Accepted Manuscript

Real-time management of transportation disruptions in forestry

Amine Amrouss, Nizar El Hachemi, Michel Gendreau, Bernard Gendron

PII: S0305-0548(17)30037-0
DOI: 10.1016/j.cor.2017.02.008
Reference: CAOR 4193

To appear in: *Computers and Operations Research*

Received date: 31 December 2015
Revised date: 5 February 2017
Accepted date: 9 February 2017

Please cite this article as: Amine Amrouss, Nizar El Hachemi, Michel Gendreau, Bernard Gendron, Real-time management of transportation disruptions in forestry, *Computers and Operations Research* (2017), doi: 10.1016/j.cor.2017.02.008

Highlights

- Real-time re-planning in reaction to disruptions can be done effectively and efficiently for realistic LTSP instances.
- Time-space networks can be exploited to incorporate impacts of disruptions and to reduce the size of the problem.
- MIP technology can be exploited in this context: effective solutions found in a short computational time.

Real-time management of transportation disruptions in forestry

Amine Amrouss[a,b,*], Nizar El Hachemi[a], Michel Gendreau[a,c], Bernard Gendron[a,b]

[a] *Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT), Canada*
[b] *Université de Montréal, P.O. Box 6128, Station Centre-Ville, Montréal, Canada H3C 3J7*
[c] *Department of Mathematics and Industrial Engineering, Polytechnique Montréal, C.P. 6079, succursale Centre-ville, Montréal, Canada H3C 3A7*

Abstract

In this paper, we present a mathematical programming model based on a time-space network representation for solving real-time transportation problems in forestry. We cover a wide range of unforeseen events that may disrupt the planned transportation operations (e.g., delays, changes in the demand and changes in the topology of the transportation network). Although each of these events has different impacts on the initial transportation plan, one key characteristic of the proposed model is that it remains valid for dealing with all the unforeseen events, regardless of their nature. Indeed, the impacts of such events are reflected in a time-space network and in the input parameters rather than in the model itself. The empirical evaluation of the proposed approach is based on data provided by Canadian forestry companies and tested under generated disruption scenarios. The test sets have been successfully solved to optimality in short computational times and demonstrate the potential improvement of transportation operations incurred by this approach.

Keywords: Real-time, Transportation, Forestry, Mathematical programming

*Corresponding author
Email address: amine.amrouss@umontreal.ca (Amine Amrouss)

1. Introduction

Optimization models and operations research (OR) methods have been used in the forest industry since the 1960s [1]. Recent reviews on how these models and methods are used to solve planning problems in forestry can be found in [2] (2015) and [3] (2014). These planning problems cover a wide range of activities such as sylviculture, harvesting, road building, production and transportation, which present to this day several challenges to OR practitioners [2, 4], as the forest industry attempts to improve its competitiveness and reduce its environmental impact. In particular, improving transportation planning in forestry has been the object of recent research of highly practical relevance, since transportation costs are estimated at more than one-third of wood procurement costs [2]. Minimizing transportation costs therefore represents a key element to improve the competitiveness of forest companies.

Recently, a number of OR models and methods have been developed to solve the *log-truck scheduling problem* (LTSP) [5, 6, 7, 8, 9], which consists in deriving schedules for trucks to transport different wood products between forest sites and wood mills. In addition, several decision support systems, such as the ASI-CAM project in Chile [9] and the EPO project in Finland [10], were developed to ease transportation planning. A review of transportation planning systems in the forest industry and the contribution of OR in their development can be found in [11]. Note that few decision support systems are available to forest companies (compared to other industrial sectors [12]), as many forest companies still rely on experienced dispatchers to manually derive their transportation plans.

Whether the transportation plans are obtained through an optimization method or manually, their implementation in practice is vulnerable to unforeseen events. For example, in Canada, spring thawing soils and summer rains degrade the forest roads condition and prevent the trucks from accomplishing their trips within the planned time. The late arrival of these trucks may also create queues for loading and unloading operations. In this case, the disruption consequences may stream through the whole supply chain and many trips could become infeasible. There is then a need to re-optimize the transportation plan as early as possible to minimize the impact of such disruptions. Real-time rescheduling of log-trucks has not been subject to much attention in the literature, in spite of the growing body of literature on similar problems in other industrial sectors, with the advent of intelligent transportation systems [13]. To the best of our knowledge, CADIS (for Computer Aided Dispatch) is the only documented decision support system for real-time dispatching in forestry [14]. The authors reported few details about this system because of non-disclosure agreements with the New Zealand company that used it. The system produced encouraging results [15], although it was used only for a short period, as the company ceased its activities because of financial issues. Other commercial decision support systems [11] may include real-time dispatching modules, but they are generally manually managed. The recent work [2] defines real-time transportation management as one of 33 open problems in the forest industry for OR practitioners.

Several sources of uncertainty exist in the forest industry [2]. The wood markets include uncertainties about the prices and demand volumes. The forest areas involve many uncertainties, such as the growth and quality of the trees, the volume estimates (global and per species), diseases and fire risks. The wood production includes inaccuracies about the harvesting and transportation plans. Other uncertainties include technology developments and regulation changes. These inaccuracies are generally handled through including extra travel times for transportation estimates, extra inventories for demand levels, extra dollars for cost estimates, etc. Some stochastic models have been lately introduced to cover some types of uncertainties in the forest industry. In [16], the authors consider a tactical harvesting and road construction problem with market uncertainty. The stochastic model that they developed tries to find the best solution that is feasible under all the generated scenarios related to timber price variations. In addition to the large number of scenarios that could be generated, the nonanticipativity constraints make the problem solution harder. These constraints state that if two different scenarios are identical up to a certain time interval, the values of the decision variables values also be identical up to that interval. The authors use a branching scheme where these constraints are implicitly satisfied. In [17], the authors present a Scandinavian case study where there are uncertainties about the demand. The original approach was to keep a safety stock to face the demand fluctuations. The authors propose, instead, a robust optimization approach to eliminate these stocks. The approach decomposes the problem into two separate problems. In the first problem, they find a feasible solution. The second gives the worst-case scenario given this solution. This is used as a valid inequality in the first model. The process is repeated until the first problem produces a solution satisfying the worst-case scenario.

Simulation can be used to evaluate the solutions found by solving the mathematical models. It allows to identify potential issues associated with the implementation of the solutions. The optimization models can be modified and solved again after the simulation. This technique was recently used to assess the performance of a transportation plan considering uncertainty in trucks arrival time at a mill [18]. Similarly, [19] uses a discrete-event simulation model to evaluate the implementation of production plans of an integrated pulp and paper mill. The simulator is also used to refine the parameters of the analytical model in order to produce more robust plans.

In stochastic programming, simulation can be used to generate a set of scenarios that are used as input to the optimization model. The method assumes that the uncertainty has a probabilistic description, which can be hard to define. Depending on the complexity of this description, the model may become hard to solve within a reasonable computational time. In robust optimization, the uncertainty is only known to belong to some uncertainty set and there is no requirement to have probability distributions. The goal is to find the optimal solution that is feasible in the worst-case scenario. To avoid conservative and costly solutions, care must be taken in the construction of the uncertainty set, which is challenging for large scale forest planning problems.

