arc. In other words, when a truck is at a pickup node, it has only one choice, i.e. choosing the solid arrow which means going to the destination of the truckload. However, when the truck is at the demand node, it can choose one of the succeeding dotted arrows, i.e. going to one of the pickup nodes or visiting the sink node. In this sub-network, φ_{iv}^{+} and φ_{iv}^{-} are the sets of nodes that succeed and precede node i by truck v, respectively.

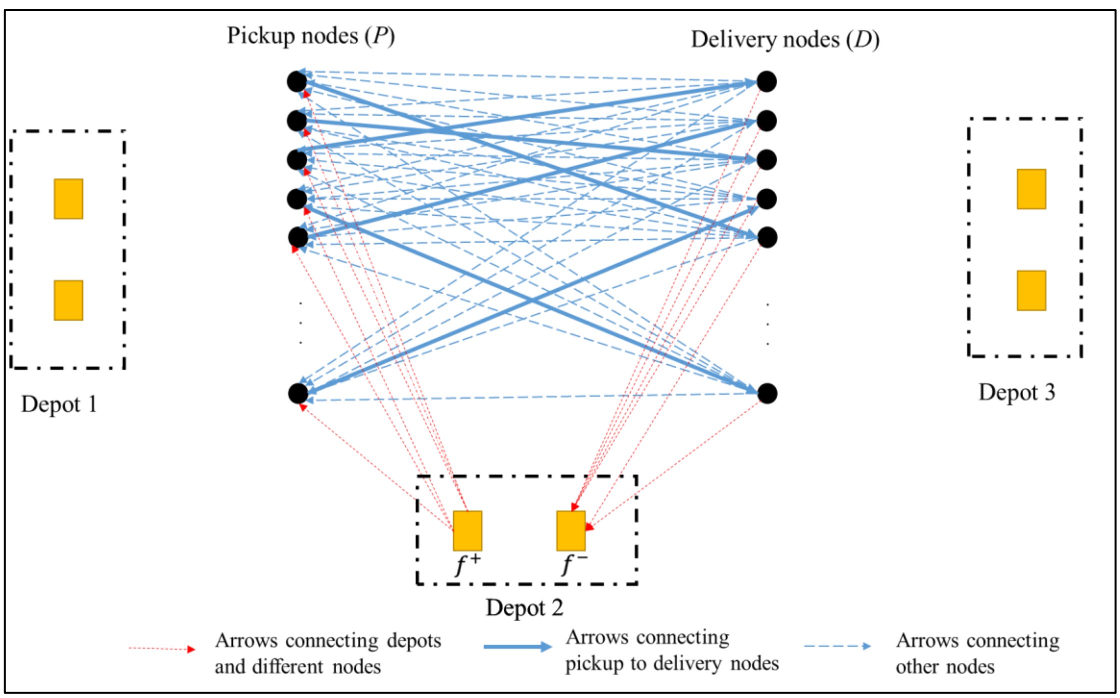

Figure 4-3. The sub-network for trucks (pickup and delivery network)

Finally, Figure 4-4 depicts a directed graph $G_3 = (N_3, A_3)$ for the loaders at the delivery nodes, where $N_3 = (g^+ \cup g^- \cup D)$ and A_3 include the arcs connecting different nodes. Similarly, a virtual start node (g^+) and a virtual sink node (g^-) are added to the graph and the problem is considered as a VRP, where each node should be visited only once, by a loader. Also, φ_{il}^+ and φ_{il}^- are the sets of nodes succeeding and preceding node i by loader l, respectively.

At each pickup and delivery node, the loaders and trucks have to be synchronized. It means that both machines should start a loading/unloading activity simultaneously at each node. If each of the machines arrived at a node earlier, it should wait until the other machine arrives at the node to start their work at the same time. As each pickup/delivery location can have several nodes, it is possible that two or more trucks can queue up for getting loaded/unloaded at each location. Each of the waiting trucks needs to wait until the loader visits the node for being synchronized with the truck.

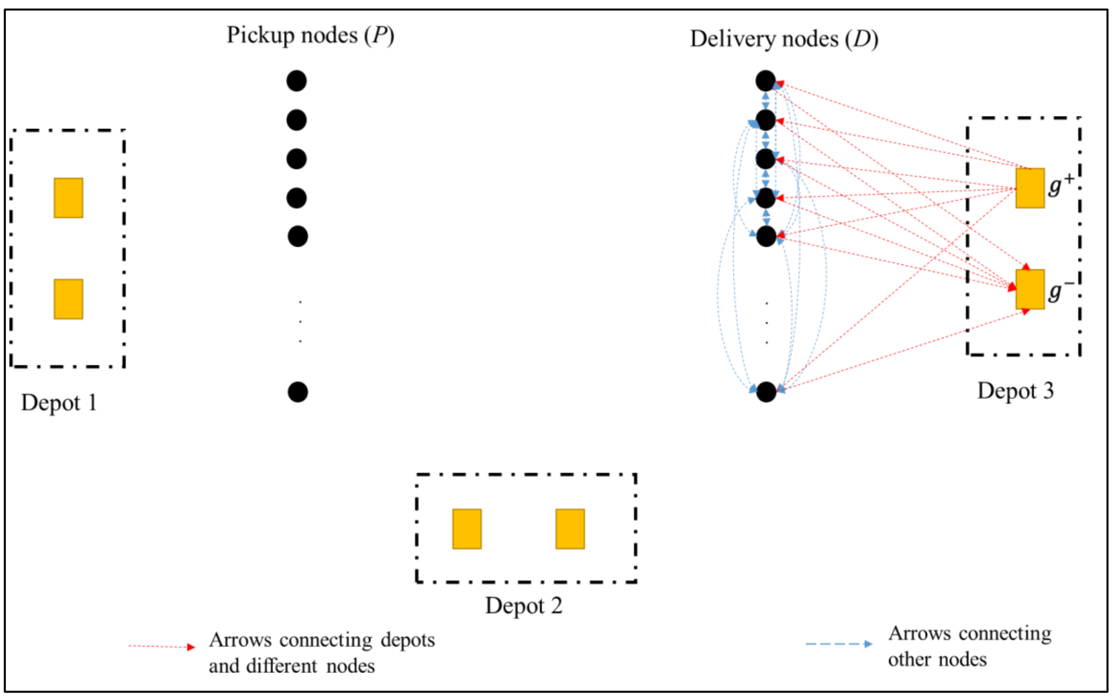

Figure 4-4. The sub-network for loaders at sort yards (delivery network)

4.4 Mathematical model

For the scheduling problem, an MIP optimization model is developed for a one-day planning horizon to determine the routing and scheduling decisions considering the synchronization of the log loaders and heterogeneous trucks at both pickup and delivery nodes. Table 4-1 lists notations of the proposed model.

Table 4-1. Notations of the daily routing and scheduling optimization model

Sets	**Description**
N	Set of all nodes $i, j \in \{1,2, \dots, N\}$
N_1	Subset of nodes at the pickup network $N_1 \subseteq N$
N_2	Subset of nodes at the pickup and delivery network $N_2 \subseteq N$
N_3	Subset of nodes at the delivery network $N_3 \subseteq N$
P	Set of the pickup nodes $P \subseteq N$
D	Set of the delivery nodes $D \subseteq N$
$\mathrm{c}^+, \mathrm{c}^-$	The start and sink nodes for the loaders at the pickup network
$\mathrm{f}^+, \mathrm{f}^-$	The start and sink nodes for the trucks at the pickup and delivery network
$\mathrm{g}^+, \mathrm{g}^-$	The start and sink nodes for the loaders at the delivery network
φ_{il}^+	Set of nodes succeeding node i by loader l
φ_{il}^-	Set of nodes preceding node i by loader l
φ_{iv}^+	Set of nodes succeeding node i by truck v
φ_{iv}^-	Set of nodes preceding node i by truck v
L	Set of all loaders $l \in \{1,2, \dots \mathrm{L}\}$
L_P	Subset of loaders at the pickup network $L_P \subseteq L$
L_D	Subset of loaders at the delivery network $L_D \subseteq L$
O	Set of trucking contractors $o \in \{1,2, \dots, \mathrm{O}\}$
K	Set of truck types $k \in \{1,2, \dots, \mathrm{K}\}$
V_{ok}	Set of trucks of type k that contractor o owns $v \in \{1,2, \dots, V_{ok}\}$

Parameters	Description
FC_k	Fixed operating cost of using truck type k ($)
VC_k	Unit variable cost of using truck type k ($/minute)
OC_k	Unit overtime cost of using truck type k ($/minute)
$\mathrm{DIS(i, j)}$	Distance between node i and node j for loaders and dummy depots (km)
DC_l	Unit travelling cost of loader l per unit of distance ($/km)
α_{ij}^{o}	If contractor o delivers a truckload from pickup node i to delivery node j the value is 1; otherwise, 0
β_{ij}^{k}	If truck type k delivers a truckload from pickup node i to delivery node j the value is 1; otherwise, 0
M	A very large number used for logical constraints
D_{ij}^{l}	Travelling time of loader l from node i to node j (minute)
D_{ij}^{k}	Travelling time of truck type k from node i to node j (minute)
S_i	Service (loading or unloading) time at node i (minute)
T_{Max}	Maximum daily driving time for each truck (minute)
E_{Max}	Maximum overtime that can be assigned to each truck (minute)
Decision variables	**Description**
x_{ij}^{l}	If loader l traverses from node i to node j (at the pickup network) the value is 1; otherwise, 0
y_{ij}^{okv}	If contractor o uses truck v of type k to traverse from node i to node j the value is 1; otherwise, 0
z_{ij}^{l}	If loader l traverses from node i to node j (at the delivery network) the value is 1; otherwise, 0
t_i^{l}	Arrival time of loader l at node i
t_i^{okv}	Arrival time of truck v of type k owned by contractor o at node i
w_i	Waiting time of trucks at node i
u_i	Waiting time of loaders at node i

Decision variables	Description
e^{okv}	Overtime assigned for truck v of type k owned by contractor o

4.4.1 Objective function

Equation (4-1) presents the objective function of the model, which is to minimize the total costs including fixed, variable, and overtime costs of using trucks, and the travelling cost of loaders between nodes. The fixed cost is an operating fixed cost, and it is different from the investment cost. It is noteworthy that incorporating the fixed cost results in a trade-off between allowing a truck to work overtime or dispatching a new truck.

$$\begin{aligned}\text{Min.}\, Z = &\sum_{v\in V_{oK}}\sum_{k\in K}\sum_{o\in O}\sum_{j\in\varphi^{+}_{f^{+}v}} \mathrm{FC}_k.\, y^{okv}_{f^{+}j} + \sum_{v\in V_{ok}}\sum_{k\in K}\sum_{o\in O}\mathrm{VC}_k.\,(t^{okv}_{f^{-}} - e^{okv}) \\ &+ \sum_{v\in V_{oK}}\sum_{k\in K}\sum_{o\in O}\mathrm{OC}_k.\, e^{okv} + \sum_{l\in L_P}\sum_{(i,j)\in N_1}\mathrm{DC}_l.\,\mathrm{DIS}_{ij}.\, x^l_{ij} \\ &+ \sum_{l\in L_D}\sum_{(i,j)\in N_3}\mathrm{DC}_l.\,\mathrm{DIS}_{ij}.\, z^l_{ij}\end{aligned} \tag{4-1}$$

4.4.2 Constraints

Constraint sets (4-2)-(4-7) are related to the first sub-problem network for the loaders at the pickup nodes. Constraint sets (4-2) and (4-3) imply that if loaders are used, they have to return to the depot at the end of the day.

$$\sum_{j\in\varphi^{+}_{c^{+}l}} x^l_{c^{+}j} = \sum_{i\in\varphi^{-}_{c^{-}l}} x^l_{ic^{-}} \qquad \forall l \in L_P \tag{4-2}$$

$$\sum_{j\in\varphi^{+}_{c^{+}l}} x^l_{c^{+}j} \le 1 \qquad \forall l \in L_P \tag{4-3}$$

Constraint set (4-4) is the flow balancing constraint, ensuring that the loaders do not get stuck at the pickup nodes. In this constraint set, if a loader enters a node, it should exit the node.

$$\sum_{i\in\varphi_{jl}^{-}} x_{ij}^{l} = \sum_{i\in\varphi_{jl}^{+}} x_{ji}^{l} \qquad \forall l \in L_P, j \in N_1 \backslash \{c^+ \cup c^-\} \qquad (4\text{-}4)$$

The arrival time of a loader at each pickup node is calculated considering the service (loading) time using constraint sets (4-5) and (4-6). Constraint set (4-5) calculates the arrival time of loaders at the first node it visits after leaving the starting node, while constraint set (4-6) determines the arrival time of the loader at a node incorporating waiting time of the loader at the previous node.

$$S_{c^+} + D_{ij}^{l} \leq t_j^{l} + M(1 - x_{c^+j}^{l}) \qquad \forall l \in L_P, j \in N_1 \backslash \{c^+\} \qquad (4\text{-}5)$$

$$t_i^{l} + S_i + D_{ij}^{l} + u_i \leq t_j^{l} + M(1 - x_{ij}^{l}) \qquad \forall l \in L_P, i \notin \{c^+\}, j \in N_1 \backslash \{c^+\} \qquad (4\text{-}6)$$

The scheduling and loader assignment decisions in each pickup node are connected in constraint set (4-7), which ensures the arrival time of each loader at each pickup node is calculated only if the loader visits the node.

$$t_j^{l} \leq M \sum_{i\in\varphi_{jl}^{-}} x_{ij}^{l} \qquad \forall l \in L_P, j \in N_1 \backslash \{c^+ \cup c^-\} \qquad (4\text{-}7)$$

Constraint sets (4-8)-(4-15) are associated with the second sub-problem network for the trucks at the pickup and delivery nodes. Constraint set (4-8) forces the dispatched trucks to return to their depot after delivering the assigned truckloads. Constraints (4-9) state that contractors have a choice between using a truck or leaving it at the depot.

$$\sum_{j\in\varphi_{f^+v}^{+}} y_{f^+j}^{okv} = \sum_{i\in\varphi_{f^-v}^{-}} y_{if^-}^{okv} \qquad \forall o \in O, k \in K, v \in V_{ok} \qquad (4\text{-}8)$$

$$\sum_{j\in\varphi_{f^+v}^{+}} y_{f^+j}^{okv} \leq 1 \qquad \forall o \in O, k \in K, v \in V_{ok} \qquad (4\text{-}9)$$

Constraint set (4-10) guarantees that a truck entering a node should exit the node to balance inflows and outflows.

$$\sum_{i\in\varphi_{jv}^{-}} y_{ij}^{okv} = \sum_{i\in\varphi_{jv}^{+}} y_{ji}^{okv} \qquad \forall o \in O, k \in K, v \in V_{ok}, j \in N_2 \backslash \{f^+ \cup f^-\} \tag{4-10}$$

Constraint set (4-11) ensures that each truckload is assigned to its contractor and compatible truck type. The information regarding the compatibility of contractors and truck types for the truckloads is obtained from the upper-level model developed in Chapter 3.

$$\sum_{v\in V_{ok}} y_{ij}^{okv} \leq M.\alpha_{ij}^{o}.\beta_{ij}^{k}, \qquad \forall o \in O, k \in K, i, j \in N_2 \backslash \{f^+ \cup f^-\} \tag{4-11}$$

Contractors have a certain number of trucks. Constraint set (4-12) indicates that the total number of trucks that each contractor uses for delivering the truckloads should not exceed the number of trucks that the contractor has.

$$\sum_{v\in V_{ok}} \sum_{j\in\varphi_{f^+v}^{+}} y_{f^+j}^{okv} \leq |V_{ok}| \qquad \forall o \in O, k \in K \tag{4-12}$$

Constraint set (4-13) calculates the arrival time of trucks, dispatched from the depot, at each cut block. Constrain set (4-14), however, determines the arrival time of trucks travelling between every pair of nodes considering the waiting time of trucks at the nodes.

$$S_{f^+} + D_{ij}^{k} \leq t_j^{okv} + M(1 - y_{f^+j}^{okv}) \qquad \forall o \in O, k \in K, v \in V_{ok}, j \in N_2 \backslash \{f^+\} \tag{4-13}$$

$$t_i^{okv} + S_i + D_{ij}^{k} + w_i \leq t_j^{okv} + M(1 - y_{ij}^{okv}) \qquad \forall o \in O, k \in K, v \in V_{ok}, i \notin \{f^+\}, j \in N_1 \backslash \{f^+\} \tag{4-14}$$