The most frequent source of uncertainty related to transportation planning problems in other industrial sectors is the arrival of new requests (e.g., new customers or change in the demand) [20, 21]. In forest transportation planning problems, one must deal with unforeseen events of a different nature such as changes in the topology of the transportation network (e.g., road closure). In this paper, we propose a mathematical programming model that remains valid for every unforeseen event that may occur during forest transportation operations, regardless of its nature. The model is based on a time-space network representation of the forest supply chain where the impacts of the unforeseen events are represented.

The remainder of this paper is organized as follows. Section 2 describes the problem, starting with a generic description of the LTSP. Section 3 presents the proposed approach to re-optimize the transportation plan in real-time in response to an unforeseen event. The description of the test sets and the results of our approach are presented in Section 4. Section 5 concludes this work.

2. Problem description

We begin this section with a generic description of the LTSP, whose solution produces a transportation plan that consists of a sequence of empty and loaded trips in addition to loading and unloading operations. Note that our approach remains valid whether such a plan is derived manually or by using optimization methods, but the LTSP provides a conceptual framework for the subsequent development of our model for real-time rescheduling of log-trucks.

We assume a homogeneous fleet of trucks. Each truck is associated with a base, usually a wood mill, where it must begin and end its shift. The planner must assign a route to each truck. A route is composed of a set of trips in addition to waiting, loading and unloading operations. Table 1 presents an example of a weekly truck route.

We define as R, V, M, F, and P the sets of routes, trucks, mills, forest sites, and wood products, respectively. R_v is the subset of routes linked to truck $v \in V$. Each route $r \in R$ has a cost c_r. This cost includes productive

SHIFT INDEX	CYCLE START DAY	CYCLE START TIME	EMPTY ORIGIN	EMPTY DRIVING DURATION	EMPTY DESTINATION	LOADING DURATION	PRODUCT	LOADED DRIVING DURATION	LOADED DESTINATION	WAITING DURATION	UNLOADING DURATION	CYCLE END TIME
1	Monday	0:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	5:20
1	Monday	5:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	10:20
1	Monday	10:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	15:20
2	Tuesday	0:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	5:20
2	Tuesday	5:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	10:20
2	Tuesday	10:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	15:20
3	Wednesday	0:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	5:20
3	Wednesday	5:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	10:20
3	Wednesday	10:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	15:20
4	Thursday	0:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	5:20
4	Thursday	5:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	10:20
4	Thursday	10:20	Sk	2:00	Ki	0:20	A	2:20	Sk	0:00	0:20	15:20
5	Friday	1:00	Sk	2:20	Pe	0:20	B	2:20	Ra	0:00	0:20	6:20
5	Friday	6:20	Ra	1:40	Lu	0:20	C	2:00	Ra	0:00	0:20	10:40
5	Friday	10:40	Ra	1:40	Lu	0:20	D	2:40	Ca	0:00	0:20	15:40
5	Friday	15:40	Ca	0:40	Sk	0:00		0:00		0:00	0:00	16:20

Table 1: Example of a route.

(loaded trips, loading and unloading) and unproductive activities (empty trips and waiting). The basic LTSP aims at minimizing the total cost while satisfying the demand D_{mp} of product $p \in P$ at each mill $m \in M$ given a certain amount of available wood products S_{fp} at each forest site $f \in F$. The problem can be formulated as follows [22]:

$$\text{Min} \quad \sum_{r \in R} c_r y_r \tag{1}$$

$$\sum_{r \in R} b_{mpr} y_r = D_{mp}, \ \forall m \in M, p \in P \tag{2}$$

$$\sum_{r \in R} a_{fpr} y_r \leq S_{fp}, \ \forall f \in F, p \in P \tag{3}$$

$$\sum_{r \in R_v} y_r \leq 1, \ \forall v \in V \tag{4}$$

$$y_r \in \{0, \ldots, |V|\}, \ \forall r \in R \tag{5}$$

The variables y_r indicate the number of trucks assigned to route r. The parameters a_{fpr} (b_{mpr}) represent the total amount of product p picked up at forest site f (delivered at mill m) by each truck assigned to route r. The objective function (1) minimizes the total cost. Constraints (2) and (3) ensure demand satisfaction while not exceeding the supply. Constraints (4) ensure that each truck is assigned to at most one route. However, constraints (5) allow the assignment of a route to several trucks.

Set R can be generated in different ways. In a manual process, an experienced dispatcher typically assigns trips to the destinations that the driver is used to visit. Trips between a forest site and a mill are repeated as long as they remain feasible. In an optimization approach, the set of feasible routes can be generated iteratively, in a branch-and-price procedure (branch-and-bound combined with column generation) that solves model (1)-(5). In this case, each generated route, at each node of the branch-and-bound tree, is a solution of the respective pricing sub-problem. This sub-problem consists in finding the shortest path in a time-space network, where the length of a path corresponds to its reduced cost. If the reduced cost of the shortest path is negative, the variable associated to the corresponding route is added to model (1)-(5). A completely different approach is to use a formulation where the routes (and thus set R) are implicitly defined through the constraints, as in the flow-based model described in [23].

The transportation cost includes a fixed cost for using a truck and a variable cost proportional to the distance, which is measured in travel time. This distance depends on whether the truck is empty or loaded, since the truck drives faster when it is empty. The trucks have to travel empty from the mills to the forest sites. Thus, a truck that operates only trips between the same mill and the same forest site loses half of its transportation capacity. Instead, once at a mill, one must try to allocate the wood products from the closest forest sites to the mills in the opposite direction. This is known in the literature as backhauling and we refer the interested reader to [24] for more details about decision support systems using backhauling in the forest industry.

Loading and unloading operations are performed by loaders at forest sites and mills. These loaders are usually operated only for a specific period of the day. Moreover, the number of loaders available at a mill or a forest site may vary during the day. To avoid creating queues at the loaders and thus reduce the cost of unproductive activities, another objective that must be met by the dispatcher is the synchronization of the trucks with the loaders given accurate information about the available loaders. These constraints appear in the recent works on the LTSP [5, 8] and are considered in our work.

In the context of real-time rescheduling of log-trucks, we assume that truck drivers receive one trip at a time, the dispatcher waiting for each truck driver to finish its current trip before revealing its next destination. This mode of transportation planning management gives more flexibility to re-optimize the routes, since it avoids drivers resistance to change.

While re-optimizing the transportation plans following the occurrence of an unforeseen event, the dispatcher must avoid diverting a truck from its destination unless the unforeseen event prevents the completion of the current trip. This improves the consistency of the proposed schedules and facilitates their real-life implementation. Moreover, in a real-time context, the amount of time available to the dispatcher to derive alternative transportations plans is limited.

The nature of the unforeseen events that arise in the forest industry is distinct from what can be found in the literature on similar problems found in other industrial sectors. In [25], the authors present a list of the most frequent unforeseen events. The list includes unforeseen events that are likely to appear at the forest sites, those involving trucks and road networks, and the events that occur at the mills. To develop effective recourse strategies when facing such events, one must focus on the impacts they have on the transportation network rather than on the events themselves. The next section describes the proposed approach to implement these recourse strategies.

3. Proposed approach

Our approach to real-time rescheduling log-trucks is built on a time-space network representation, which is used in the definition of our mathematical

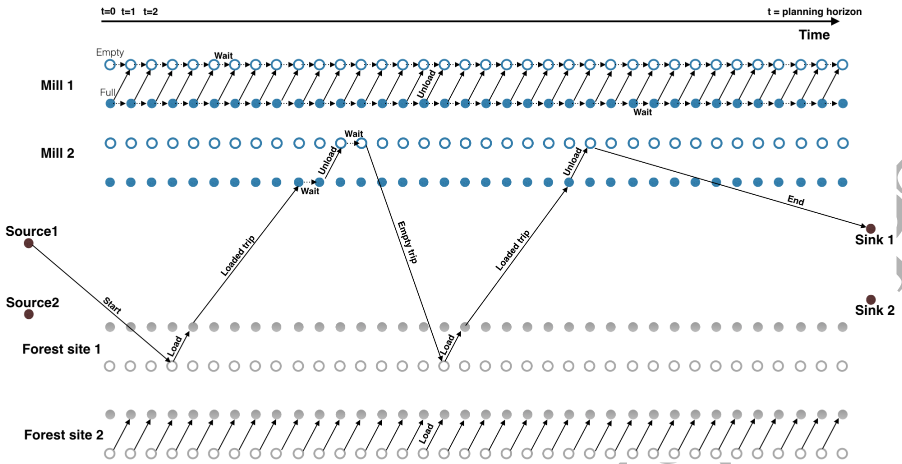


Figure 1: Time-space network.

programming model. The time-space network represents the evolution of the forest supply chain over time. This representation varies depending on the nature of the unforeseen events that are revealed over time. The space and time dimensions of the network allow to track the trucks in real-time and to capture the impacts of the unforeseen events on the transportation network (e.g., by removing the arcs that become inaccessible). The distances between two locations in the transportation network are expressed as a time measure. This helps to capture the impact of some unforeseen events. In the case of a road degradation or a traffic jam, for example, the trip duration may become longer, while the geographical distance remains the same. The mathematical programming model takes this time-space network as an input and is solved using a commercial solver.

3.1. Time-space network

When an unforeseen event is revealed, one must collect real-time information about the state of the transportation network elements. We refer to the state of a truck, for example, as the information about its position, its destination and the product it is transporting if it is loaded. Moreover, if the truck is directly impacted by the unforeseen event as in the case of a truck breakdown, we assume that we have additional information about the estimated characteristics of the corresponding event, such as an estimate of the truck repair duration. The collection and validation of these estimates is beyond the scope of this work, but the current development of onboard computers, geo-location and communication technologies, in addition to the development of big data algorithms, make the collection of good quality estimates of the disruptions characteristics more affordable and easier. In this paper, we do not simulate how the plan will evolve after the disruption. In practice, one can use simulation to decide whether or not to re-optimize the transportation plan.

The state of the transportation network can be seen as an instant picture of this network that we represent as a time-space network. The space dimension of the network contains the set of wood mills and forest sites in addition to their linking roads. For the time dimension of the network, we divide the planning horizon into a set of intervals. The necessary time for loading and unloading operations is approximately equal and the driven distances are quite large in the context we consider in this paper. Therefore, we use the loading duration as a time-step for discretizing the planning horizon. Time-space networks are used for generating routes to solve daily, weekly, and annual LTSPs, but they are generally not formally described in the LTSP literature [8, 26]. The network that we use in this paper is adapted from the one proposed in [23]. The main differences are the use of a source vertex per truck, the duplication of loaded arcs by wood product, and the use of different arc capacities. The novelty is also that we modify the network after each disruption. Figure 1 presents this time-space network, which contains four types of vertices :

- A *source vertex for each truck* representing its current location (or its base if it has not yet started its shift) when the unforeseen event is revealed. These individual truck vertices are different from what can be found in a conventional time-space network. We need to introduce them to track the truck positions in real-time. Note also that the trucks that finish their shift before the occurrence of the disruption are not represented in the network.

- A *sink vertex for each truck.* It corresponds to its base and represents the shift end for the truck.

- *Forest site vertices.* Each vertex is replicated for each time interval of the discretized planning horizon. This allows to capture real-time information about the forest sites. This includes the current supply of each product and the number of loaders available at the correspondent interval. These vertices are duplicated to represent whether the truck is full or empty.

- *Mill vertices.* They are similarly replicated. The vertex state contains information about the current demand for each product and the number of loaders available at the corresponding interval.

The replication of the vertices is done horizontally in Figure 1. Each pair of lines represents either a mill or a forest site evolving over time. For reasons of clarity, only a subset of the arcs is represented in Figure 1 and their length does not represent the real distances. The arcs kept for the first truck give an example of a small sequence of trips. There are seven types of capacitated arcs in the time-space network:

- Start arcs connecting source vertices to empty forest site vertices, if the corresponding truck is empty, and to full mill vertices, otherwise. Their capacity is one truck.

- End arcs connecting empty mill vertices that correspond to a truck base to this truck sink vertex. Their capacity is one truck.

- Loaded driven arcs connecting a full forest site vertex to a full mill vertex demanding at least one of the available products at this forest site. They are duplicated for each available product. Their capacity is equal to the number of available trucks.

- Empty driven arcs connecting an empty mill vertex to an empty forest site vertex supplying at least one requested product. Their capacity is equal to the number of available trucks.
- Waiting arcs connecting two successive mill vertices. Their capacity is equal to the number of available trucks. Note that, as the number of mills is usually smaller than the number of forest sites and to reduce the symmetry, we prefer that the trucks wait at mills instead of at forest sites. We mean by symmetry that if a truck waits either at a forest site or at a mill, this will lead to a solution that has the same cost.
- Loading arcs connecting two successive empty and full forest site vertices. Their capacity is equal to the number of available loaders at the forest site during the corresponding time interval. Note that the number of available loaders is smaller than the number of trucks (there is generally one loader per site).
- Unloading arcs connecting two successive full and empty mill vertices. Their capacity is equal to the number of available loaders at the mill during the corresponding time interval.

It should be noted that the length of the arcs represents the duration of the corresponding operation. Therefore, these arcs exist only between vertices at intervals separated by at least this duration. Moreover, the vertices and arcs constituting this time-space network vary over time and depend on the nature of the revealed unforeseen events. We describe how these transformations are done in the following subsection.

3.2. Dealing with disruptions

At the occurrence of an unforeseen event, we first collect the necessary information about the trips that were executed before the disruption in order to update the remaining demand and supply and the number of trucks still in operation. We also collect the relevant information about the trucks, their positions and if they are loaded or empty. Having this information in addition to the estimates of the unforeseen event impacts, a new time-space network is produced. All the vertices and arcs that start before the occurrence of the event are removed from the initial time-space network. One exception is the truck start vertices. Outgoing arcs from these start vertices are updated according to the nature of the unforeseen event and to the corresponding truck positions.

The recourse strategies when an unforeseen event is revealed depend on its impact on the transportation network rather than on the event itself. Different unforeseen events can have the same impact on the transportation network. For example, in the case of the presence of a single loader at a forest site or at a mill, the breakdown of this loader can be seen as the corresponding site closure, assuming that the loaders are not allowed to move between different sites and that the trucks do not include onboard loaders. The following describes the disruptions categories based on their impact on the network, in addition to the corresponding recourse strategies.