Constraint set (4-15) guarantees that the arrival time of trucks can be calculated only at the nodes that the trucks visit.

$$t_j^{okv} \leq M \sum_{i \in \varphi_{jv}^-} y_{ij}^{okv} \qquad \forall o \in O, k \in K, v \in V_{ok}, j \in N_1 \backslash \{e^+ \cup e^-\} \qquad (4\text{-}15)$$

Constraint sets (4-16)-(4-21) are related to the third sub-problem for the loaders at the delivery nodes. Constraint sets (4-16) and (4-17) state that if a loader for unloading a truck is used, it should start from the dummy depot and return to it.

$$\sum_{j \in \varphi_{g^+l}^+} z_{g^+j}^l = \sum_{i \in \varphi_{g^-l}^-} z_{ig^-}^l \qquad \forall l \in L_D \qquad (4\text{-}16)$$

$$\sum_{j \in \varphi_{g^+l}^+} z_{g^+j}^l \leq 1 \qquad \forall l \in L_D \qquad (4\text{-}17)$$

Constraint set (4-18) balances the inflows and outflows of each demand node for each loader.

$$\sum_{i \in \varphi_{jl}^-} z_{ij}^l = \sum_{i \in \varphi_{jl}^+} z_{ji}^l \qquad \forall l \in L_D, j \in N_3 \backslash \{g^+ \cup g^-\} \qquad (4\text{-}18)$$

The arrival times of loaders at each demand node is calculated using constraint sets (4-19) and (4-20). Constraint set (4-19) calculates the arrival time of the first trip of loaders dispatched from the dummy depot, while the arrival times of loaders at nodes in other trips are calculated by constraint set (4-20).

$$S_{g^+} + D_{ij}^l \leq t_j^l + M(1 - z_{g^+j}^l) \qquad \forall l \in L_D, j \in N_3 \backslash \{g^+\} \qquad (4\text{-}19)$$

$$t_i^l + S_i + D_{ij}^l + wl_i \leq t_j^l + M(1 - z_{ij}^l) \qquad \forall l \in L_D, i \notin \{g^+\}, j \in N_3 \backslash \{g^+\} \qquad (4\text{-}20)$$

In each demand node, constraint set (4-21) enforces the model to calculate the arrival time of the loaders visiting the node.

$$t_j^l \leq M \sum_{i \in \varphi_{jl}^-} z_{ij}^l \qquad \forall l \in L_D, j \in N_3 \backslash \{g^+ \cup g^-\} \qquad (4\text{-}21)$$

Constraint sets (4-22)-(4-24) ensure that each node is visited by appropriate machines. Constraint sets (4-22) and (4-23) impose that each pickup and delivery node would be visited exactly once by a loader. Constraint set (4-24) implies that pickup and delivery nodes must be visited exactly once by one truck, meaning that all truckloads should be delivered.

$$\sum_{l \in L_P} \sum_{i \in \varphi_{jl}^-} x_{ij}^l = 1 \qquad \forall j \in P \tag{4-22}$$

$$\sum_{l \in L_D} \sum_{i \in \varphi_{jl}^-} z_{ij}^l = 1 \qquad \forall j \in D \tag{4-23}$$

$$\sum_{v \in V_{ok}} \sum_{k \in K} \sum_{o \in O} \sum_{i \in \varphi_{jv}^-} y_{ij}^{okv} = 1 \qquad \forall j \in (P \cup D) \tag{4-24}$$

Constraint sets (4-25) and (4-26) synchronize the log loaders and trucks performing a task together (loading or unloading) at cut blocks and sort yards, respectively. These constraints determine the waiting times of the loaders and trucks and ensure that the machines start loading/unloading activities simultaneously.

$$\sum_{l \in L_P} t_i^l + u_i = \sum_{v \in V_{oK}} \sum_{k \in K} \sum_{o \in O} t_i^{okv} + w_i \qquad \forall i \in P \tag{4-25}$$

$$\sum_{l \in L_D} t_i^l + u_i = \sum_{v \in V_{oK}} \sum_{k \in K} \sum_{o \in O} t_i^{okv} + w_i \qquad \forall i \in D \tag{4-26}$$

Trucks have a maximum number of working hours, but these trucks can be assigned overtime. The amount of overtime for each truck is calculated using constraint set (4-27). Constraint set (4-28) states that the amount of overtime assigned to each truck should be less than the maximum amount of overtime that can be assigned.

$$t_{f^-}^{okv} \leq \mathrm{T}_{max} + e^{okv} \qquad \forall o \in O, k \in K, v \in V_{oK} \tag{4-27}$$

$$e^{okv} \leq \mathrm{E}_{max} \qquad \forall o \in O, k \in K, v \in V_{oK} \qquad (4\text{-}28)$$

Constraint sets (4-29) and (4-30) control the domain of variables.

$$x_{ij}^{l}, y_{ij}^{okv}, z_{ij}^{l} \in \{0,1\} \qquad \forall i, j \in (N_1 \cup N_2 \cup N_3), l \in L, o \in O, k \in K, v \in V_{oK} \qquad (4\text{-}29)$$

$$t_i^l, t_i^{okv}, w_i, u_i, e^{okv} \geq 0 \qquad \forall i \in (N_1 \cup N_2 \cup N_3), l \in L, o \in O, k \in K, v \in V_{oK} \qquad (4\text{-}30)$$

4.4.3 Execution of the model

According to the provided information by the forest company, each truck driver has a maximum regular working time of 8.5 hours (510 minutes). In addition, 2.5 hours (150 minutes) of overtime can be assigned. For confidentiality purposes, values for the cost parameters are not shown in this chapter. Additionally, it is assumed that there is one stationary loader at each pickup location and each delivery location. It means that loaders cannot visit those nodes that are in different locations since they are stationary and cannot move between cut blocks (or sort yards). Therefore, in the model, a loader has to be forced to visit only the nodes in the similar location. This is done by assigning zero to the distance between nodes within a location and a very large number to the distance between nodes in different locations. This assumption avoids the loaders to visit nodes in different locations.

Similar to other papers in the literature (e.g. Flisberg et al. 2009; Melchiori et al. 2022), the proposed model is applied to several test problems from the real case. All the test problems are solved by CPLEX solver in AIMMS software package (*CPLEX — AIMMS*, 2022) on a desktop computer with Intel® Core ™ i7-6700 CPU, 3.40 GHz processor, and 16 GB RAM.

4.5 Test problems and results

This section presents the results of the model applied to the test problems from the company's case study, where pickup and delivery locations, responsible contractor, and truck type of truckloads are determined from an upper-level model. Eight test problems, called TP 1 to TP 8, are solved. In the test problems, three sort yards (delivery locations) are considered. It is assumed that there is one loader in each location and 2 contractors deliver the truckloads. Each contractor has 3 highway and 3 off-highway trucks. Trucks 1-6 belong to contractor 1, while contractor 2 owns trucks 7-12. While TP 1 to TP 4 have 2 cut blocks, there are 3 cut blocks in TP 5 to TP 8. Table 4-2 summarizes the test problems and results. The total number of truckloads, nodes, and cut blocks are shown in the second, third, and fourth columns of Table 4-2, respectively. For each test problem, the fifth and sixth columns show the objective function and the percentage of improvement compared to the direct delivery of the truckloads. In the direct delivery case, there is no backhauling and each truck returns to the depot after delivering a truckload to a sort yard. Finally, the last column lists the amount of computational time for getting the optimum solution. It can be observed that by increasing the size of the case, the problem would not be solvable in a reasonable time.

Table 4-2. Summary of test problems and the results

Test problems	**No. of truckloads**	**No. of nodes**	**No. of cut blocks**	**Obj. function**	**Improvement compared to direct delivery**	**CPU time (second)**
TP 1	9	24	2	$10,458	10.6%	3
TP 2	10	26	2	$11,191	14%	8
TP 3	11	28	2	$12,584	14%	47
TP 4	12	30	2	$14,053	10.3%	794
TP 5	9	24	3	$13,229	4.1%	9
TP 6	10	26	3	$13,910	9.8%	11
TP 7	11	28	3	$15,253	9.7%	839
TP 8	12	30	3	$15,935	12.7%	3417

For further analysis, test problem TP 8 is investigated in detail as it is the largest sized problem. The detailed schedule of one of the off-highway trucks is shown in Figure 4-5, where the truck is assigned to deliver 2 truckloads (truckload 6 and truckload 12). First, the truck is dispatched from the depot to the third cut block to get loaded. When the truck arrives at the cut block, the loader is not idle as it is loading another truck. Therefore, the truck has to wait for 20 minutes to be synchronized with the loader for the loading activity. After loading, the truck delivers truckload 6 to the second sort yard at minute 281, when the loader at the yard is idle and can be synchronized with the truck immediately. Finally, the truck returns to the depot at minute 558 after fulfilling truckload 12. As the arrival time at the depot is more than the maximum daily driving hours, which is 510 minutes, the truck has 48 minutes of overtime.

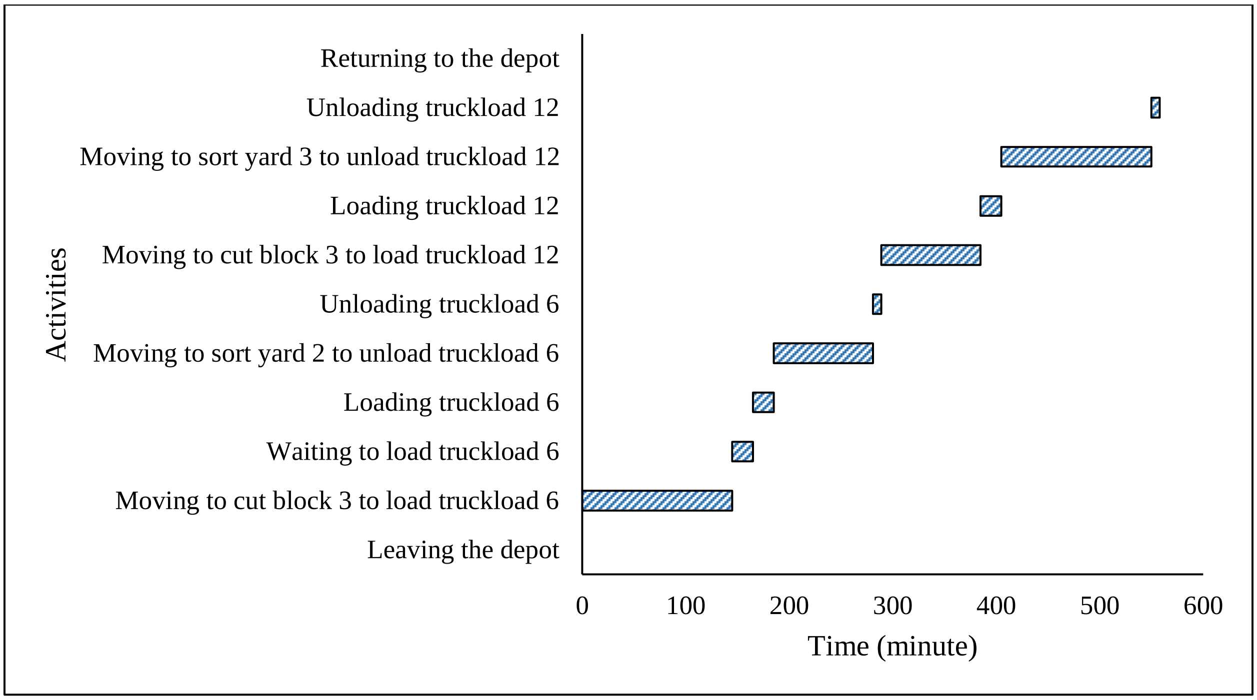

Figure 4-5. Schedule of an off-highway truck in TP 8

As shown in Figure 4-6, seven trucks have overtime to deliver their assigned truckloads. Some trucks (e.g. trucks 4 and 12) deliver more than one truckload. However, four trucks are not used by the contractors. In other words, in this problem, it would be more economical to assign overtime to existing trucks than dispatching a new truck.

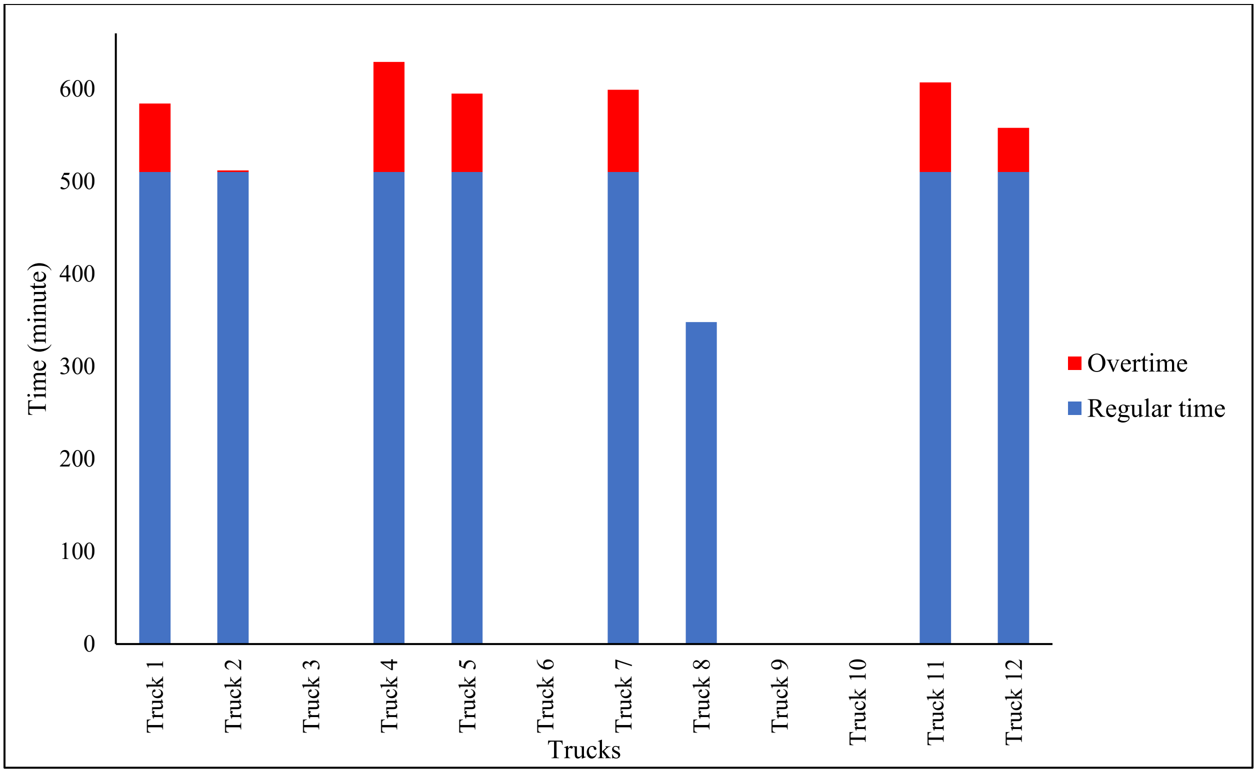

Figure 4-6. Working time of trucks in TP 8

In this problem, loaders are the resources required for loading and unloading trucks at cut blocks and sort yards, respectively. As dummy depots are considered for the loaders at cut blocks (sort yards), these loaders finish their work by loading (unloading) the last truckload, and they remain at their cut block (sort yard). The schedule of a loader in a cut block is shown in Figure 4-7, where the loader loads four truckloads and must wait for 177 and 167 minutes to load the first and the last truckloads, respectively.