Closures

This category contains the closures of forest sites, wood mills and roads. Also, there is generally one single forest road to access a forest site in contrast with urban context where the same point may be reached by different paths. Therefore, the closure of such road can also be considered as a forest site closure. A mill closure means that no product can be delivered to this mill during the closure. This can be caused, for example, by a decrease in the storage capacity or by the breakdown of the loader associated with this mill.

In the event of such disruptions at a mill or at a forest site, we remove the loading or unloading arcs at the corresponding vertices in addition to outgoing driven arcs for all time intervals that lie within the estimated duration of the disruption. We keep the waiting arcs at the mills. For trucks planned to arrive at the closed vertices before the operations start back, their start vertices are connected to the other mills or forest sites depending on whether they are loaded or not. The remaining truck start vertices are connected to their current destination at the time the disruption is revealed. The rest of the network is unchanged. If the disruption occurs on a road linking a mill to a forest site, we remove the corresponding arcs in the network for all the time intervals that lie within the closure duration.

Delays

Delays can be caused by a variety of unforeseen events. This includes bad weather conditions (poor visibility, thawing soils, heavy rains), degradation of forest roads, traffic jams, opening of hunting or fishing season and so on. Delays can be observed at a single truck level. This is the case, for example, when the truck is undergoing some mechanical issues and thus slowing down. In contrast, when a forest road is damaged, for instance, all the trucks taking this road will be impacted.

When a truck is delayed, we link its start vertex to its current destination vertex but at an interval that takes into account both the remaining distance and the estimation of the delay. For delays observed between two vertices, we move the arcs to take into account the delay estimation. We do so for all the arcs that lie within the estimation of the duration necessary to return to normal operations.

A truck breakdown can also be seen as a delayed truck. We assume that we have an estimate of the necessary time to repair this truck. If the repair time does not exceed the planning horizon, the arrival time of the truck to its next destination is delayed by the repair duration. Otherwise, we just remove the truck from the network.

Demand and supply variations

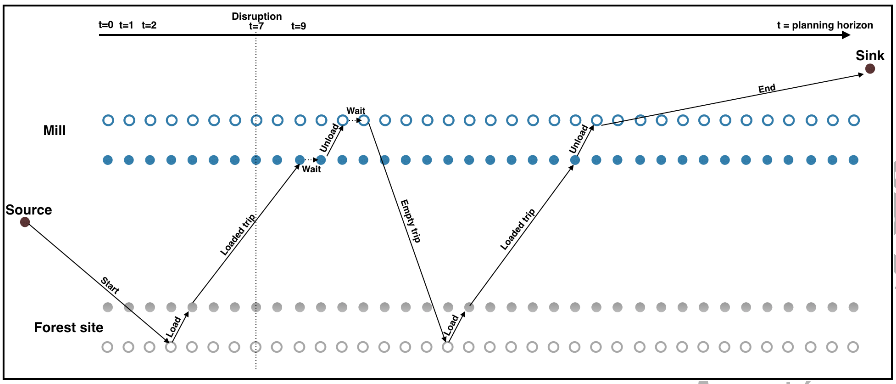
Mill breakdowns may lead to a decrease in its storage capacity. The demand of some products must therefore be adjusted downwards. Also, we may have an increase in the demand for some products. If the mill is not already connected to forest sites where the product is available, we add empty and loaded driven arcs between the mill and these forest sites. We also adjust the demand parameter in the input data. Similarly, if, during the day, we have more accurate data about the supply, its parameter is updated in the input data.

Loader breakdowns

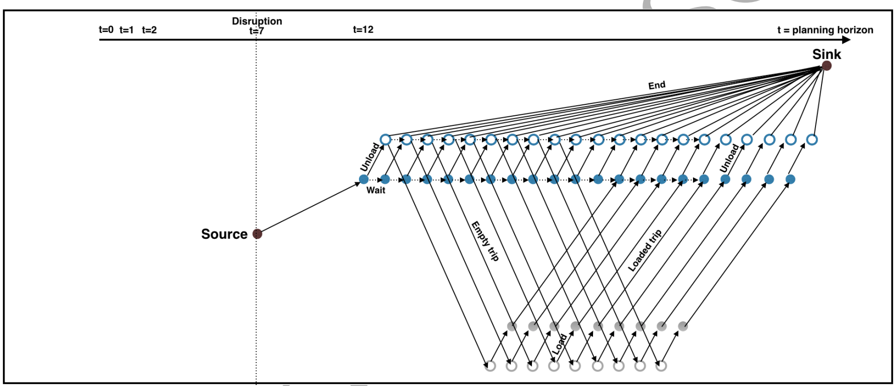
We assume to have an estimate of the necessary repair time and we update the number of available loaders during this period.

Figure 2 presents an example of a time-space network modification. This is a simple case involving one mill, one forest site, and one truck. We assume that the truck has a breakdown at the 7th time interval while it was heading to the mill. The truck was planned to arrive at the 9th time interval and we assume that three time intervals are necessary to fix it. Therefore, it is now planned to arrive at the 12th time interval at the mill. The source vertex is moved to represent the current truck position. The only arc that the truck is allowed to take from this vertex is linked to the mill at the 12th time interval. After that, it can either wait or unload. Note that there is no need to use waiting arcs in this case since there is only one truck. We keep them only for explanation purposes because these arcs are used when we have more than one truck. The remaining arcs are feasible for the truck and it is up to the mathematical model to choose the ones to include in the optimal solution.

Note that the number of forest vertices is smaller than mill vertices. This is because we take into account the travel time necessary to go back and forth between the mill and forest site within the mill opening hours. Other constraints may include limits on maximal driving hours, which can be incorporated in the network by removing end arcs leaving mill vertices at time intervals that exceed these limits. A disruption might happen in the middle of a time interval and the truck will not arrive exactly at one of the vertices of the network. In this case, we link its source vertex to the closest following vertex. In practice, the truck might have to wait anyway if other trucks are being unloaded. Otherwise, this can be considered as an additional time margin for its following trips. Another solution could be to refine the time-space network by decreasing the time step.



(a) Initial network.



(b) Modified network.

Figure 2: Example of network modification.

This would yield, however, a larger network and therefore higher computational time. To solve a weekly LTSP, which is decomposed into daily LTSPs, [23] studied the impact of using a 10-minute discretization step to refine the solution found with a 20-minute step. The solution was improved only for 2 out of 21 daily LTSPs by about 2%. For a real-time application, solutions must be found quickly. Therefore, we do not consider further refinement of the solution.

When an arc is modified in the network, its cost is also updated according the nature of the disruption. Once the new time-space network is obtained, it is combined with the new cost matrix, the remaining demand and supply, and the number of available trucks and loaders. These constitute the input parameters of the mathematical programming model.

3.3. Mathematical programming model

A two-phase approach for solving a weekly LTSP is introduced in [23]. The authors solve, in the first phase, a tactical MIP to assign forest supply to mills. In the second phase, they solve seven daily LTSPs where the demand is expressed as a set of trips between forest sites and mills obtained from the assignment phase. As the resulting transportation plans are vulnerable to unforeseen events, the following mathematical model presents the results of adapting this work to a real-time context. For example, as the demand and supply may vary over time, we reintroduce supply constraints and disaggregate the demand by products in the daily LTSP. The demand and supply are expressed in full truckloads since the fleet is homogeneous and the supply is quite large in the case studies we consider.

Some unforeseen events can have severe impacts on the supply chain and prevent the demand satisfaction. A penalty cost for each unmet demand is incurred. The penalty cost is chosen large enough to ensure demand satisfaction whenever it is possible.

As the input data and the time-space network evolve over time, depending on the nature of the revealed unforeseen events, one must index all the model parameters and variables by the event category and by their occurrence time. However, for the sake of clarity and ease of reading, we omit these indices. Hereafter, we list the parameters and the variables of the model, and then introduce the model itself.

Parameters

F	:	set of forest sites,
M	:	set of mills,
V	:	set of trucks,
P	:	set of wood products,
I	:	set of time intervals,
N	:	set of vertices,
A	:	set of arcs,
$A^+(n)$	:	set of outgoing arcs from vertex n,
$A^-(n)$	:	set of incoming arcs into vertex n,
A^{loaded}_{fmp}	:	set of loaded driven arcs from forest site f to mill m transporting wood product p,
A^{WLE}	:	set of waiting, loaded and empty driven arcs,
$Start_v$	:	start vertex for truck v,
End_v	:	end vertex for truck v,
A^U_{mi}	:	unloading arc at mill m at time interval i,
A^L_{fi}	:	loading arc at forest site f at time interval i,
c_a	:	cost associated with arc a,
c	:	penalty cost of unmet demand,
d_{mp}	:	demand of product p at mill m in full truckloads,
s_{fp}	:	supply of product p at forest site f in full truckloads,
l_{mi}	:	number of available loaders at mill m at time interval i,
l_{fi}	:	number of available loaders at forest site f at time interval i.

Variables

x_a	:	number of trucks that follow arc a,
δ_{mp}	:	unmet demand of product p at mill m.

Model

$$\text{Min} \sum_{a\in A} c_a x_a + \sum_{m\in M}\sum_{p\in P} c\delta_{mp} \tag{6}$$

$$\sum_{a\in A^+(Start_v)} x_a \leq 1,\ \forall v \in V \tag{7}$$

$$\sum_{a\in A^+(Start_v)} x_a = \sum_{a\in A^-(End_v)} x_a,\ \forall v \in V \tag{8}$$

$$\sum_{a\in A^+(n)} x_a = \sum_{a\in A^-(n)} x_a,\ \forall n \in N \setminus \cup_{v\in V} \{(Start_v, End_v)\} \tag{9}$$

$$\sum_{f\in F}\sum_{a\in A^{loaded}_{fmp}} x_a + \delta_{mp} = d_{mp},\ \forall m \in M, \forall p \in P \tag{10}$$

$$\sum_{m\in M}\sum_{a\in A^{loaded}_{fmp}} x_a \leq s_{fp},\ \forall f \in F, \forall p \in P \tag{11}$$

$$x_a \in \{0,1\},\ \forall a \in A^+(Start_v) \cup A^-(End_v) \tag{12}$$

$$x_a \in \{0,\ldots,l_{mi}\},\ \forall m \in M, \forall i \in I, \forall a \in A^U_{mi} \tag{13}$$

$$x_a \in \{0,\ldots,l_{fi}\},\ \forall f \in F, \forall i \in I, \forall a \in A^L_{fi} \tag{14}$$

$$x_a \in \{0,\ldots,|V|\},\ \forall a \in A^{WLE} \tag{15}$$

$$\delta_{mp} \in \{0,\ldots,d_{mp}\},\ \forall m \in M, \forall p \in P \tag{16}$$

The objective function (6) minimizes the total cost, including waiting, loading and unloading, and loaded and empty driven trips. The total cost includes also the penalty costs of the unmet demand.Constraints (7) ensure that each truck uses, at most, one start arc. Constraints (8) ensure that every used truck goes back to its base. Constraints (9) are flow conservation constraints for each mill and forest site vertex. This means that the number of trucks entering a vertex must be equal to the number of trucks exiting from this vertex. Constraints (10) and (11) guarantee the satisfaction of the remaining demand while not exceeding the supply. Constraints (12) ensure the unicity of the capacity of start and end arcs. Constraints (13) and (14) ensure that each loader only serves one truck at a time. Constraints (15) limit the capacity of waiting, loaded and empty driven arcs to the number of available trucks. Finally, constraints

(16) ensure the non-negativity of the unmet demand and limits its value to the actual demand.

We assume that we have a weekly transportation plan as the starting point. The transportation operations follow this schedule until an unforeseen event is revealed. The time-space network and the input parameters are updated according to the nature of the unforeseen event, then we solve the model for the current day. Many vertices and arcs are removed from the time-space network to take into account operational constraints. Indeed, the opening hours of wood mills limit the number of feasible vertices. In practice, some forest sites are assigned to only a subset of mills, which reduces the number of feasible arcs. Moreover, the size of the time-space network becomes smaller as the transportation operations progress. The mathematical model can then be solved within a reasonable computational time using a state-of-the-art commercial solver. These solvers include some routines that are able to further reduce the size of the model during the pre-processing phase. The transportation plan obtained for the current day is used until another unforeseen event is revealed, and the optimization approach starts over again. In the following day, we start with the initial transportation plan for that day and solve the new daily problem if an unforeseen event occurs. We use this approach in a controlled testing environment, where we limit the impact of the disruptions to the current day. In practice, if an event lasts beyond the end of the current day, the initial transportation plan for the following day is no more relevant. In this case, optimization methods for solving daily and weekly LTSPs ([8, 23, 26]) can be used offline to produce a new transportation plan for the following days, since more computational time is available.

4. Computational results

FPInnovations, a non-profit forest research centre dedicated to the improvement of the Canadian forest industry through innovation, provided us with six case studies from Canadian forest companies. All these case studies represent weekly planning problems. Moreover, we developed a disruptions generator that produces several "weeks" of unforeseen events. A week of unforeseen events is a set of disruptions scattered over one week. The goal is to assess the performance of the proposed approach on different forest supply chain configurations under different disruption scenarios. The main performance indicators considered in this paper are demand satisfaction, transportation cost and computational time.

4.1. Unforeseen events

Unforeseen events have different impacts on the transportation network. For testing purposes, these events and their impacts are randomly generated. We developed a discrete-event simulation procedure that produces a succession of events that happen at different discrete times. Note that different events are allowed to happen at the same time. The aim of this simulation is to generate unforeseen events that may happen during a full week. Therefore, after running the simulation procedure several times, we obtain different types of weeks with regard to the severity of the impacts. A hard week, for example, may be considered as a spring week with thawing soils, traffic jams and increasing risk of accidents because of the opening of the fishing season.