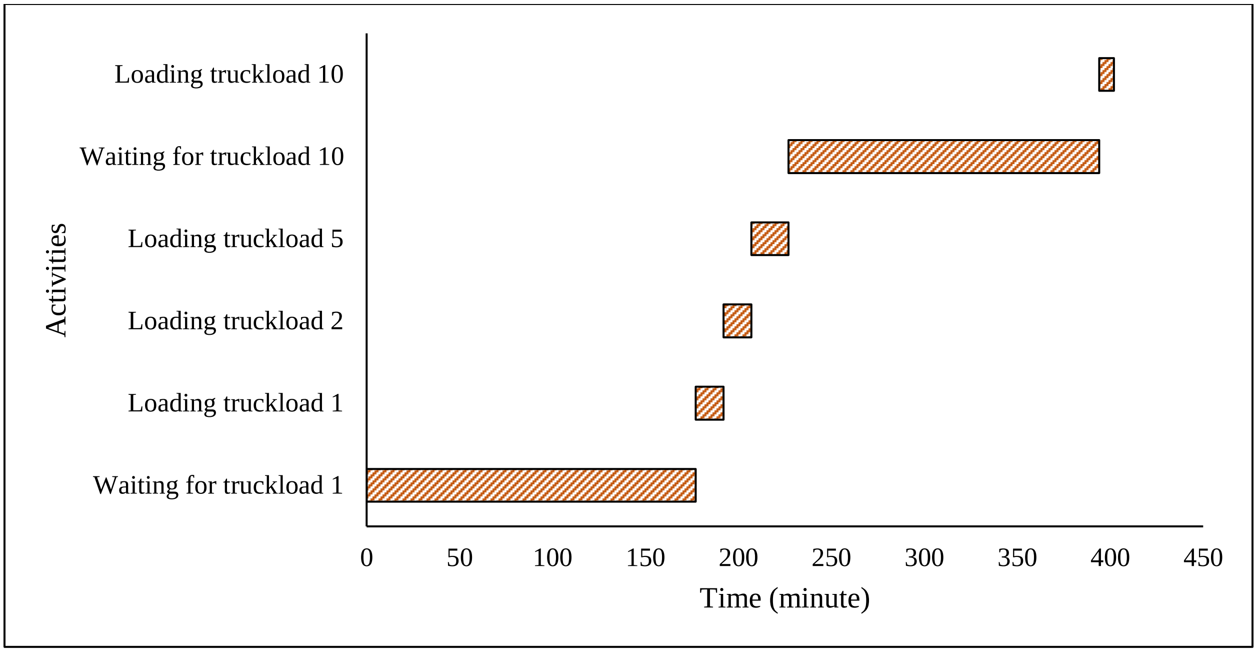

Figure 4-7. Schedule of a loader at cut block 1 in TP 8

Similarly, Figure 4-8 depicts the schedule of a loader that unloads five truckloads at sort yard 2. The loader remains idle for 214 minutes to unload truckload 8, and it has to wait for 15 minutes to be synchronized with a truck delivering truckload 4 to finish its work.

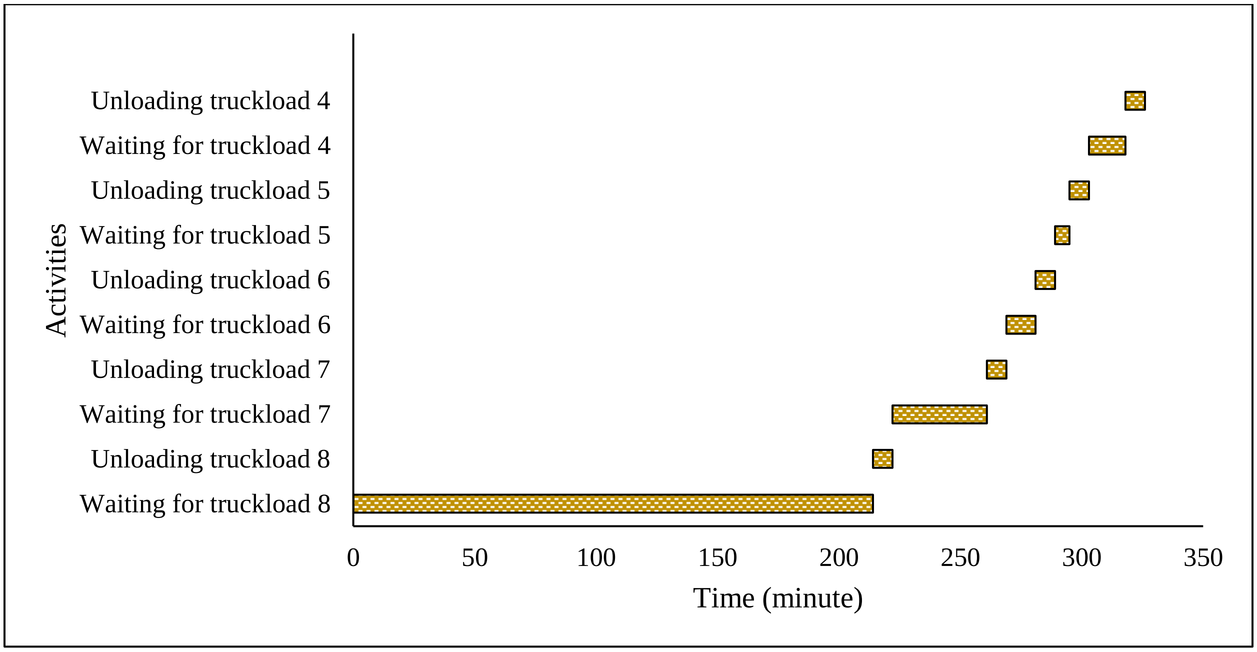

Figure 4-8. Schedule of a loader at sort yard 2 in TP 8

We conducted a sensitivity analysis to examine how the objective function varies when input parameters are changed. Considered parameters are the fixed operating cost of using trucks, variable and overtime costs of using trucks, service (loading and unloading) time, maximum driving time, and maximum amount of overtime that can be assigned to each truck. As suggested in (Vancas, 2003), the parameter are changed by ±20% to have a proper accuracy in the feasibility study. Figure 4-9 summarizes the results of the sensitivity analysis for test problem TP 8.

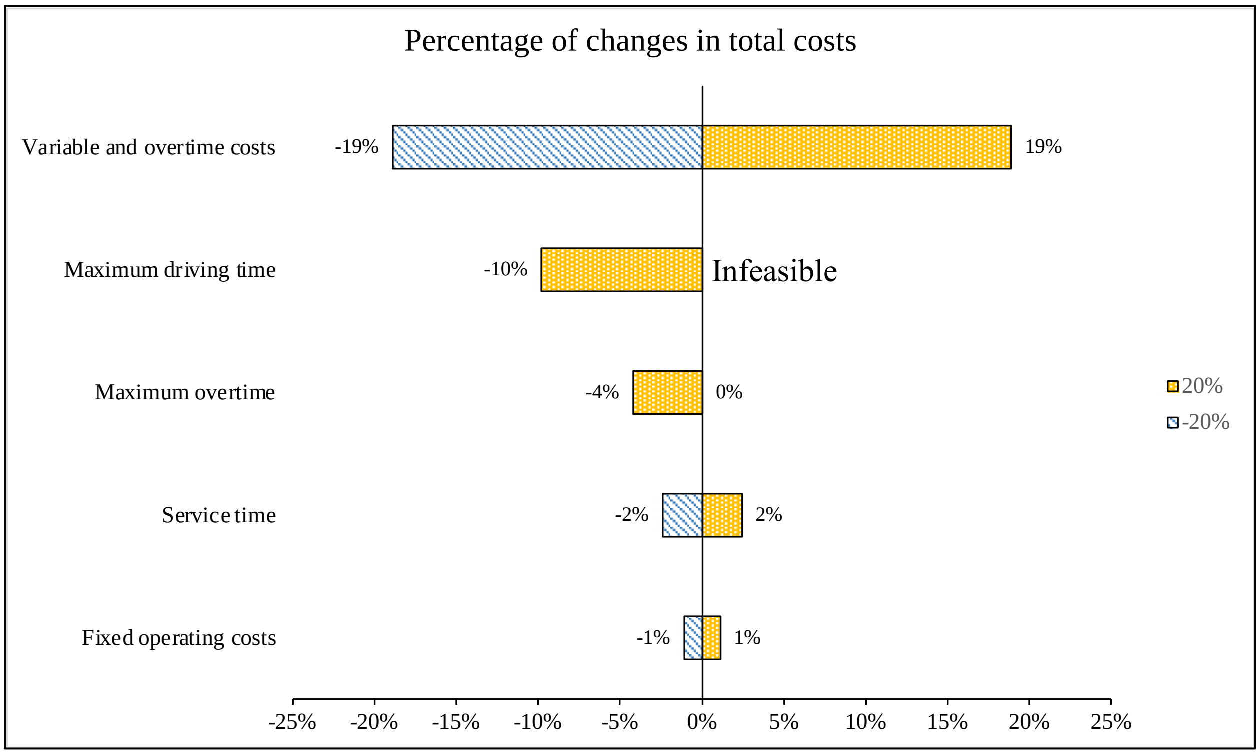

Figure 4-9. Sensitivity analysis of TP 8 when parameters are changed by 20%

As expected, when variable and overtime costs increase (decrease) by 20%, the total costs increase (decrease) by 19%. Reducing the maximum driving time by 20% leads to infeasibility as the required time for delivering a truckload to sort yard 1 would be greater than the summation of reduced maximum driving time and overtime. Also, the total costs will decrease by 10% when the maximum driving time increases because truckloads can be delivered during the regular driving time and the need for overtime will decrease. The effects of changing the maximum allowable overtime, service time, and fixed operating costs are negligible. Because cut blocks and sort yards are not close to each other and it takes considerable time for a truck to deliver a truckload, variable costs of trucks have a higher proportion in the total costs compared to fixed operating costs and changing the fixed operating costs would not significantly impact the total costs.

4.6 Discussion

The scheduling of log trucks without synchronizing trucks and loaders may lead to an infeasible solution because waiting times of the trucks can cause delays in delivering the truckloads, which consequently will result in exceeding the maximum driving time or violating time windows. Therefore, it is important to calculate waiting times of trucks at different locations. As shown in Figure 4-5, the developed model in this chapter allows for obtaining the detailed schedule of a truck departing and returning to the depot using continuous time representation, which leads to accurate daily plans. In some of the previous papers (e.g. El Hachemi et al. 2015; Melchiori et al. 2022), scheduling and synchronization of resources were addressed using discrete time slots, which might generate unnecessary waiting times. In other words, if a truck arrives after the beginning of a time slot, it has to wait until the starting time of the next slot, which adds additional unnecessary waiting time. Besides, defining discrete time slots is more challenging for this problem as the trucks are heterogeneous, and the loading time is different for each truck type. Hence, using continuous time representation instead of the discrete one generates more accurate scheduling that can reflect the overall performance of the loaders (as shown in Figure 4-7 and Figure 4-8).

In the problem, there are contractors working in independent cut blocks. However, they all deliver the logs to three sort yards where the loaders need to be synchronized with trucks of different contractors. Thus, having separate planning for a contractor’s truckloads cannot be appropriate for calculating the detailed unloading times as schedules of trucks of other contractors at the same sort yard are disregarded. Therefore, from the modeling perspective, the proposed model integrates decisions for all contractors, facilitating synchronization of trucks and loaders at sort yards.

Incorporating contractors in optimization models have impacts on the transportation planning. It was shown in (Ghotb et al., 2022) that considering contractors and satisfying their expectations and preferences affect decisions related to distribution of logs in a 1-month planning horizon and increased the costs by 0.4%. Also, the sensitivity analysis of the study highlighted the importance of contractual details in the feasibility and profitability of the daily scheduling of trucks. Proper cost rate, maximum driving time and overtime would generate costs savings.

In TP 8, for each contractor, two trucks were not used, while the other trucks were assigned overtime (Figure 4-6). Indeed, dispatching a new truck resulted in additional costs, which included the fixed operating cost of using the truck and the variable cost from the depot to the cut block to pick up the truckload. In this problem, as the depot was far from cut blocks, it was more economical to pay for overtime and assign more truckloads to the existing trucks than using a new truck. Similar conclusions could be drawn from the sensitivity analysis (Figure 4-9), where increasing the maximum amount of overtime by 20% decreased the total transportation costs. When each truck can be assigned more overtime, contractors may realize cost savings from dispatching fewer number of trucks.

As shown in Table 4-2, when the number of nodes increased, it took more time to get the optimal solution. Thus, when a truck had to deliver a significant number of truckloads, the problem could not be solved in a reasonable time using commercial software packages. As the scheduling problem needs to be solved daily, non-exact solution approaches such as metaheuristic algorithms are required for larger problems to get good solutions in a short period of time.

In this chapter, we introduced an optimization model for log transportation planning at the operational level considering different complexities that can address real world log transportation problems. Having the optimization model is useful in validation of heuristics methods for the scheduling of log trucks. According to (Bettinger et al. 2009), the highest level of validation of results generated by heuristics methods is to compare them with the results from mixed integer optimization models. Hence, as the proposed model is flexible and can be relaxed to consider one contractor or homogeneous trucks by having only one truck type, it can be used to validate heuristics methods for a wide variety of problems.

4.7 Conclusions

This chapter presented an MIP model for daily routing and scheduling of heterogeneous trucks using continuous time representation to address the second objective of the thesis. The proposed model synchronized log loaders and trucks owned by trucking contractors at both cut blocks and sort yards by determining the detailed schedules. The performance of the model was assessed by applying it to eight test problems from the real case of a large forest company in British Columbia, Canada. The results indicated that it was more economical to pay overtime than dispatching a new truck although the unit cost of overtime was 1.5 times the unit cost of regular time. As a result, there were some trucks that remained idle at the depot. Based on the conducted sensitivity analysis, variable costs and the maximum driving time were the most sensitive parameters, while changing the fixed operating costs had the least impact on the total transportation costs.

When the size of the problem increases, the model will have more binary decision variables and constraint. Hence, the model will not be solvable in a reasonable time. Therefore, Chapter 5 will focus on developing non-exact solution approaches to solve the problem in a reasonable time.

Chapter 5: Solution approach for the daily routing and scheduling problem

5.1 Synopsis

Due to the significant volume of the supply and demand, forest companies usually deliver large number of truckloads between forest areas and demand locations. However, the introduced model in Chapter 4 could address daily routing and scheduling only for small and medium-sized problems. Thus, a solution approach based on the simulated annealing algorithm is developed in this chapter and is applied to the case study to address the third and fourth research objectives of this dissertation, respectively, for solving and getting good solutions in a reasonable time for the real case and large-sized problems. The main challenge is to incorporate details and complexities such as trucking contractors and a heterogeneous fleet of trucks with different service times into the solution approach. Additionally, the parameters of the algorithm are calibrated using the Taguchi method to improve the performance of the algorithm. The solution approach is then applied to the case where the upper-level planning developed in Chapter 3 determined the daily flows for a 1-month planning horizon.

5.2 Problem definition

In this thesis, a decomposition approach is used to determine the daily flows of logs, routing, and scheduling of log trucks for the forest company with a 1-month planning horizon. The approach divided the problem into two phases. Figure 5-1 depicts the scheme of the decomposition approach.

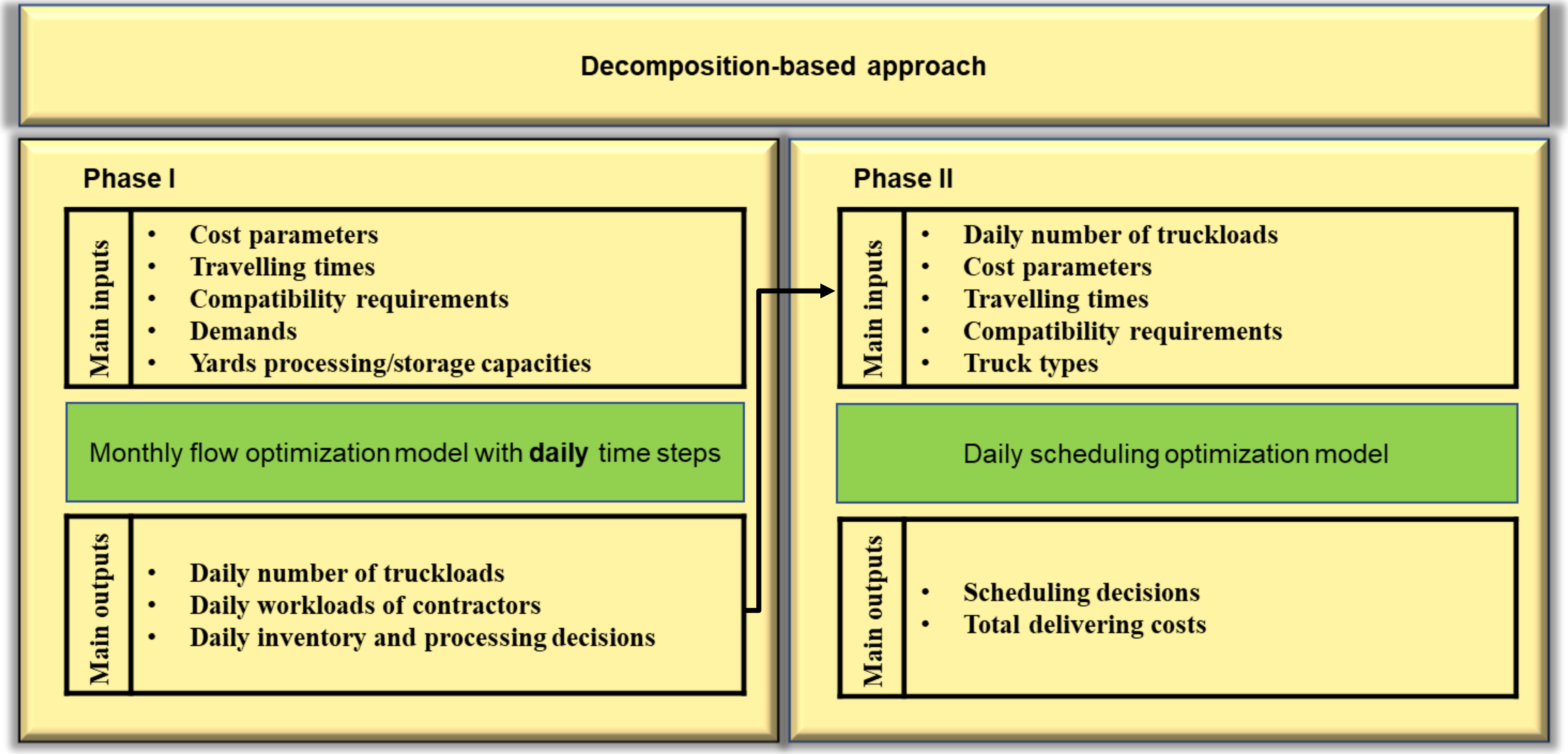

Figure 5-1. The schematic view of the proposed decomposition approach

In the first phase, a bi-objective MIP model using the goal programming approach was developed in Chapter 3. The main outputs of model (the main decisions) are listed below.

- The inventory levels of each log sort in both sorted and unsorted logs at every cut block at the end of the planning horizon.
- The daily volume of each log sort in both sorted and unsorted logs delivered between each pair of cut blocks and sort yards.
- The daily number of both sorted and unsorted truckloads transported between cut blocks and sort yards by each contractor using each truck type.
- The daily volume of each log sort that is sorted at each sort yard.
- The daily inventory level of each log sort in the unsorted logs at each sort yard.
- The daily inventory level of each sort in the water at each sort yard.

In the second phase, an MIP model was introduced in Chapter 4 for the daily routing and scheduling of a heterogeneous fleet of trucks using continuous time representation. The model determined the number of dispatched trucks, assigned the truckloads obtained from the first phase to the compatible trucks, calculated the detailed schedules of trucks and loaders, synchronized them at both the pickup and delivery locations, and assigned overtime to the trucks. The model was solved for test problems with different sizes from the case study.

However, as the size of the problem increased, commercial software packages could not solve the model in a reasonable time. Therefore, a non-exact solution approach is needed to solve the daily scheduling optimization model (Phase II) in a reasonable time. To address the third and fourth research objective, a suitable solution approach for the daily scheduling of the trucks is developed in this chapter and the solution approach is applied to the real case, which addresses the fourth objective of this thesis.

5.3 Solution approach

As shown in Chapter 4, the daily scheduling optimization model becomes computationally intractable when the number of truckloads increased. The main challenge of the solution approach is to synchronize the log loaders and the trucks at both cut blocks and sort yards in order to get detailed schedules. Also, heterogeneous trucks and compatibility requirements of truckloads, trucks, and contractors increase the complexity of the solution approach.

To obtain near optimal solutions, the Simulated Annealing (SA) algorithm introduced by (Kirkpatrick et al., 1983) is used in this chapter. SA is a metaheuristic algorithm inspired by the annealing process of metals and starts with an initial solution. The algorithm explores the search space by moving to the neighboring solutions. Due to its ease of implementation, and its ability in local search without getting trapped in local optimum solutions, the SA algorithm has been employed in a wide variety of scheduling optimization problems (e.g. Haridass et al. 2014; Yağmur and Kesen 2021; Kress and Müller 2022). The main steps of the proposed solution approach including creating an initial solution, cost evaluation, creating a new neighborhood solution, and SA procedure are shown in Figure 5-2.

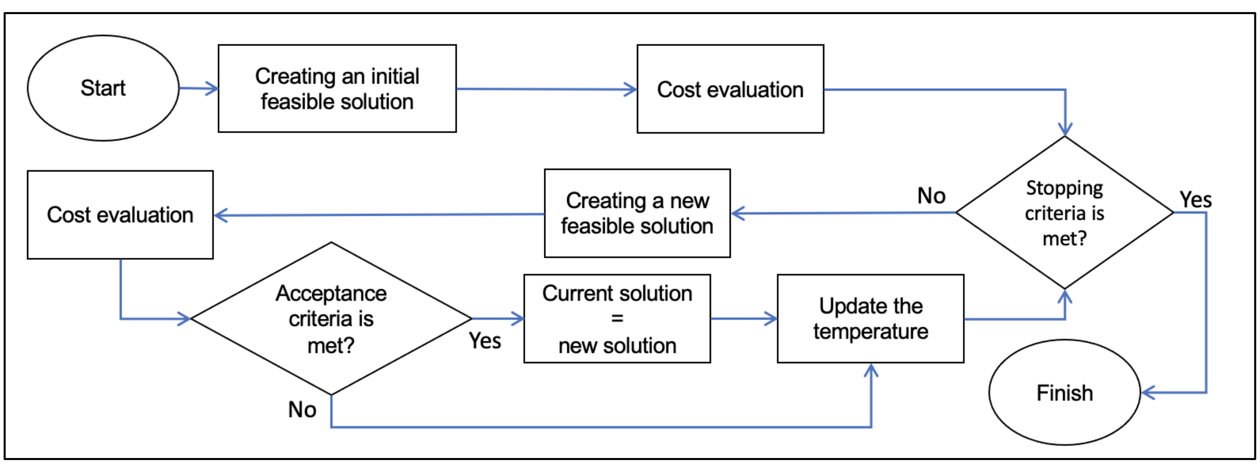

Figure 5-2. The main steps of the proposed algorithm

In the following sections, the solution representation and the main steps are described.

5.3.1 Solution representation

A solution of the problem to be used in the algorithm is represented by a permutation of delimiters and truckloads. The delimiters separate truckloads of different trucks, truck types, and trucking contractors. Each truckload in the permutation has a known cut block (pickup) and sort yard (delivery). It means that when a truckload is assigned to a truck, the truck must first visit the cut block to pick up the load and then it must move to the corresponding sort yard for delivering the truckload. In addition, when extracting the assigned truckloads from the permutation, the central depot has to be added to the beginning and the end of the list of the truckloads that a truck carries to determine its route.

An example of the solution representation with two contractors is shown in Figure 5-3, where each contractor has two truck types. First, the truckloads of each truck of every truck type are assigned to each contractor (Figure 5-3(a) and Figure 5-3(b)). Then, the permutations generated for contractors are combined to form the integrated solution representation (Figure 5-3(c)). As mentioned earlier, the truckloads of different contractors are separated by the delimiters. Now, the route of each truck can be obtained from the solution representation. For instance, truckloads 10 and 4 are assigned to Truck 5. Therefore, Truck 5 starts its work by leaving the depot and moving to cut block of truckload 10 to pickup the truckload. Then, it delivers the load to the corresponding sort yard. After that, the truck fulfills truckload 4. Finally, Truck 5 returns to the depot after delivering the assigned truckloads.

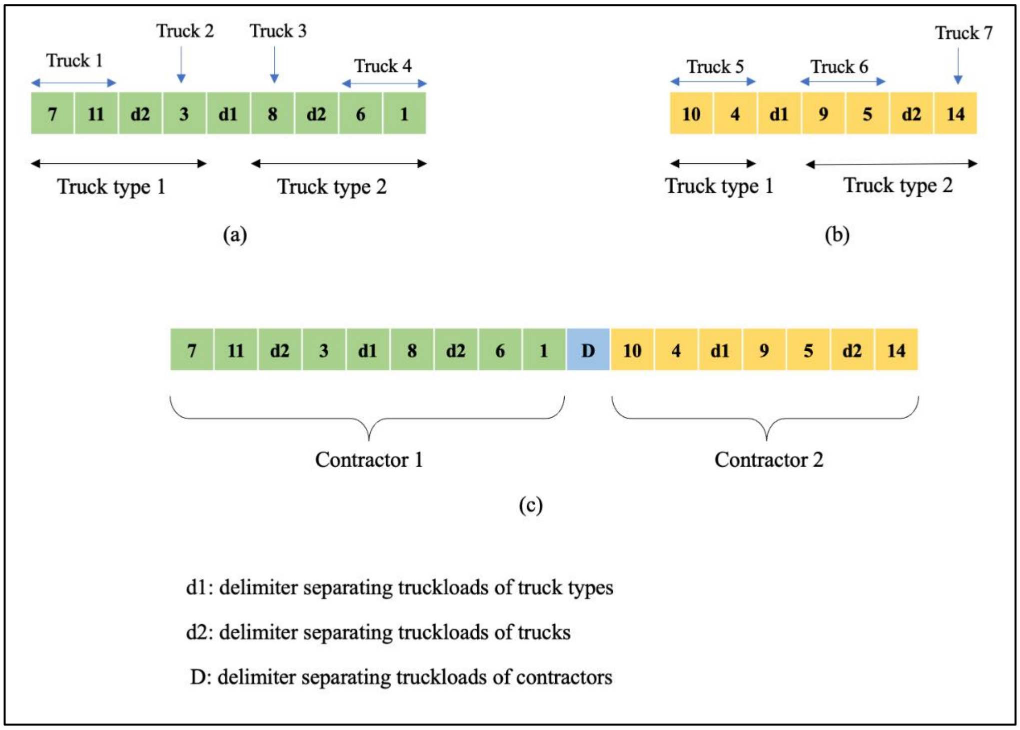

Figure 5-3. The solution representation for (a) contractor 1, (b) contractor 2, and (c) for both contractors 1 and 2

5.3.2 Creating initial solution

The SA algorithm starts with an initial solution. The initial solution is randomly generated considering feasibility requirements. It means that each truckload has to be assigned to the responsible contractor and the compatible truck type. Algorithm 1 shows the pseudocode of the initial solution generating algorithm, which consists of integrating randomly generated permutations for every truck type of each contractor.

Algorithm 1. Pseudocode for creating initial solution

Input: List of truckloads for every truck type of each contractor

Output: Initial solution

For each contractor

    For each truck type

        Generate a random permutation of truckloads and delimiters

    End for

    Integrate strings of truck types for the contractor

End for

Integrate strings of the contractors

5.3.3 Cost evaluation

To calculate the total costs and obtain the detailed schedules, the solution (string) needs to be evaluated. As mentioned earlier, each string shows which truckloads are assigned to which truck. First, it is assumed that there is no waiting time at the pickup and delivery locations, and trucks get loaded/unloaded once they arrive at cut blocks/sort yards. Therefore, we can calculate the arrival time of every truckload at sort yards using equation (5-1).

$$\text{ArrivalTime} = \text{ArrivalTime (for previous truckload)} + T1 + T2 + T3 + T4 \qquad (5\text{-}1)$$

Where:

- ArrivalTime: The arrival time of truckload at its corresponding sort yard
- T1: Unloading time of previous truckload
- T2: Travelling time from the sort yard of previous truckload to the cut block of the current truckload
- T3: Loading time of the current truckload
- T4: Travelling time from the cut block of current truckload to the sort yard of the current truckload

As mentioned earlier, there is only one loader at each cut block and each sort yard. Therefore, activities need to be assigned according to an appropriate order. There are different priority rules for scheduling problems where a single machine (loader) performs its activities. In this research, we employed the shortest processing time (SPT) rule to minimize the total completion time (readers are referred to (Pinedo, 2012) for more information). According to this rule, activities are prioritized based on their processing time for the scheduling. In this problem, the processing time for each truckload includes the unloading time of previous truckload, the travelling time between the sort yard of previous truckload and the cut block of current truckload, the loading time of the current truckload, and the travelling time between the cut block and sort yard of current truckload. In other words, the processing time of each truckload shows the required time for the assigned truck to arrive at the sort yard of the truckload. Therefore, truckloads with the earliest arrival time at the sort yards are first scheduled and assigned to the loaders.

Therefore, we define a Pool matrix, in which sorted elements are arrival time of each truckload at its sort yard determined by equation (5-1). Hence, the algorithm starts with the first element of the Pool matrix and calculates the waiting time at cut block (WTC), starting time at cut block (STC), finishing time at cut block (FTC), waiting time at sort yard (WTS), starting time at sort yard (STS), and finishing time at sort yard (FTS). The algorithm continues until the detailed schedules for all truckloads are determined. The detailed algorithm and calculations are shown in Algorithm 2.

Whenever a truck carrying a truckload has waiting time at cut blocks and/or sort yards, the arrival times of the following truckloads of the truck and the Pool matrix are updated immediately, ensuring that the remaining unassigned truckloads are selected and scheduled based on the SPT priority rule.

When the detailed schedules for all truckloads are determined, the total working time for each truck can be extracted. It is noteworthy that each solution must be feasible. The feasibility of the assignment of truckloads to compatible contractors and truck types are addressed in the initial solution and in creating a new solution algorithm. Also, having an overtime more than 150 minutes leads to infeasibility. In this case, the penalty cost for the violation of maximum overtime, which is 150 minutes, is added to the objective function. The detailed algorithm of the cost calculation is shown in Algorithm 2.

Algorithm 2. Pseudocode for cost evaluation

```
Input: Solution string
Output: Detailed schedules, overtime violation, and transportation costs
For each truckload
        Calculate ArrivalTime
End for
Pool ← sort (ArrivalTime)
For j = 1 to |Pool|
        X(j) ← Calculate arrival time of truckload (j) at the cut block
        if X(j) >= Finishing time of the loader for the previous loading activity
                WTC(j) =0
                STC(j) = X(j)
        Else
                WTC(j) = max. (Finishing time of loader for the previous loading activity –
                X(j),0)
                STC(j) = X(j)+WTC(j)
        End if
        FTC(j)=STC(j)+LoadingTime
        Update the schedules of the loader in the cut block
        Y(j) ← Calculate arrival time of truckload (j) at the sort yard considering waiting time
        at the cut block
        If Y(j) >= Finishing time of the loader for the previous unloading activity
                WTS(j) = 0
                STS(j)=Y(j)
        Else
                WTS(j) = max. (Finishing time of loader for the previous unloading activity –
                Y(j),0)
```

STS(j) = Y(j)+WTS(j)

End if

FTS(j)=STS(j)+UnloadingTime

Update the schedules of the loader in the sort yard

If WTC(j)+WTS(j) >0

Update ArrivalTime

Pool ← sort (ArrivalTime)

End if

End for

For each truck

ArrivalTimeAtDepot ← FTS (Last activity) + travelling time (sort yard, depot)

Overtime = max (ArrivalTimeAtDepot-510,0)

RegularTime=min (ArrivalTimeAtDepot, 510)

Violation = max (Overtime - 150,0)

End for

TotalCost = (FixedCost*number of truck) + (RegularTime*RegularRate) + (Overtime*OvertimeRate) + (Penalty*Violation)

5.3.4 Creating a new neighbourhood solution

In the SA algorithm, a new neighbourhood solution is generated using the swap, reversion, and insertion operators (Yu et al., 2021). In this study, a random operator is applied to truckloads of both truck types for a randomly selected contractor to generate a new solution.

In the swap operator, two random cells are chosen, and the position of the cells are swapped in order to generate a new string. In the reversion operator, after swapping the two cells randomly, the in-between cells are reversed. Finally, in the inversion operator, first two random cells are selected. Then, one of the cells is excluded from its position and placed after the other one in the string. An example for each operator is shown in Figure 5-4, where truckloads 14 and 6 are randomly selected. The positions of truckloads 14 and 6 are swapped by the swap operator to get a new string (Figure 5-4(a)), while in the reversion operator truckloads between truckloads 14 and 6 are reversed in Figure 5-4(b), and in the insertion operator, truckload 6 is placed right after truckload 14 (Figure 5-4(c)).