Some assumptions regarding the probability distributions of the disruptions and their impacts were made. To represent the impacts of these events, one needs to have an estimate of the expected time of the return to normal operations. It is common for the impacts to last for a shorter time and only a smaller amount of the impacts lasts for a longer time. We use then an exponential distribution to generate the disruptions duration. Note that the impacts of some unforeseen events are not measured in time units such as changes in the demand but the same observation could be applied to the demand variation volumes. As for the disruptions occurrence time, we assume that they can occur at any time in the week. Therefore, we use the uniform distribution to generate their occurrence time. We make also some assumptions about the maximum number of events that can happen simultaneously. This is done for each single unforeseen event category presented in Section 3.2 and also for the total number of all the event categories. During the events generation, if an unforeseen event is generated and the maximum number of simultaneous disruptions is attained, this event is rejected. Consequently, we need to keep track of the start and the end of the unforeseen events and to maintain a list of the current events. To generate the sequence of disruptions, we represent each disruption category by a special data type in our program that memorizes the occurrence time and duration of the disruption. For each disruption, we consider two types of simulation events : *Start* and *End*. The role of these events is to update the state of the simulation given that a disruption starts or ends. This includes generating the occurrence time and duration of the disruption, in addition to scheduling future events as follows:

Event 1 *Start*

if the maximum number of simultaneous events is not attained **then**
  Generate the current disruption random duration d
  Schedule the end of the event in d time units
else
  Reject the event
end if
Generate a random occurrence time t
Schedule the future disruption at time t
Update the number of current events and the statistics.

Event 2 *End*

Update the number of current events and the statistics.

To start the simulation, we schedule a dummy first *Start* event at the beginning of the planning horizon. We also schedule an end-of-simulation event at the planning horizon end to stop the simulation and extract the statistics. This simulation was done using SSJ, a framework for Stochastic Simulation in Java [27] .

4.2. Case studies

The collaboration with FPInnovations allowed us to obtain realistic data about the forest supply chain and to validate the proposed methods. We were provided with six weekly planning problems. We assume that these problems are initially solved using an optimization method rather than manually by a dispatcher. For testing purposes, we use the method described in [23] to derive a weekly transportation plan. In these case studies, the number of initially available trucks is provided. However, the optimization method may pick only a subset of these trucks to transport the wood products. Table 2 describes the six case studies that we denote C1 through C6. For each case study, we provide the number of wood mills ($|M|$), forest sites ($|F|$), wood products ($|P|$), the total demand (D) in full truckloads, the number of initially available trucks ($|V|$) and the number of trucks used in the resulting transportation plan ($|V_u|$). The approximate driving cost (c^D) is around 100$ per hour in average and the average waiting cost (c^W) is about 75$ per hour. The difference between loaded and empty driving costs is captured in the duration of these trips. The trip duration between forest sites and wood mills ranges from 1 to 6 hours in the 6 case studies. The loading and unloading times (t^{LU}) depend on the used equipment and the nature of the wood products. They are estimated at 20 or 30 minutes for these case studies. Therefore, we use 20 or 30 minutes steps to discretize the planning horizon. The 6 case studies are weekly LTSPs, but we solve the model (6) – (16) only for the current day of the disruption. The size of the daily problem varies depending on the nature and the occurrence time of the disruption. The last two columns of Table 2 represent the average number of variables (Var) and constraints ($Constr$) of the daily models that we solve for each case.

To assess our approach, we performed complete information tests on the case studies and compared the results to our real-time re-optimization approach. We refer to complete information tests as settings where we assume we know all the unforeseen events in advance and we run the optimization method on the case studies taking into account these disruptions. In contrast, as we progress

Case	$\vert M\vert$	$\vert F\vert$	$\vert P\vert$	D	$\vert V\vert$	$\vert V_u\vert$	$\vert c^D\vert$	$\vert c^W\vert$	$\vert t^{LU}\vert$	Var	Constr
C1	5	6	3	618	26	11	90	75	30	717	251
C2	5	6	3	400	13	8	90	75	30	628	238
C3	1	5	1	200	37	7	110	100	20	480	169
C4	1	5	1	215	10	8	90	75	20	373	142
C5	1	5	1	215	8	8	90	75	20	351	140
C6	4	59	12	273	40	11	90	60	20	5686	2002

Table 2: Description of case studies.

through the planning horizon and each time an unforeseen event is revealed, our real-time re-optimization approach produces a new transportation plan for the current day. This plan is used until the next disruption. Although the complete information setting is expected to outperform our approach because it takes into account all the disruptions in advance, we are nevertheless able to demonstrate the effectiveness of our real-time approach, as we show next.

4.3. Experimental results

We implemented the algorithms in C++, and used Gurobi 6.0 with default settings to solve the mathematical programming model. All experimentation was done on an Intel Core i7, 2.2 GHz processor with 16 GB of memory. We used the disruptions generator to derive several "weeks" of unforeseen events. We used two copies of each week and sorted the weeks according to two criteria: the total duration of all disruptions of a week for the first copy and the average occurrence time for the second one. We then picked the 10th, 50th, 75th and 90th percentiles of these weeks. The lowest percentile, for instance, consists of a week with events having the lowest impacts among the generated weeks (close to the 10th percentile of disruption duration) and happening at the beginning of the day (close to the 10th percentile of occurrence time). In contrast, the highest percentile means that the events have hard impacts and occur close to the end of the days. We also combined weeks with hard impacts (75th and 90th percentiles of disruption duration) and early occurrences (10th percentile of occurrence time), and vice-versa (10th and 50th percentiles of disruption duration with 90th percentile of occurrence time). Note that a different set of weeks is generated for each case study. The first part of Table 3 describes 8 weeks (W) that we picked for each case study. For each week, we provide the number of additional demand (DM) in full truckloads, the number of loader breakdowns (LO), the number of closures (CL) and the number of delays (DL). We do not generate additional supply since the latter is up to three times larger than the demand. This kind of events will not have a considerable impact on the solution. Some weeks may have the same number of disruptions but their occurrence times are different, which explains the differences in performance.

For each of these weeks, we first transform the weekly time-space network according to the generated events. Note that we limit the duration of an unforeseen event to the current day, to have a fair comparison with the real-time approach. We then solve the problem for the whole week. This is the complete information test. The second part of Table 3 compares the results of complete information tests to the initial transportation plan without any disruption. All the instances were solved to optimality. We first report the number of additional trucks (AT) used in the optimal solution compared to the initial transportation plan. The usage of an additional truck implies a fixed cost so the model tries to minimize the number of used trucks. This allows to use the under-utilized trucks rather than using additional trucks. However, the model prioritizes the demand satisfaction since a higher penalty is incurred in the event of default. We report the unmet demand (UD) under these disruptions. In fact, in some cases, even if the disruptions are known in advance, nothing can be done to satisfy all the demand within the planning time. This includes, for example, the case where a product is available at only a set of forest sites that are closed by an unforeseen event or the case where the unloading equipment at a mill is broken for a long time. The results for case study $C6$ show an example of this behaviour.