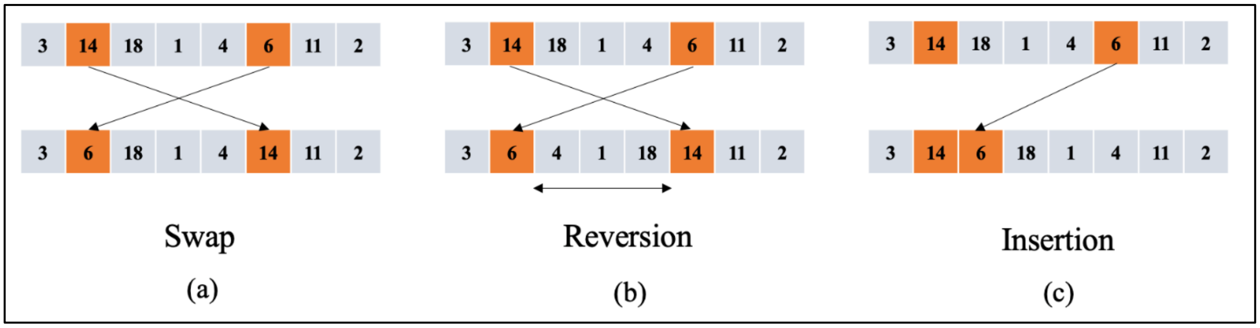

Figure 5-4. Neighbourhood operators (a) Swap, (b) Reversion, and (c) Insertion

5.3.5 SA procedure

Algorithm 3 describes the SA procedure, where the initial temperature (T^0), minimum temperature (T^{min}), maximum number of iterations in each temperature (It^{max}), and the cooling rate (α) are the parameters of the algorithm. The algorithm generates a new neighborhood solution using one of the operators (swap, reversion, and insertion) for certain number of iterations (It^{max}) at each temperature. In every iteration, a new solution is accepted if it surpasses the current solution. For the worse solution, however, a random number (r) is generated to investigate if the solution is accepted with a probability of $p = e^{\left(-\frac{\Delta}{T}\right)}$, where T is the current temperature, and $\Delta = Cost\ (new\ solution) - Cost\ (current\ solution)$. Then, the current temperature is updated using equation (5-2).

$$T_{Updated} = \alpha T_{Current}\,, \tag{5-2}$$

where α is the cooling rate for reducing the temperature. It should be noted that accepting the worse solution results in more diversification and avoids getting stuck in the local optimum. However, as the temperature decreases, the probability of accepting a worse solution reduces. The algorithm keeps searching the solution space until the current temperature becomes less than the minimum temperature.

Algorithm 3. Pseudocode for SA algorithm

Input: SA parameters: T^0, T^{min}, It^{max}, α
Output: Best solution
Create an initial solution (Sol)
Calculate Cost (Sol)
$T \leftarrow T^0$
While $T \geq T^{min}$
  While $i \leq It^{max}$
    Create a new solution (Sol_i^{new})
    Calculate $Cost(Sol_i^{new})$
    If $Cost(Sol_i^{new}) \leq Cost\ (Sol)$
      $Sol \leftarrow Sol_i^{new}$
    Else
      r ← random (0,1)
      If $r \leq \mathrm{e}^{(-\frac{Cost(Sol_i^{new})-Cost(Sol)}{T})}$
        $Sol \leftarrow Sol_i^{new}$
      End if
    End if
    If $Cost(Sol) \leq BestCost$
      BestSol=Sol
    End if
    $\boldsymbol{i \leftarrow i + 1}$
  End while
  $T \leftarrow \alpha T$
End while

5.3.6 Parameter calibration

As mentioned in (Turanoğlu & Akkaya, 2018), the parameters of the SA algorithm are the initial temperature, the maximum number of iterations, the cooling rate, and the minimum temperature. The performance of metaheuristic algorithms is impacted by their input parameters, and proper design of the parameters improve the efficiency of the algorithms (Hamzadayi & Yildiz, 2013). Hence, it is required to design experiments to calibrate the input parameters of the metaheuristic algorithms. The Taguchi method is usually employed to calibrate parameters of metaheuristic algorithms (Mousavi et al., 2016). In this method, the orthogonal arrays are employed to determine the required experiments. Orthogonal arrays are fractional factorial designs that require less experiments compared to the full factorial design, leading to less computational expenses (Banks and Fienberg, 2003). The Taguchi method classifies the factors into two groups: the controllable ones and the noise factor. The goal is to minimize the noise factor to assign the optimal levels for the controllable factors. In other words, the method tries to maximize a measure called the signal to noise (S/N) ratio. As the objective function of our problem is to minimize the total costs, the S/N ratio is calculated using equation (5-3).

$$\frac{S}{N} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{5-3}$$

In equation (5-3), y_i and n are the values of the response variables in ith experiments and the number of experiments, respectively. As mentioned earlier, our algorithm has four parameters, and three levels are defined for each parameter (Table 5-1). The same number of levels was considered for SA parameters in previous studies (e.g. Zandieh et al. 2017; Salama and Srinivas 2021).

Table 5-1. Factor levels in the SA algorithm

Factors	Level 1	Level 2	Level 3
Initial temperature (T^0)	300	350	400
Minimum temperature (T^{min})	$0.00025T^0$	$0.0005T^0$	$0.00075T^0$
Cooling rate (α)	0.85	0.9	0.95
Maximum number of iterations (It^{max})	50	70	90

Based on the number of parameters and levels, a standard orthogonal array of L9 in the Taguchi method is chosen. The selected orthogonal array (L9) has nine different combinations of parameter levels, and the goal is to find the best combination. To conduct the experiments, three instances (small, medium, and large-sized) using the parameters with uniform distributions are generated (Table 5-2). Each instance is solved 5 times for every combination of parameters to have more reliable results. Hence, the number of experiments will be 9×3×5=135.

Table 5-2. Characteristics of instances

Instance size	Number of truckloads
Small	40
Medium	60
Large	80

Similar to other studies (e.g. Ramezanian and Saidi-Mehrabad 2013; Turanoğlu and Akkaya 2018), the Relative Percentage Deviation (RPD) is used in this chapter as the response variable for each experiment (equation (5-4)).

$$RPD_i = \frac{Sol_i - Sol_{min}}{Sol_{min}} \qquad (5\text{-}4)$$

In equation (5-4), Sol_i is the solution obtained for experiment i, and Sol_{min} is the best solution found.

For all instances, we calculated RPD_i for each experiment. The resulted mean S/N ratios are displayed in Figure 5-5.

Figure 5-5. The S/N ratio plot for level of parameters

As the goal is to maximize the S/N ratios, the highest level of each parameter in Figure 5-5 is considered as the optimal value for the value of the parameter (Table 5-3).

Table 5-3. The optimal values of SA parameters

Parameter	**Optimal value**
Initial temperature (T^0)	300
Minimum temperature (T^{min})	$0.0005\times T^0$
Cooling rate (α)	0.95
Maximum number of iterations (It^{max})	90

5.4 Results

In this section, the results of the algorithm are shown for different test problems and the real case study. For parameters of the algorithm, we used their optimal values listed in Table 5-3. The algorithm is coded in MATLAB and is implemented on a desktop computer with a configuration of Intel® CoreTMi7-6700, 3.40 GHz CPU, and 16 GB RAM.

5.4.1 Results for test problems

When developing heuristic and metaheuristic algorithms, validation of the results is of great importance. Comparing the results obtained from the developed algorithm with the results of mathematical optimization models has the highest level of validation (Bettinger et al., 2009). Therefore, we compared the solution of the proposed algorithm with the results of the optimization model developed in Chapter 4 for different test problems. Columns 1-3 of Table 5-4 summarize the test problems and their characteristics, while the objective function and the optimality gap are shown in the fourth and fifth columns, respectively. Finally, the last two columns represent the CPU time for the CPLEX solver in AIMMS (*CPLEX — AIMMS*, 2022) and our SA algorithm, respectively.

Table 5-4. Comparison of CPLEX solver and the SA algorithm for test problems

Test problems	**|Truckloads| |Nodes|**	**|Cut blocks| |yards|**	**Obj. function (Total cost)**	**GAP**	**CPLEX CPU time (second)**	**SA CPU time (second)**
TP 1	|9| |24|	|2| |3|	$10,458	0	3	0.33
TP 2	|10| |26|	|2| |3|	$11,191	0	8	0.37
TP 3	|11| |28|	|2| |3|	$12,584	0	47	0.65
TP 4	|12| |30|	|2| |3|	$14,053	0	794	0.98
TP 5	|9| |24|	|3| |3|	$13,229	0	9	0.36
TP 6	|10| |26|	|3| |3|	$13,910	0	11	0.39
TP 7	|11| |28|	|3| |3|	$15,253	0	839	0.77
TP 8	|12| |30|	|3| |3|	$15,935	0	3417	1.23

As it can be observed from Table 5-4, the algorithm compared with the CPLEX solver can get solutions with zero optimality gap in a shorter amount of time for all test problems. The strong performance of the SA algorithm can be attributed to several reasons. First, the proposed operators avoid generating infeasible solutions. This reduces the search space for the SA algorithm. In addition, the operators are applied to all contractors when creating a new solution string, which leads to diverse solutions. Moreover, accepting the worse solutions in the search procedure helps the algorithm to avoid getting trapped into local optimum. It is remarkable that when the number of truckloads increases to 13, the problem becomes computationally intractable, and the CPLEX solver cannot solve the problems. Hence, the SA algorithm is proposed for solving larger problems in a reasonable amount of time.

5.4.2 Results for the real case

In this section, the solution approach is applied to the real case study, in which the daily number of truckloads between cut blocks and sort yards are obtained from the first phase of the proposed framework (Chapter 3). To ensure that loaders at both cut blocks and sort yards can process all delivered truckloads within the regular time and overtime, the following constraints are added to the MIP model developed in Chapter 3.

- Yard 1 cannot receive more than 12 truckloads each day.
- Yards 2 and 3 cannot process more than 42 truckloads each day.
- Each cut block can send up to 10 truckloads to sort yards each day.

The aforementioned modifications to the first phase are determined according to the input data and tested by several trials.

Based on the results obtained from the first phase model, 81 truckloads are transported from cut blocks to sort yards each day. In this section, we are focusing on one of the days in which truckloads should be delivered from 13 cut blocks to three sort yards resulting in 168 nodes. As the problem cannot be solved by CPLEX solver, our algorithm was applied, and it took 125.8 seconds to get a solution. The proposed algorithm could synchronize loaders and log trucks at both cut blocks and sort yards and generate detailed schedules.

According to the results, some trucks are not dispatched at all, while other trucks have one to three assigned truckloads. As Truck 55, which belongs to contractor 8, delivers three truckloads, it is considered as an example to show the detailed schedule (Figure 5-6). First, the truck arrives at cut block 4 for loading the first truckload. As the loader is idle at the cut block, the truck immediately gets loaded. Then, the truck carries the truckload to sort yard 3 for unloading. However, in order to be synchronized with the loader at sort yard 3, the truck has to wait for 8 minutes as the loader is unloading another truck. Similarly, the truck continues its work to deliver the second and the third truckloads. Finally, the truck returns to the depot once it delivers all the assigned truckloads. It should be mentioned that as sort yard 3 is very close to the central depot, the travelling time from the sort yard to the depot is assumed to be zero. Similar to Truck 55, the detailed schedules can be shown for all trucks.

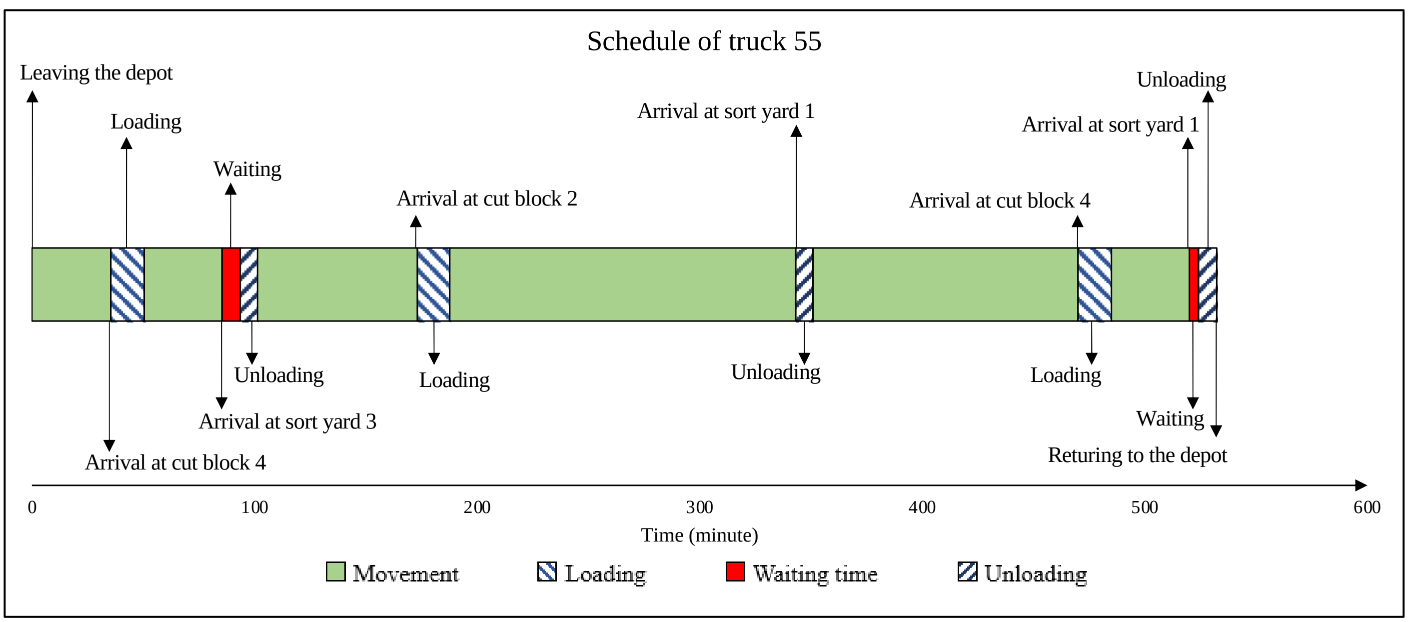

Figure 5-6. The schedule of Truck 55

For unloading the trucks, there is only one loader at each sort yard. As there is a large number of trucks delivering truckloads to sort yards, some trucks may need to wait in order to be synchronized and get unloaded by the loader in each sort yard. As shown in Figure 5-7, sort yard 2 has the highest waiting times among the sort yards as it receives the largest number of truckloads.

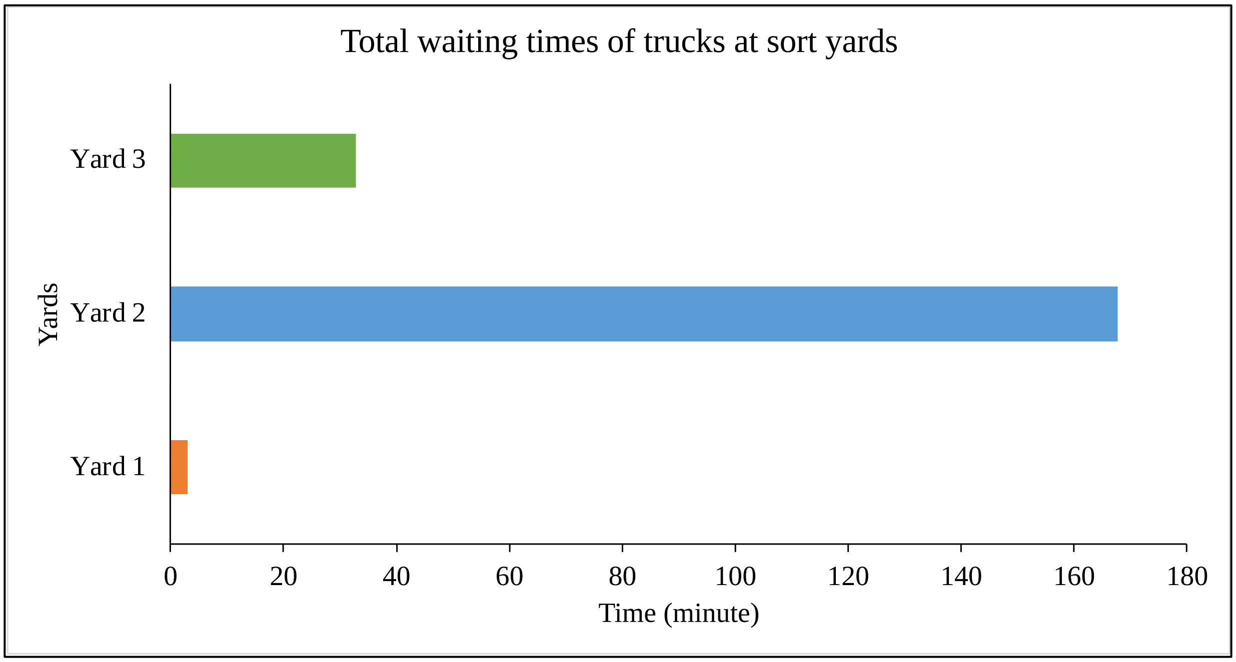

Figure 5-7. Total waiting times at sort yards

Table 5-5 lists the arrival times and waiting times of trucks at sort Yard 2. Hence, having more loaders may reduce the total waiting times of trucks at this sort yard. Alternatively, the demand of sort yards can be adjusted in the upper-level model to reduce the number of truckloads that sort yard 2 receives, thereby balancing the waiting times among the sort yards.

Table 5-5. Schedules of trucks arriving at Yard 2

Truck	Truckload	Arrival time (minute)	Waiting time (minute)
Truck 2	Truckload 33	141.8	0
Truck 4	Truckload 31	156.8	0
Truck 6	Truckload 28	171.8	9
Truck 13	Truckload 32	186.8	2
Truck 69	Truckload 59	164.6	0.2
Truck 1	Truckload 26	167.3	5.5
Truck 48	Truckload 58	190.1	6.7
Truck 54	Truckload 57	205.1	0

Truck 44	Truckload 63	205.1	8
Truck 47	Truckload 61	225.1	4
Truck 42	Truckload 9	213.5	7.6
Truck 3	Truckload 34	235.2	1.9
Truck 34	Truckload 54	243.2	1.9
Truck 37	Truckload 56	258.2	2.9
Truck 39	Truckload 49	273.2	11.9
Truck 40	Truckload 50	288.2	12.9
Truck 14	Truckload 41	251.6	1.5
Truck 18	Truckload 40	266.6	2.5
Truck 22	Truckload 45	281.6	11.5
Truck 23	Truckload 46	296.6	12.5
Truck 2	Truckload 36	271.8	5.3
Truck 13	Truckload 37	318.8	0
Truck 4	Truckload 27	320.4	6.4
Truck 6	Truckload 30	344.4	0
Truck 42	Truckload 10	351.7	0.7
Truck 68	Truckload 11	352.6	7.8
Truck 3	Truckload 39	367.1	1.3
Truck 34	Truckload 52	379.3	0
Truck 37	Truckload 48	395.3	0
Truck 14	Truckload 44	395.7	7.6
Truck 2	Truckload 35	407.1	4.2
Truck 47	Truckload 62	417.3	2
Truck 39	Truckload 53	419.3	8
Truck 40	Truckload 55	435.3	0
Truck 22	Truckload 42	435.7	7.6
Truck 13	Truckload 38	448.8	2.5
Truck 23	Truckload 43	451.7	7.6
Truck 34	Truckload 47	476.3	0
Truck 42	Truckload 51	486.6	0
Truck 4	Truckload 29	490.4	4.2
Truck 44	Truckload 60	503.9	0

The loaders at sort yards operate until all trucks deliver their loads. Figure 5-8 shows the distribution of start times of loaders for unloading the trucks at the sort yards. In Figure 5-8, the line inside each box indicates the median of start times. It means that 50 percent of start times occur above the line. Therefore, half of the unloading activities of the loader at sort yard 3 start in the last 160 minutes of the working day as trucks getting unloaded at the sort yard can immediately return to the depot after leaving the yard without exceeding the maximum overtime. However, sort yards 2 and 3 are far from the depot. Hence, unloading activities are scheduled and assigned to the loaders of these sort yards in a way that trucks have enough time to return to the depot without having more than the maximum amount of overtime (150 minutes). Also, the loader at sort yard 1 starts to unload the trucks later than the loaders at the other sort yards as sort yard 1 is the furthest yard from the cut blocks.

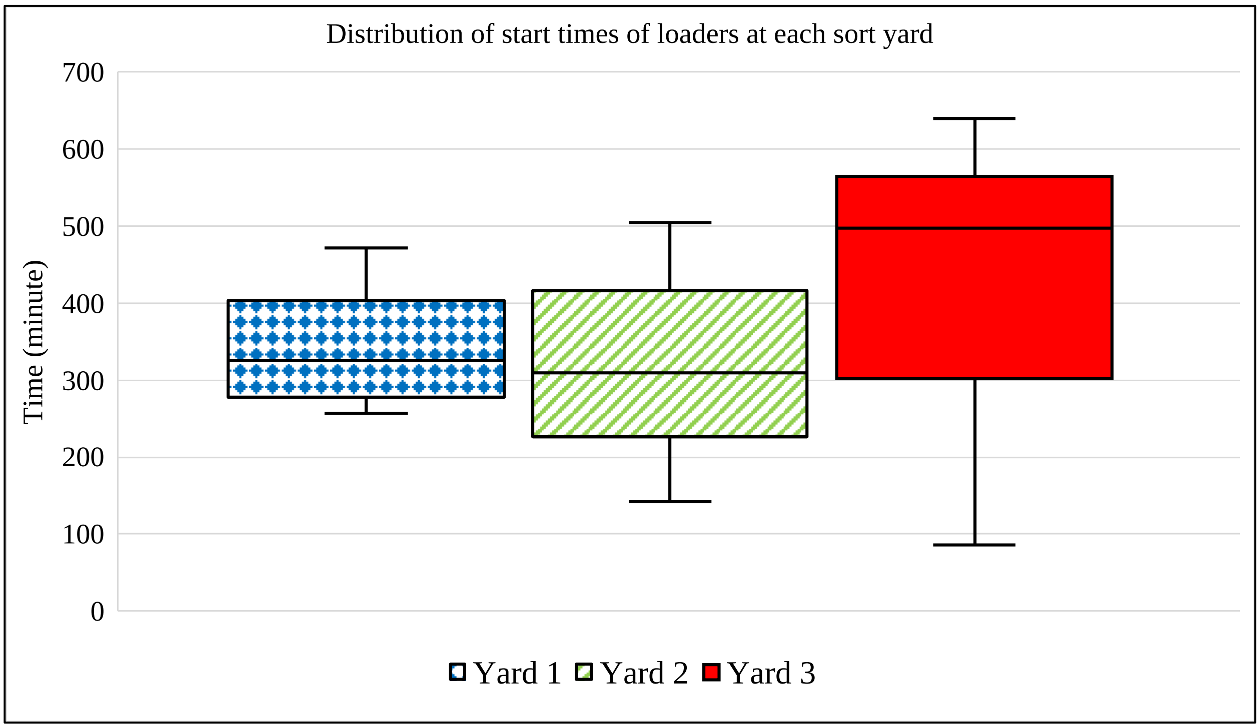

Figure 5-8. The quartile chart for start times of loaders at the sort yards

The trucking contractors have a different number of trucks to deliver truckloads to sort yards. When contractors dispatch a new truck, the fixed operating costs are incurred. In Figure 5-9, the utilization rate of trucks for each contractor is shown. Most contractors have used less than

60% of their trucks to fulfill their truckloads. Contractor 1, however, has only one truck, leading to a 100% utilization rate.

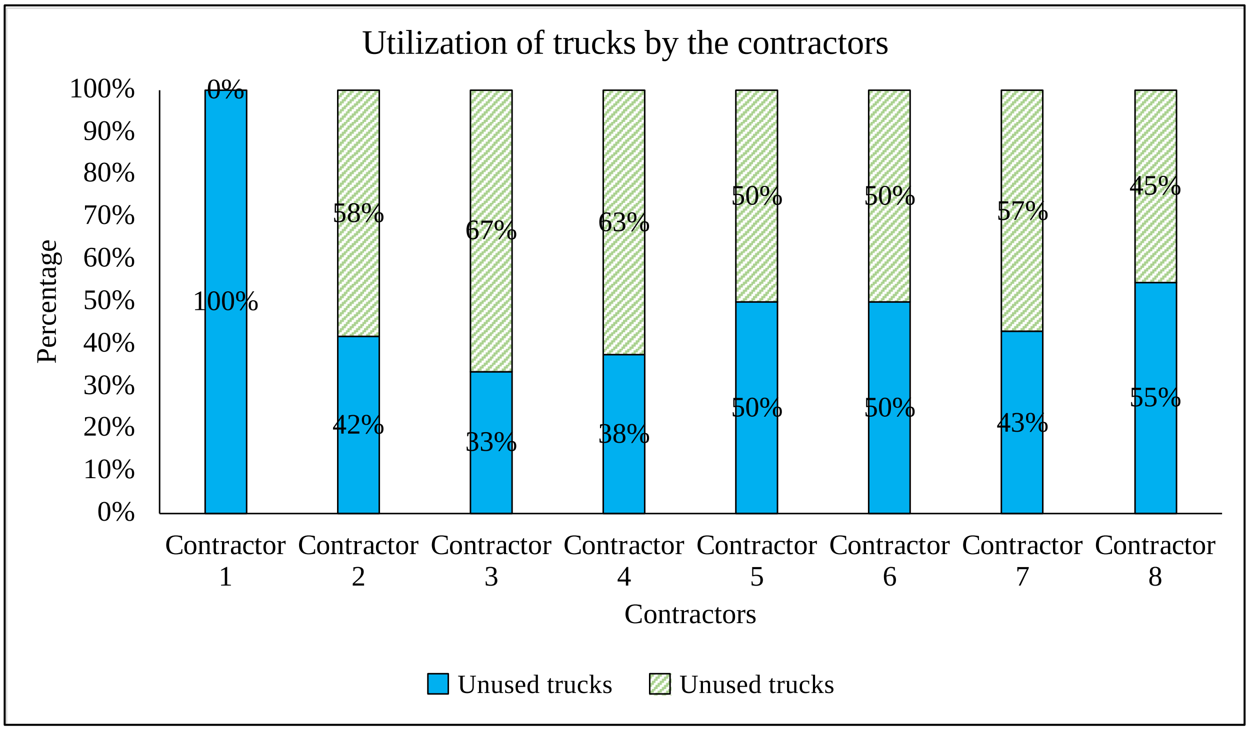

Figure 5-9. Resource utilization of contractors

As mentioned earlier, the contractors can assign overtime for each truck. The unit overtime cost is 1.5 times greater than the regular time cost. For the contractors, the decision to assign overtime to existing trucks or dispatching new trucks has a trade-off. While overtime has a higher rate than the regular time, assigning a truckload to a new truck leads to the fixed cost of using the truck and a variable cost of empty travel time from the central depot to a cut block to load the truck. Figure 5-10 indicates that most contractors have trucks with overtime. As the contractors underutilized their trucks (Figure 5-9), these results suggest that although overtime has a higher cost rate, assigning it to trucks generates costs savings compared to using a new truck.

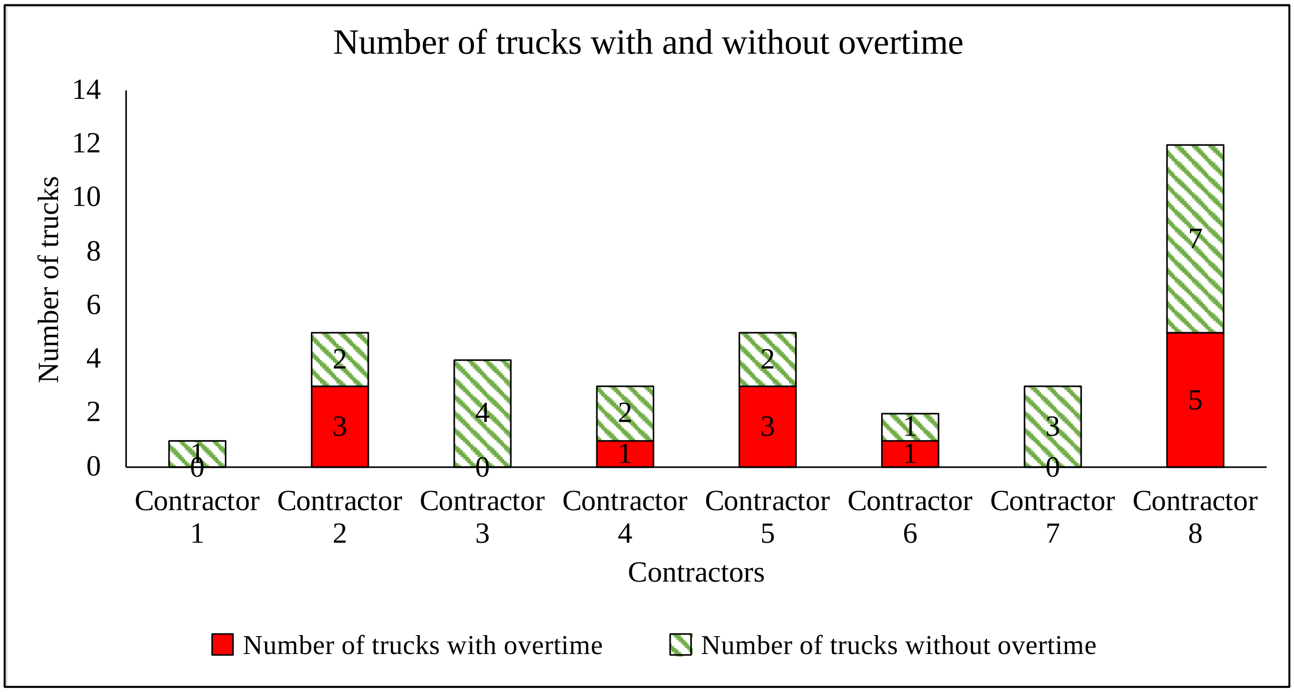

Figure 5-10. Distribution of trucks of contractors

5.5 Discussion

In the case, the company aims to get a detailed schedule of each activity and reduce the total daily transportation costs, which can be translated into minimizing the total completion time of delivering the truckloads to the yards. Therefore, in this chapter, log loaders and trucks are synchronized at both cut blocks and sort yards to get waiting times and detailed schedules. In addition, the SPT first rule is employed in the proposed heuristic method for assigning and scheduling the truckloads. Here, the processing time for a given truckload includes unloading time of the previous truckload, travelling time to arrive at the cut block, loading time of the truckload, and travelling time from the cut block to the sort yard. Based on the proposed approach, the FIFO rule is met at sort yards. The rule, however, may lead to violation of the FIFO rule at cut blocks in rare cases. In these rare cases, a truck may arrive later at a cut block, but may get loaded earlier than other trucks waiting at the cut block. This violation happens when trucks, waiting at the cut block, have different destinations. Under this scenario, a truck with the shortest processing time (or earliest arrival time at the destination) gets loaded first even if it arrives later than other waiting trucks. Despite the violation, according to (Pinedo, 2012), the SPT first rule is optimal when the goal is to minimize the completion time of a single machine (loader in our problem). Additionally, as the schedules of different activities are highly interdependent, fixing the schedules at cut blocks to meet the FIFO rule may result in infeasibility of the problem because some trucks would have excessive waiting times, leading to having overtime greater than the maximum amount of overtime that can be assigned to each truck.

As 81 truckloads are sent to three sort yards with only one loader at each yard, the loaders at yards are the bottleneck. Therefore, the problem is sensitive to the unloading time, and any loader breakdown or lower productivity of loaders can cause more waiting times. Adding one more loader to each sort yard may reduce the total completion time of truckloads. Thus, as the schedule of activities are highly interdependent, the waiting times at both cut blocks and sort yards may change if the trucks get unloaded by more than one loader at sort yards. Nevertheless, the decision to add one more loader to a sort yard requires consideration of incurred costs such as capital costs, insurance costs, and labour costs. Also, as shown in Figure 5-8, loaders unload more truckloads in some time intervals. For instance, the loader at yard 3 unloads 50% of the assigned truckloads in the last 2.5 hours of the day. Therefore, it would be recommended to avoid considering any breaks (e.g., lunch break) during peak times, when more trucks arrive at the yard to prevent causing further delays in unloading of trucks.