The third part of Table 3 compares the results of the proposed real-time approach, where the model is solved every time an unforeseen event is revealed, to the initial transportation plan. The model is solved for a planning horizon

Disruptions					Complete information		Real-time		Deviation	
W	DM	LO	CL	DL	AT	UD	AT	UD	Co	De
C1										
1	5	3	2	13	0	0.48%	1	0.48%	0.00%	0.00%
2	20	6	6	17	0	1.72%	0	1.72%	0.00%	0.00%
3	22	7	7	20	0	2.03%	0	2.19%	-0.15%	0.16%
4	31	9	7	23	0	0.92%	1	2.47%	-1.06%	1.54%
5	6	3	3	13	0	0.00%	0	0.00%	0.00%	0.00%
6	21	6	3	17	1	0.47%	1	0.47%	0.25%	0.00%
7	14	7	5	20	0	1.58%	0	1.58%	0.00%	0.00%
8	26	9	9	23	0	1.86%	1	2.48%	-0.33%	0.62%
C2										
1	5	1	1	10	0	0.74%	0	0.74%	0.00%	0.00%
2	12	5	3	15	0	2.18%	0	2.18%	0.00%	0.00%
3	19	5	4	15	0	2.39%	1	2.63%	0.20%	0.24%
4	15	8	6	18	0	0.00%	1	0.00%	0.00%	0.00%
5	7	2	2	10	0	0.00%	0	0.25%	-0.27%	0.25%
6	10	4	4	15	0	0.00%	0	0.00%	0.13%	0.00%
7	14	6	4	19	0	0.48%	0	0.48%	0.00%	0.00%
8	19	8	7	20	0	0.95%	1	1.19%	0.13%	0.24%
C3										
1	7	2	1	8	1	0.00%	2	0.00%	1.05%	0.00%
2	14	5	5	13	0	0.00%	1	0.00%	0.52%	0.00%
3	17	6	5	16	1	0.00%	3	0.92%	-0.40%	0.92%
4	19	8	6	19	2	0.00%	2	0.00%	0.49%	0.00%
5	9	2	2	9	3	0.00%	4	0.96%	-1.93%	0.96%
6	11	5	6	14	0	0.00%	1	0.00%	0.00%	0.00%
7	17	5	6	16	1	0.00%	2	0.00%	0.50%	0.00%
8	23	9	7	20	2	0.00%	8	2.69%	-3.08%	2.69%

DM	number of additional demand in full truckloads	LO	number of loader breakdowns
CL	number of closures	DL	number of delays
AT	number of additional trucks	UD	proportion of unmet demand
Co	transportation cost	De	deviation in unmet demand

Disruptions					Complete information		Real-time		Deviation	
W	DM	LO	CL	DL	AT	UD	AT	UD	Co	De
C4										
1	7	2	2	10	0	0.00%	1	0.00%	0.00%	0.00%
2	14	5	5	15	0	0.00%	1	1.75%	-1.86%	1.75%
3	24	6	6	17	0	0.00%	2	1.67%	-1.74%	1.67%
4	19	8	7	20	0	0.00%	1	0.85%	-0.91%	0.85%
5	9	2	2	10	0	0.00%	2	0.00%	0.00%	0.00%
6	11	5	5	15	0	0.00%	2	0.00%	0.00%	0.00%
7	17	6	6	17	0	0.00%	0	0.00%	0.00%	0.00%
8	19	8	7	20	0	0.00%	1	2.99%	-3.01%	2.99%
C5										
1	7	2	2	10	0	0.00%	0	0.00%	0.00%	0.00%
2	14	5	5	15	0	0.00%	0	2.62%	-2.80%	2.62%
3	24	6	6	17	0	0.00%	0	2.51%	-2.63%	2.51%
4	19	8	7	20	0	0.00%	0	2.56%	-2.73%	2.56%
5	9	2	2	10	0	0.00%	0	1.34%	-1.43%	1.34%
6	11	5	5	15	0	0.00%	0	0.88%	-0.95%	0.88%
7	17	6	6	17	0	0.00%	0	0.43%	-0.46%	0.43%
8	19	8	7	20	0	0.00%	0	3.42%	-3.64%	3.42%
C6										
1	5	2	2	8	0	0.72%	0	0.72%	0.00%	0.00%
2	12	5	4	16	0	1.05%	6	1.05%	0.74%	0.00%
3	19	7	4	17	0	4.79%	0	4.79%	0.00%	0.00%
4	15	9	5	20	0	5.21%	0	5.21%	0.00%	0.00%
5	7	2	1	10	0	2.50%	0	2.50%	0.00%	0.00%
6	10	5	3	15	0	3.53%	0	3.53%	0.00%	0.00%
7	14	8	6	18	0	4.88%	0	4.88%	0.00%	0.00%
8	19	10	7	21	0	5.14%	0	5.14%	0.06%	0.00%

Table 3: Results on case studies.

starting at the event occurrence time and ending at the current day end. For case studies $C1$ through $C5$, an optimal solution was found within 1 minute. Case $C6$ is larger and was solved to optimality within 10 seconds to 5 minutes depending on the nature of the events. We report the number of additional trucks used by our approach compared to the initial transportation plan and the unmet demand. The fourth part of Table 3 represents the deviation in transportation cost (Co) and unmet demand (De) compared to the complete information test. The unmet demand deviation is computed as the difference between the two approaches resulting unmet demand divided by the total demand. This includes both the initial demand and the new requests revealed during the week. The deviation in transportation cost does not include both the fixed cost for using trucks and the unmet demand penalty. The comparison is done only for routing costs. Negative values of cost deviation do not mean that the real-time approach does better than the complete information approach. It only means that the real-time model was unable to satisfy as much demand as in the complete information setting. This happens generally when the request of additional volumes is revealed close to the end of the day. Knowing in advance this information, the complete information approach manages to satisfy the demand. In contrast, the real-time approach does not have enough time to satisfy this late revealed demand.

Although the complete information benefits from an information advantage, the real-time approach offers the same performance in about 50% of the cases. Only, one must note that in some cases, even though the unmet demand and cost deviation are equal for both approaches, the number of used trucks might be unequal. If a truck undergoes a breakdown or a lot of delay, the first approach, knowing this information in advance, picks another truck instead beforehand. In contrast, the real-time approach uses this truck until these events are revealed and decides then to add an additional truck as a replacement. The routes produced by the two approaches are the same, but they are not operated by the same trucks.

The case study $C5$ is the same as $C4$ under the same disruptions scenarios.

The only difference is that no additional truck is allowed in $C5$. The results show that the real-time approach yields an average difference between the two cases of 0.81% for the unmet demand and -0.89% for transportation cost. Since the main goal is to satisfy the demand, adding a truck is the best option for this context. Also, for these two case studies, one may notice that the deviations in costs are approximately proportional to the unmet demand deviations. This is due to the configuration of these case studies. In fact, we have one product and one mill and the distances between the forest sites and the mill are approximately similar. Therefore, the cost of transportation is approximately proportional to the number of demand that is satisfied.

Compared to the complete information scenario, the proposed real-time approach produces good quality solutions since the cost deviation remains under 3.64% and the demand deviation is under 3.42%. This includes three extreme cases: $C3$, $C4$ and $C5$ under week 8. In these cases, there were late requests for new wood loads. Around 5% of the total initial demand was added close to the end of the day. This naturally explains the performance difference between the two approaches. In the real-time approach, some demand is revealed too late that it is impossible to satisfy it, while we assume that we are aware of this demand in the beginning of the week in the complete information approach. Another extreme case is $C6$. The results for $C6$ show an example where difficulties are met to satisfy the demand even for the complete information setting. We recall that some events prevent the demand satisfaction. For example, the demand cannot be satisfied if a loader at a mill is broken for a long period on a certain day. With an equal performance with regards to demand satisfaction, the complete information approach outperforms our approach by 0.06 and 0.75% in two of the eight generated weeks for this case, while it produces the same results for the 6 remaining weeks. This shows that the proposed approach results deviate slightly from the ideal setting where all the information about the disruptions is known in advance, and therefore demonstrates effectiveness of the real-time approach.