From Figure 5-9 and Figure 5-10, it was concluded that assigning overtime to the trucks would be more economical than dispatching new trucks because of the reduced deadhead trips. Therefore, it is expected that the company can have more cost savings if they increase the maximum amount of over time that is assigned to each truck to avoid sending new trucks. However, the contractors may have other limitations such as contractual requirements for their drivers. Indeed, the balanced workload as the social aspect of the problem was addressed in the first phase for the contractors in Chapter 3, while the contractors may need to consider a balanced workload for their drivers. It means that if the contractors try to assign more overtime and reduce the number of trucks, they may violate their contractual requirements as some drivers may not get enough driving time or a balanced workload.

The solution approach developed in this chapter was tested for all days of a 1-month planning horizon. Due to the balanced workload generated by the upper-level model, all truckloads could be delivered without violating the overtime of drivers on each day. However, the transportation costs of different days were not the same as contractors had to deliver truckloads from different cut blocks.

It is noteworthy to mention that transportation activities are contracted out, and the trucking contractors serve at specific cut blocks. In this study, it was assumed that the contractors were independent, and there was no partnership among them. However, it is useful to consider potential collaborations among the trucking contractors. According to (Piltan & Sowlati, 2014), companies can collaborate through sharing resources and information to have partnership advantages such as reducing logistics costs, improving overall logistic services, and reducing emissions. In our case, the contractors can collaborate by sharing their cut blocks. In other words, trucks of a contractor can visit cut blocks originally served by another contractor to pick up truckloads. Therefore, the proposed solution approach should be adjusted by removing the delimiters that was separating the truckloads of collaborating contractors. Despite this, the contractors would be willing to have a collaboration only if they get benefit. Therefore, different types of collaboration among the contractors need to be investigated to assess the benefits or cost savings that each contractor may gain.

5.6 Conclusions

In this research, a decomposition approach was introduced for addressing the log logistics problem considering real world operational details. In the first phase, a bi-objective mixed integer programming model was developed in Chapter 3 to minimize the transportation costs and balance the workload of contractors, and to determine the daily flows of logs and sorting decisions. In the second phase, truckloads were assigned to compatible trucks and daily schedules of trucks were obtained. As the proposed MIP model introduced in Chapter 4 could solve only small and medium-sized problems, the SA algorithm was employed in this chapter to solve large-sized problems and to achieve the third and fourth research objectives. The parameters of the algorithm were calibrated using the Taguchi method. The performance of the proposed metaheuristic approach was validated by comparing its solution with the results from the optimization model for the small and medium sized problems. We applied the algorithm to a real case of transportation planning of a forest company in British Columbia, Canada with a 1-month planning horizon. Using the algorithm, it was possible to synchronize loaders and trucks at both cut blocks and sort yards and generate detailed schedules. It was shown that assigning overtime would be less costly than dispatching new trucks for delivering the truckloads.

Chapter 6: Conclusions, strengths, limitations, and future research

6.1 Summary and conclusions

Log logistics deal with a variety of different activities before logs arrive at their destinations. The logs need to be processed, stored, and transported to the demand locations in a timely manner considering complexities and limitations. These activities have a significant contribution to the total log procurement costs and impact the competitiveness of forest companies. Thus, efficient logistics planning helps the forest industry to flourish.

The main goal of this dissertation was to propose a practical logistics plan at the operational level incorporating specific log logistics considerations. The goal was achieved through a decomposition framework, which suggested mathematical optimization models and a solution approach for allocation of logs, routing, and scheduling of log trucks. To illustrate the applicability of the proposed methodology, the models and solution approach were applied to a real case of a large forest company in British Columbia, Canada. In the case, the planning horizon was one month, and the logs were sent from cut blocks to sort yards by trucking contractors using a heterogeneous fleet of trucks. The company intends to know the daily allocation of logs between cut blocks and sort yards, and detailed scheduling of trucks with minimum costs considering contractors' limitations.

In Chapter 2, the log logistics problem was briefly described, and the main decisions and issues were elaborated. Then, the log logistics studies were reviewed. The previous studies addressed the log logistics for one day or a longer planning horizon using mathematical optimization models solved by exact or non-exact solution approaches. These studies were divided into two groups: (1) Integrated optimization approach, (2) Decomposition optimization approach. In the former group, the decisions of the problems were integrated, while in the latter group, the decisions were determined in different stages. In both groups, there were studies determining the log allocation along with routing and scheduling decisions, and there were studies in which the log flows were the inputs of the problem. In the existing literature, some log logistics aspects such as inventory decisions, time windows, and road weight requirements were addressed. Also, previous studies used discretized time slots for scheduling purposes. It was concluded that the existing log logistics planning could be more practical by incorporating operational details including social aspects, sorting decisions, trucking contractors, and compatibility requirements. In addition, continuous time representation can also be used for scheduling logistics activities to have a detailed schedule.

In Chapter 3, a bi-objective mixed integer programming (MIP) model using the goal programming approach was developed to determine the daily allocation of logs between cut blocks and sort yards considering compatibility requirements and trucking contractors. The first objective of this model was to minimize the total transportation costs, while the second objective balanced the workload of trucking contractors by minimizing the summation of maximum difference between daily workload and a preferred level defined by each contractor. As the generated workload could lead to contractors' satisfaction and indirectly could satisfy drivers, the second objective was called the social objective. This research could determine how much volume of logs should be sorted each day. To the best of my knowledge, previous studies did not consider sorting decisions in the log logistics planning and assumed that the logs had been already sorted. The proposed model was applied to the case study and solved using the CPLEX solver in AIMMS (*CPLEX — AIMMS*, 2022). The results indicated that the proposed model could generate a smooth workload for the contractors with only 0.4% increase in total transportation costs compared to the single objective model, in which the objective was only to minimize the costs. The sensitivity analysis was conducted on goal weights and input parameters, which showed that there was a trade-off between the two objectives. Additionally, decreasing transportation costs and demands and increasing yard capacities by 20% led to the full achievement of both goals.

An MIP model was developed in Chapter 4 for daily routing and scheduling of log trucks considering synchronization requirements at both origins (cut blocks) and destinations (sort yards). It was assumed that the heterogeneous fleet of trucks would be dispatched from a central depot to cut blocks and would return to the depot after fulfilling their truckloads. The outputs of the model were the assignment of truckloads to trucks considering compatibility requirements, routing, and detailed scheduling of activities including arrival times and waiting times of trucks at each location, and the amount of overtime assigned to each truck. The model was solved for eight test problems taken from the case. In conclusion, for the test problems, the model could synchronize log loaders and trucks at both cut blocks and sort yards and generate detailed schedules of different activities. The results of the sensitivity analysis highlighted that variable and overtime costs were the most sensitive parameters. However, the fixed operating costs of trucks had the least impact on the total costs.

As the MIP model presented in Chapter 4 could be solved only for small-sized problems, a solution approach using the simulated annealing (SA) algorithm was developed in Chapter 5 for the daily routing and scheduling of log trucks for the real case. The solution approach incorporated the complexities of the problem including the heterogeneous fleet of trucks with different service times (loading times), trucking contractors, and synchronization of machines at both pickup and delivery locations using continuous time representation. The parameters of the SA algorithm were calibrated using the Taguchi method. The performance of the algorithm was validated by comparing the results of the test problems with the results obtained from the MIP model. The results showed that the algorithm could synchronize log loaders and trucks at both cut blocks and sort yards. The number of dispatched trucks and the amount of assigned overtime for each truck were other outputs of the algorithm.

6.2 Strengths

This research provided a practical framework for addressing log logistics optimization problem considering real-world complexities. This work is based on a real case study and represents real-world log logistics operations. For example, sorting of logs is one of the primary activities of the company in daily operations. Unlike previous studies, sorting decisions are considered in this work that help the company to keep track of daily volume of log sorts that are processed and dumped into the water. Moreover, this study could address one of the forest company's concerns by generating smooth workloads for the trucking contractors. The balanced workload results in contractors' satisfaction and leads to more sustainable planning through incorporating social aspects. It is noteworthy that the problem, issues, considerations, and limitations were understood through numerous meetings and an in-person visit of the operations, and the results of this study were verified by the forest company's manager. Furthermore, in order to facilitate the implementation, the proposed models and solution approach are delivered on platforms that are compatible with the company's existing internal tools.

Synchronizing log loaders and trucks at both pickup and delivery locations and using continuous time representation are the essential considerations of the daily scheduling of activities as they could generate detailed schedules. It is notable that neglecting the synchronization in the problem, where more than 80 truckloads should be delivered, can reduce the accuracy of schedules and increase the costs. These detailed schedules guarantee the feasibility of the problem and decrease the transportation costs. Besides, inaccurate schedules may cause unwanted overtime which can potentially make the problem infeasible by assigning an overtime more than the maximum value.

The important managerial insights are another strength of this dissertation. The decision makers can identify the bottlenecks of operations. For instance, they can investigate if adding more resources (loaders or operators) in sort yards to have smoother operations, considering upper-level limitations such as investment costs, is economically reasonable. Also, the company can understand how contractual details such as the maximum amount of regular time and overtime of trucks and the flexibility of contractors in their daily workload can play a crucial role in the log logistics plans. In addition, the advantage of assigning overtime and better utilization of trucks are important managerial insights for the trucking contractors.

From the modelling perspective, this work has some strengths. This research could overcome the challenge of quantifying the social index at the operational level. Considering the social aspect as a separate objective rather than constraints was useful as it could generate a balanced workload over the entire planning horizon and not just between consecutive days. Additionally, the trucking contractors can be involved in the planning by specifying their preferred levels.

Unlike previous studies (e.g. El Hachemi et al., 2013; Melchiori et al., 2022), the planning horizon in this work is one month with daily continuous decision variables, indicating the huge size and complexity of the problem. The suggested decomposition framework can handle the size of the problem where the daily log allocations considering various complexities are addressed in the first phase using the goal programming model solved by CPLEX solver in eight hours with less than 3% optimality gap. This solution time of the first phase is reasonable for the company as the model is executed once a month. The presented solution approach in Chapter 5 would be implemented daily and can obtain the schedules in less than three minutes. In addition, the input data are defined in a way that could reduce the complexities of the problem. For instance, the compatibility requirements are addressed through binary parameters. These data modifications can avoid increased computational burden.

Using the goal programming approach for solving the bi-objective model allows the company to prioritize the goals by modifying the weight of the goals and assess how decisions would change under different scenarios. Moreover, the sensitivity analysis on the parameters of the first phase model may give an insight to decision makers to achieve the defined goals by improving operational practices such as expanding the processing capacities of the sort yards.

6.3 Limitations

Despite the strengths, this research has some limitations. This work did not consider some operational details. Lunch break and driver changes, for instance, were not considered in this work. Besides, due to high volume of supply and demand, a large number of trips is required to fulfill the demands. Additionally, loaders and trucks may have waiting times for loading/unloading activities. These trips and waiting times are sources of emissions. Although this research indirectly addresses environmental impacts through minimization of travel time of trucks, these impacts were not quantified in this research.

In this work, it was assumed that all parameters have deterministic values, but there are multiple uncertainty sources that affect the log logistics planning at the operational level. Demand and supply variations impact the upper-level plans and affect the workload of contractors. Breakdown of machines is another source of uncertainty that may disrupt logistics activities. If a loader breakdown happens at one location, trucks need to wait more, resulting in delays for the following trips of the trucks. Hence, the costs would increase as a result of increased total travelling time of trucks. These uncertainty sources were not incorporated in the proposed logistics planning.

6.4 Future work

For future studies, environmental impacts of log logistics activities such as emissions can be quantified as another objective function in the optimization model. Looking into environmental concerns along with economic and social aspects leads to more sustainable log logistics plans and can address one of the open questions identified in (Rönnqvist et al., 2015). Also incorporating more operational details such as lunch breaks for drivers can enhance the applicability of the logistics plans.

Moreover, electrifying the fleets of trucks is getting more attention in recent years. However, employing electric trucks can raise different challenges. These trucks have limited driving ranges that may impact the delivering of the truckloads. In addition, charging stations need to be established in appropriate locations to improve the overall transportation planning. Also, these charging stations may need to be synchronized with the trucks to reduce waiting times of trucks. Addressing these aspects in future research paves the way to improve log transportation, leading to a more sustainable logistics planning.

Furthermore, uncertainty of input parameters can be incorporated into the log logistics by developing robust optimization models. In addition, the variation of supply and demand volumes can be addressed by defining scenarios to implement stochastic programming approaches. This would assist decision makers to evaluate the logistics under uncertain circumstances such as loader breakdowns. Collaborative log logistics planning is another avenue for future research. This dissertation can be extended by considering collaboration among contractors by sharing their assigned cut blocks.

Finally, new metaheuristic algorithms can be employed for solving the daily routing and scheduling of log trucks to get better solutions. Another method to improve the solution approach is to hybridize different metaheuristic algorithms to take advantage of different algorithms.

References

Amrouss, A., El Hachemi, N., Gendreau, M., & Gendron, B. (2017). Real-time management of transportation disruptions in forestry. *Computers and Operations Research*, *83*, 95–105. https://doi.org/10.1016/j.cor.2017.02.008

Asikainen, A. (2001). Simulation of Logging and Barge Transport of Wood from Forests on Islands. *International Journal of Forest Engineering*, *12*(2), 43–50. https://doi.org/10.1080/14942119.2001.10702445

Audy, J., D'Amours, S., & Rönnqvist, M. (2012). Planning methods and decision dupport systems in vehicle routing problems for timber transportation : A review. *Montreal, Cirrelt*, 45.

Audy, J. F., Rönnqvist, M., D'Amours, S., & Yahiaoui, A. E. (2022). Planning methods and decision support systems in vehicle routing problems for timber transportation: a review. *International Journal of Forest Engineering*, *00*(00), 1–25. https://doi.org/10.1080/14942119.2022.2142367

Banasik, A., Bloemhof-Ruwaard, J. M., Kanellopoulos, A., Claassen, G. D. H., & van der Vorst, J. G. A. J. (2018). Multi-criteria decision making approaches for green supply chains: a review. *Flexible Services and Manufacturing Journal*, *30*(3), 366–396. https://doi.org/10.1007/s10696-016-9263-5

Banks, D. L., & Fienberg, S. E. (2003). Statistics, Multivariate. *Encyclopedia of Physical Science and Technology*, 851–889. https://doi.org/10.1016/B0-12-227410-5/00731-6

Bettinger, P., Sessions, J., Boston, K. (2009). A review of the status and use of validation procedures for heuristics used in forest planning. *Mathematical and Computational Forestry and Natural-Resource Sciences*, *1*(1), 26–37.

Bordón, M. R., Montagna, J. M., & Corsano, G. (2018). An exact mathematical formulation for the optimal log transportation. *Forest Policy and Economics*, *95*(August), 115–122. https://doi.org/10.1016/j.forpol.2018.07.017

Bordón, M. R., Montagna, J. M., & Corsano, G. (2020). Mixed integer linear programming approaches for solving the raw material allocation, routing and scheduling problems in the forest industry. *International Journal of Industrial Engineering Computations*, *11*(4), 525–548. https://doi.org/10.5267/j.ijiec.2020.5.001

British Columbia Forest Safety Council. (2015). Logging Trucks in British Columbia. *Forest Safety Council*, 1–7. https://www2.bcforestsafe.org/files/ref_LoggingTrucksInBritishColumbia.pdf

Chang, C. Ter. (2011). Multi-choice goal programming with utility functions. *European Journal of Operational Research*, *215*(2), 439–445. https://doi.org/10.1016/j.ejor.2011.06.041

Colapinto, C., Jayaraman, R., & Marsiglio, S. (2017). Multi-criteria decision analysis with goal programming in engineering, management and social sciences: a state-of-the art review. *Annals of Operations Research*, *251*(1–2), 7–40. https://doi.org/10.1007/s10479-015-1829-1

CPLEX — AIMMS. (2022). https://documentation.aimms.com/platform/solvers/cplex.html

Derigs, U., Pullmann, M., Vogel, U., Oberscheider, M., Gronalt, M., & Hirsch, P. (2012). Multilevel neighborhood search for solving full truckload routing problems arising in timber transportation. *Electronic Notes in Discrete Mathematics*, *39*, 281–288. https://doi.org/10.1016/j.endm.2012.10.037

El Hachemi, N., El Hallaoui, I., Gendreau, M., & Rousseau, L. M. (2015). Flow-based integer linear programs to solve the weekly log-truck scheduling problem. *Annals of Operations*

Research, *232*(1), 87–97. https://doi.org/10.1007/s10479-014-1527-4

El Hachemi, N., Gendreau, M., & Rousseau, L. M. (2011). A hybrid constraint programming approach to the log-truck scheduling problem. *Annals of Operations Research*, *184*(1), 163–178. https://doi.org/10.1007/s10479-010-0698-x

El Hachemi, N., Gendreau, M., & Rousseau, L. M. (2013). A heuristic to solve the synchronized log-truck scheduling problem. *Computers and Operations Research*, *40*(3), 666–673. https://doi.org/10.1016/j.cor.2011.02.002

Flisberg, P., Lidén, B., & Rönnqvist, M. (2009). A hybrid method based on linear programming and tabu search for routing of logging trucks. *Computers and Operations Research*, *36*(4), 1122–1144. https://doi.org/10.1016/j.cor.2007.12.012

Gendreau, M., & Potvin, J.-Y. (2019). Tabu Search. In *Handbook of Metaheuristics* (Vol. 272, pp. 37–55). https://doi.org/10.1007/978-3-319-91086-4_2

Ghotb, S., Sowlati, T., Mortyn, J., Roeser, D., & Griess, V. C. (2022). A goal programming model for the optimization of log logistics considering sorting decisions and social objective. *Canadian Journal of Forest Research*, *11*(February), 1–11. https://doi.org/10.1139/cjfr-2021-0203

Girvan, J., & Taylor, R. (2020). Can stumpage reform save the BC Interior Forest Industry? *Truck Logger BC*, 26–29. https://mydigitalpublication.com/publication/?m=66280&i=707506&p=28&ver=html5

Gracia, C., Velázquez-Martí, B., & Estornell, J. (2014). An application of the vehicle routing problem to biomass transportation. *Biosystems Engineering*, *124*, 40–52. https://doi.org/10.1016/j.biosystemseng.2014.06.009

Gronalt, M., Hirsch, P. (2007). *Metaheuristics* (K. F. Doerner, M. Gendreau, P. Greistorfer, W. J.

Gutjahr, R. F. Hartl, & M. Reimann (Eds.)). Springer US.

Gronalt, M., & Rauch, P. (2018). Analyzing railroad terminal performance in the timber industry supply chain – a simulation study. *International Journal of Forest Engineering*, *29*(3), 162–170. https://doi.org/10.1080/14942119.2018.1488913

Hamzadayi, A., & Yildiz, G. (2013). A simulated annealing algorithm based approach for balancing and sequencing of mixed-model U-lines. *Computers and Industrial Engineering*, *66*(4), 1070–1084. https://doi.org/10.1016/j.cie.2013.08.008

Han, S. K., & Murphy, G. E. (2012). Solving a woody biomass truck scheduling problem for a transport company in Western Oregon, USA. *Biomass and Bioenergy*, *44*, 47–55. https://doi.org/10.1016/j.biombioe.2012.04.015

Haridass, K., Valenzuela, J., Yucekaya, A. D., & McDonald, T. (2014). Scheduling a log transport system using simulated annealing. *Information Sciences*, *264*, 302–316. https://doi.org/10.1016/j.ins.2013.12.005

Hirsch, P. (2011). Minimizing empty truck loads in round Timber Transport with Tabu Search strategies. *International Journal of Information Systems and Supply Chain Management*, *4*(2), 15–41. https://doi.org/10.4018/jisscm.2011040102

Hirsch, P., & Gronalt, M. (2013). The timber transport order smoothing problem as part of the three-stage planning approach for round timber transport. *Journal of Applied Operational Research*, *5*(2), 70–81. http://orlabanalytics.ca/jaor/archive/v5/n2/jaorv5n2p70.pdf

Jones, D. (2010). *Practical Goal Programming*. Springer. https://link.springer.com/content/pdf/10.1007/978-1-4419-5771-9.pdf

Karttunen, K., Lättilä, L., Korpinen, O., & Ranta, T. (2013). *for Forest Chips*. *47*(4), 1–24.

Karttunen, K., Väätäinen, K., Asikainen, A., & Ranta, T. (2012). The operational efficiency of waterway transport of forest chips on Finland's lake Saimaa. *Silva Fennica*, *46*(3), 395–413. https://doi.org/10.14214/sf.49

Kirkpatrick, A. S., Gelatt, C. D., Vecchi, M. P., Science, S., Series, N., & May, N. (1983). Optimization by Simulated Annealing Published by : American Association for the Advancement of Science Stable URL : http://www.jstor.com/stable/1690046. *Science*, *220*(4598), 671–680. https://doi.org/DOI: 10.1126/science.220.4598.671

Kogler, C., & Rauch, P. (2018). Discrete event simulation of multimodal and unimodal transportation in the wood supply chain: A literature review. *Silva Fennica*, *52*(4). https://doi.org/10.14214/sf.9984

Kress, D., & Müller, D. (2022). Semiconductor final-test scheduling under setup operator constraints. *Computers and Operations Research*, *138*(October 2021), 105619. https://doi.org/10.1016/j.cor.2021.105619

Lagzi, S. (2016). *A Study of Time Representation in a Class of Short Term Scheduling Problems*. https://uwspace.uwaterloo.ca/handle/10012/10642

Lee, H., & Maravelias, C. T. (2018). Combining the advantages of discrete- and continuous-time scheduling models: Part 1. Framework and mathematical formulations. *Computers and Chemical Engineering*, *116*, 176–190. https://doi.org/10.1016/j.compchemeng.2017.12.003

Malladi, K. T., Quirion-Blais, O., & Sowlati, T. (2018). Development of a decision support tool for optimizing the short-term logistics of forest-based biomass. *Applied Energy*, *216*(December 2017), 662–677. https://doi.org/10.1016/j.apenergy.2018.02.027

Malladi, K. T., & Sowlati, T. (2017). Optimization of operational level transportation planning in forestry: a review. *International Journal of Forest Engineering*, *28*(3), 198–210. https://doi.org/10.1080/14942119.2017.1362825

Mancini, S., Gansterer, M., & Hartl, R. F. (2021). The collaborative consistent vehicle routing problem with workload balance. *European Journal of Operational Research*, *293*(3), 955–965. https://doi.org/10.1016/j.ejor.2020.12.064

Matl, P., Hartl, R. F., & Vidal, T. (2019). Workload equity in vehicle routing: The impact of alternative workload resources. *Computers and Operations Research*, *110*, 116–129. https://doi.org/10.1016/j.cor.2019.05.016

Melchiori, L., Nasini, G., Montagna, J. M., & Corsano, G. (2022). A mathematical modeling for simultaneous routing and scheduling of logging trucks in the forest supply chain. *Forest Policy and Economics*, *136*(September 2021), 102693. https://doi.org/10.1016/j.forpol.2022.102693

Melchiori, L., Nasini, G., Montagna, J. M., & Corsano, G. (2023). Resources synchronization in a full truckload pickup and delivery problem: An exact approach. *Computers and Operations Research*, *151*(December 2022), 106118. https://doi.org/10.1016/j.cor.2022.106118

Moghdani, R., Salimifard, K., Demir, E., & Benyettou, A. (2021). The green vehicle routing problem: A systematic literature review. *Journal of Cleaner Production*, *279*, 123691. https://doi.org/10.1016/j.jclepro.2020.123691

Mousavi, S. M., Sadeghi, J., Niaki, S. T. A., & Tavana, M. (2016). A bi-objective inventory optimization model under inflation and discount using tuned Pareto-based algorithms: NSGA-II, NRGA, and MOPSO. *Applied Soft Computing Journal*, *43*, 57–72. https://doi.org/10.1016/j.asoc.2016.02.014

Murphy, G. (2003). Reducing trucks on the road through optimal route scheduling and shared log transport services. *Southern Journal of Applied Forestry*, *27*(3), 198–205.

https://doi.org/10.1093/sjaf/27.3.198

Nadimi, F., Submitted, A. T., Partial, I. N., Of, F., For, R., Degree, T. H. E., Of, M., Science, A., & Studies, P. (2015). *TRUCK ROUTING AND SCHEDULING FOR WOOD CHIP TRANSPORTATION TO A PULP MILL USING SIMULATED ANNEALING FATTANE NADIMI B . Sc ., Industrial Engineering , Sharif University of Technology , 2007 M . Sc ., Industrial Engineering , Sharif University of Technology . January*.

Natural Resources Institute Finland. (2023). *Unit costs in harvesting and transportation of industrial roundwood (€/m³) 1985-2021 by year and unit cost. PxWeb*. https://statdb.luke.fi/PxWeb/pxweb/en/LUKE/LUKE__04 Metsa__08 Muut__Teollisuuspuun korjuu ja kaukokuljetus/05.17_Teollisuuspuun_korjuun_kaukokuljetukse.px/table/tableViewLayout2/?rxid=001bc7da-70f4-47c4-a6c2-c9100d8b50db

Oberscheider, M., Zazgornik, J., Henriksen, C. B., Gronalt, M., & Hirsch, P. (2013). Minimizing driving times and greenhouse gas emissions in timber transport with a near-exact solution approach. *Scandinavian Journal of Forest Research*, *28*(5), 493–506. https://doi.org/10.1080/02827581.2012.758309

Palmgren, M., Rönnqvist, M., Värbrand, P., Palmgren, M., & Ro, M. (2003). A solution approach for log truck scheduling based on composite pricing and branch bound. *International Transactions in Operational Research*, *10*, 15.

Palmgren, M., Rönnqvist, M., & Värbrand, P. (2004). A near-exact method for solving the log-truck scheduling problem. *International Transactions in Operational Research*, *11*(4), 447–464. https://doi.org/10.1111/j.1475-3995.2004.00469.x

Piltan, M., & Sowlati, T. (2014). A review of partnership studies in the forest products value chain: With a focus on developed countries (United States, Canada, and Western Europe). *Forest Products Journal*, *64*(1–2), 4–10. https://doi.org/10.13073/FPJ-D-13-00076

Pinedo, M. L. (2012). *Scheduling*. Springer. https://doi.org/10.1007/978-1-4614-2361-4_3

Ramezanian, R., & Saidi-Mehrabad, M. (2013). Hybrid simulated annealing and MIP-based heuristics for stochastic lot-sizing and scheduling problem in capacitated multi-stage production system. *Applied Mathematical Modelling*, *37*(7), 5134–5147. https://doi.org/10.1016/j.apm.2012.10.024

Rantala, J. (2004). Linear Programming and Mixed Integer Programming in Management of Seedling Transportation. *International Journal of Forest Engineering*, *15*(1), 41–51. https://doi.org/10.1080/14942119.2004.10702488

Rantala, J., Kiljunen, N., & Harstela, P. (2003). Effect of Seedling Production and Long-Distance Transportation Planning Strategies on Transportation Costs of a Nursery Company. *International Journal of Forest Engineering*, *14*(2), 65–73. https://doi.org/10.1080/14942119.2003.10702479

Rey, P. A., Muñoz, J. A., & Weintraub, A. (2009). A column generation model for truck routing in the chilean forest industry. *Infor*, *47*(3), 215–221. https://doi.org/10.3138/infor.47.3.215

Rix, G., Rousseau, L. M., & Pesant, G. (2015). A column generation algorithm for tactical timber transportation planning. *Journal of the Operational Research Society*, *66*(2), 278–287. https://doi.org/10.1057/jors.2013.170

Rodrigues, T., Ramos, P., Isabel, M., & Barbosa-póvoa, A. P. (2014). Planning a sustainable reverse logistics system : Balancing costs with environmental and social concerns. *Omega*, *48*, 60–74. https://doi.org/10.1016/j.omega.2013.11.006

Rönnqvist, M., D’Amours, S., Weintraub, A., Jofre, A., Gunn, E., Haight, R. G., Martell, D., Murray, A. T., & Romero, C. (2015). Operations Research challenges in forestry: 33 open problems. *Annals of Operations Research*, *232*(1), 11–40. https://doi.org/10.1007/s10479-015-1907-4

Rummukainen, T., Kinnari, T., & Laakso, M. (2009). Optimization of wood transportation. *Optimization of Wood Transportation*, 1–10. http://www.vtt.fi/inf/julkaisut/muut/2009/PRS2009.pdf

Salama, M., & Srinivas, S. (2021). Adaptive neighborhood simulated annealing for sustainability-oriented single machine scheduling with deterioration effect. *Applied Soft Computing*, *110*, 107632. https://doi.org/10.1016/j.asoc.2021.107632

Schneeweiss, C. (1999). *Hierarchies in Distributed Decision Making*. Springer Berlin Heidelberg.

Sherafati, M., Bashiri, M., Tavakkoli-Moghaddam, R., & Pishvaee, M. S. (2020). Achieving sustainable development of supply chain by incorporating various carbon regulatory mechanisms. *Transportation Research Part D: Transport and Environment*, *81*(February), 102253. https://doi.org/10.1016/j.trd.2020.102253

Soares, R., Marques, A., Amorim, P., & Rasinmäki, J. (2019). Multiple vehicle synchronisation in a full truck-load pickup and delivery problem: A case-study in the biomass supply chain. *European Journal of Operational Research*, *277*(1), 174–194. https://doi.org/10.1016/j.ejor.2019.02.025

Stefansson, H., Sigmarsdottir, S., Jensson, P., & Shah, N. (2011). Discrete and continuous time representations and mathematical models for large production scheduling problems: A case study from the pharmaceutical industry. *European Journal of Operational Research*, *215*(2), 383–392. https://doi.org/10.1016/j.ejor.2011.06.021

Swedish Forest Agency. (2014). Skogsstatistisk årsbok 2014 - Swedish Statistical Yearbook of Forestry. In *Swedish Forest Agency*. https://www.skogsstyrelsen.se/globalassets/statistik/historisk-statistik/skogsstatistisk-arsbok-2010-2014/skogsstatistisk-arsbok-2014.pdf

Turanoğlu, B., & Akkaya, G. (2018). A new hybrid heuristic algorithm based on bacterial foraging optimization for the dynamic facility layout problem. *Expert Systems with Applications*, *98*, 93–104. https://doi.org/10.1016/j.eswa.2018.01.011

Vacca, I., Salani, M., & Bierlaire, M. (2010). *Optimization of operations in container terminals : hierarchical vs integrated approaches Optimization of operations in container terminals : hierarchi- cal vs integrated approaches*. *September*.

Vancas, M. F. (2003). *Feasibility studies: Just how good are they? 2*, 1407–1413. https://onlinelibrary.wiley.com/doi/abs/10.1002/9781118804407.ch26

Vidal, T., Laporte, G., & Matl, P. (2020). A concise guide to existing and emerging vehicle routing problem variants. *European Journal of Operational Research*, *286*(2), 401–416. https://doi.org/10.1016/j.ejor.2019.10.010

Vitale, I., Broz, D., & Dondo, R. (2021). Optimizing log transportation in the Argentinean forest industry by column generation. *Forest Policy and Economics*, *128*(April), 102483. https://doi.org/10.1016/j.forpol.2021.102483

Yağmur, E., & Kesen, S. E. (2021). Multi-trip heterogeneous vehicle routing problem coordinated with production scheduling: Memetic algorithm and simulated annealing approaches. *Computers and Industrial Engineering*, *161*(August). https://doi.org/10.1016/j.cie.2021.107649

Yu, V. F., Jewpanya, P., Redi, A. A. N. P., & Tsao, Y. C. (2021). Adaptive neighborhood simulated annealing for the heterogeneous fleet vehicle routing problem with multiple cross-docks. *Computers and Operations Research*, *129*, 105205. https://doi.org/10.1016/j.cor.2020.105205

Zandieh, M., Khatami, A. R., & Rahmati, S. H. A. (2017). Flexible job shop scheduling under condition-based maintenance: Improved version of imperialist competitive algorithm. *Applied Soft Computing Journal*, *58*, 449–464. https://doi.org/10.1016/j.asoc.2017.04.060

Zazgornik, J., Gronalt, M., & Hirsch, P. (2012). The combined vehicle routing and foldable container scheduling problem: A model formulation and tabu search based solution approaches. *Infor*, *50*(4), 147–162. https://doi.org/10.3138/infor.50.4.147