5. Conclusion

We have introduced a new approach to re-optimize the log-truck transportation plans in real-time when an unforeseen event is revealed. This approach uses a time-space network to represent the evolution of the transportation network over time and the changes it undergoes following a disruption. The allowed trips and loading/unloading operations are used as an input for the mathematical model. The latter is solved to obtain a new transportation plan. Ease of deployment of this new plan is taken into account through ensuring the continuity of trips that are in progress when the disruption is revealed unless they are directly impacted by the disruption. A simulation procedure was developed to generate the unforeseen events for real applications provided by FPInnovations. Compared to a complete information scenario where disruptions are assumed to be known in advance, the proposed approach produces very good results. Also, the mathematical model was solved in a few seconds and is thus well suited for a real-time context.

Future work involves using a heterogeneous fleet of trucks. The presence of trucks with a loader onboard may give more recourse strategies especially when facing loader breakdowns at forest sites or mills. The approach proposed in this paper could be adapted to this context. The time-space network could be used to represent the disruptions impacts on the forest supply chain. However, since the trucks may have different capacities and loading constraints, one must duplicate the arcs for each truck class. This will increase the size of the problem. In this context, column generation could be used for solving this problem.

In the problem that we study, a part of the input is revealed dynamically and the routes are modified accordingly. The dynamic input corresponds to the unforeseen events and the transportation plan is re-optimized every time a disruption happens. One drawback of this approach is that it does not anticipate the disruptions. A stochastic model would be able to produce solutions that are less vulnerable to disruptions. Unfortunately, there exists no study on the probability distributions of such events in the forest industry. Conducting such a study is challenging given that it is hard to get historical data. This is, however, an avenue for future research since many forest companies are investing in log-trucks with onboard computers, positioning systems, and communication technologies that can be used to collect accurate data on disruptions.

Acknowledgements

The authors would like to thank the Natural Sciences and Engineering Research Council of Canada (NSERC) Strategic Network on Value Chain Optimization (VCO) for their financial support. In addition, we wish to thank FPInnovations for their valuable collaboration.

References

[1] A. Weintraub, C. Romero, Operations research models and the management of agricultural and forestry resources: a review and comparison, Interfaces 36 (5) (2006) 446–457.

[2] M. Rönnqvist, S. D'Amours, A. Weintraub, A. Jofre, E. Gunn, R. G. Haight, D. Martell, A. T. Murray, C. Romero, Operations research challenges in forestry: 33 open problems, Annals of Operations Research 232 (1) (2015) 11–40.

[3] J. G. Borges, L. Diaz-Balteiro, M. E. McDill, L. C. Rodriguez, The management of industrial forest plantations, Springer, 2014.

[4] D. L. Martell, E. A. Gunn, A. Weintraub, Forest management challenges for operational researchers, European Journal of Operational Research 104 (1) (1998) 1–17.

[5] N. El Hachemi, M. Gendreau, L.-M. Rousseau, A heuristic to solve the synchronized log-truck scheduling problem, Computers & Operations Research 40 (3) (2013) 666–673.

[6] M. Gronalt, P. Hirsch, Log-truck scheduling with a tabu search strategy, in: Metaheuristics, Springer, 2007, pp. 65–88.

[7] M. Palmgren, M. Rönnqvist, P. Värbrand, A near-exact method for solving the log-truck scheduling problem, International Transactions in Operational Research 11 (4) (2004) 447–464.

[8] G. Rix, L.-M. Rousseau, G. Pesant, A column generation algorithm for tactical timber transportation planning, Journal of the Operational Research Society 66 (2) (2014) 278–287.

[9] A. Weintraub, R. Epstein, R. Morales, J. Seron, P. Traverso, A truck scheduling system improves efficiency in the forest industries, Interfaces 26 (4) (1996) 1–12.

[10] S. Linnainmaa, J. Savola, O. Jokinen, Epo: A knowledge based system for wood procurement management., in: Proceedings of the 7th Innovative Applications of Artificial Intelligence conference, 1995, pp. 107–113.

[11] J.-F. Audy, S. D'Amours, M. Rönnqvist, Planning methods and decision support systems in vehicle routing problems for timber transportation: A review, Tech. Rep. CIRRELT-2012-38, CIRRELT (2012).

[12] D. Carlsson, M. Rönnqvist, Supply chain management in forestry—-case studies at södra cell ab, European Journal of Operational Research 163 (3) (2005) 589–616.

[13] T. G. Crainic, M. Gendreau, J.-Y. Potvin, Intelligent freight-transportation systems: Assessment and the contribution of operations research, Transportation Research Part C: Emerging Technologies 17 (6) (2009) 541–557.

[14] M. Rönnqvist, D. Ryan, Solving truck despatch problems in real time, in: Proceedings of the 31st annual conference of the operational research society of New Zealand, Vol. 31, 1995, pp. 165–172.

[15] M. Rönnqvist, Or challenges and experiences from solving industrial applications, International Transactions in Operational Research 19 (1-2) (2012) 227–251.

[16] A. Alonso-Ayuso, L. F. Escudero, M. Guignard, M. Quinteros, A. Weintraub, Forestry management under uncertainty, Annals of Operations Research 190 (1) (2011) 17–39.

[17] D. Carlsson, P. Flisberg, M. Rönnqvist, Using robust optimization for distribution and inventory planning for a large pulp producer, Computers & Operations Research 44 (2014) 214–225.

[18] A. F. Marques, J. P. de Sousa, M. Rönnqvist, Combining optimization and simulation tools for short-term planning of forest operations, Scandinavian Journal of Forest Research 29 (sup1) (2014) 166–177.

[19] G. Figueira, M. Furlan, B. Almada-Lobo, Predictive production planning in an integrated pulp and paper mill, IFAC Proceedings Volumes 46 (9) (2013) 371–376.

[20] N. Secomandi, F. Margot, Reoptimization approaches for the vehicle-routing problem with stochastic demands, Operations Research 57 (1) (2009) 214–230.

[21] C. Novoa, R. Storer, An approximate dynamic programming approach for the vehicle routing problem with stochastic demands, European Journal of Operational Research 196 (2) (2009) 509–515.

[22] M. Rönnqvist, Optimization in forestry, Mathematical programming 97 (1-2) (2003) 267–284.

[23] N. El Hachemi, I. El Hallaoui, M. Gendreau, L.-M. Rousseau, Flow-based integer linear programs to solve the weekly log-truck scheduling problem, Annals of Operations Research 232 (1) (2015) 87–97.

[24] D. Carlsson, M. Rönnqvist, Backhauling in forest transportation: models, methods, and practical usage, Canadian Journal of Forest Research 37 (12) (2007) 2612–2623.

[25] A. Amrouss, M. Gendreau, B. Gendron, Managing unforeseen events in forest transportation, J-FOR- Journal of Science & Technology for Forest Products and Processes 5 (5) (2016) 40–50.

[26] P. A. Rey, J. A. Muñoz, A. Weintraub, A column generation model for truck routing in the Chilean forest industry, INFOR: Information Systems and Operational Research 47 (3) (2009) 215–221.

[27] P. L'Ecuyer, L. Meliani, J. Vaucher, Ssj: a framework for stochastic simulation in java, in: Proceedings of the 34th conference on Winter simulation: exploring new frontiers, Winter Simulation Conference, 2002, pp. 234–242.