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# MANAGING UNFORESEEN EVENTS IN FOREST TRANSPORTATION

AMINE AMROUSS\*, MICHEL GENDREAU, BERNARD GENDRON

**ABSTRACT** When wood is transported from forest areas to plants, unforeseen events may occur and disrupt planned trips. In this paper, we present heuristic methods for solving real-time transportation problems in which the initial plan must be re-optimized to deal with unforeseen events. Here, the nature of the events that must be dealt with differs radically from what can be found in the routing literature because changes involve not only demand (e.g., the arrival of a new request), but also the topology of the transportation network (e.g., road closures). Because the consequences of such events on transportation are trip cancellations and/or delays, the proposed approach deals first with single cancellations and single delayed trips and builds on these simple events to deal with more complex ones. The heuristic methods proposed here can provide dispatchers with alternative plans in a few seconds.

## INTRODUCTION

According to Natural Resources Canada [1], Canada is by any measure a forest nation. With 348 million hectares of forests, it is the second largest exporter of raw forest products after the United States. In 2013, the contribution of the forest industry to Canada's GDP stood at \$19.8 billion. However, recent years have been difficult for the forest industry. It was heavily impacted by the global economic downturn, the collapse of the American housing market, and the detrimental effect of growing electronic media on newspapers. Meanwhile, Canadian companies have managed to reduce their dependence on the American market by opening up to Asian markets.

To stay competitive, Canadian companies must place innovation at the core of their competitive strategies. In this context, using optimization models and methods arises naturally as a way to reduce costs, respond efficiently to customer needs, and reduce the negative environmental impacts of forest operations. In particular, Canadian firms are using optimization models and methods to improve

the efficiency of various forest supply chain components, including transportation of forest products [2,3]. This paper focuses particularly on optimizing real-time timber transportation from forest sites to wood mills. During transportation, unforeseen events may occur and disrupt the original plan. Recent technological advances have made it possible to capture such events in real time, providing oppor-

tunities to improve the performance of existing dispatching systems that generally rely on the dispatcher's experience. We propose methods that can process information in real time and react to various unforeseen events that may occur during transportation plan execution.

The rest of this paper is organized as follows. The first section describes the challenges related to forest transportation



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planning and control in real time. The next section reviews the literature related to real-time transportation in forestry. Proposed methods to react to real-time disruptions are then described. The results of this approach are presented in the following section. Finally, the last section concludes this paper.

**PROBLEM DESCRIPTION**

This paper focusses on real-time transportation operations that move timber from forest sites to wood mills, i.e., the first half of the forest supply chain. The other half of this supply chain, linking wood mills to consumers of finished wood products, is beyond the scope of this work.

Every wood mill and every forest site is equipped with a loader. The mills are usually open only for a specific period of the day. There are a number of forest products to transport. A product is defined by its species, quality, length, and diameter. The truck fleet is homogeneous, and each truck is associated with a base, usually at a wood mill, at which it must begin and end its day. Mill demand for forest products and their availability are generally given for a period of one week, but may be divided by days. Volumes can be expressed in terms of full truckloads because the truck fleet is homogeneous.

When transporting wood from forest sites to mills according to a predefined plan, many unexpected events may disrupt the plan. When an event becomes known only during a trip, the truck that accomplishes this trip should be provided with an alternative plan. In the absence of relevant information on the state of the supply chain, the truck driver may choose an

alternative trip that is unnecessarily long, or worse, that becomes infeasible following another unforeseen event. It is therefore essential to provide drivers with real-time information, especially alternative itinerary suggestions, when a planned route is impracticable. Such events can disrupt the entire supply chain. For example, when a forest site becomes inaccessible, several trucks that are planned to visit this site may be impacted. The dispatcher must then proceed with major changes to the initial transportation plan. In this case, the dispatcher must provide a new plan in real time to the drivers, taking into account their current positions and whether or not their trucks are already loaded. Little time is available to solve such a heavily constrained problem, which leads to the need for a real-time decision support system.

Table 1 presents a list of the unforeseen events that often disrupt transportation plans. We have classified these unforeseen events into three categories. The first covers disturbances that are likely to appear at forest sites. The second concerns those affecting trucks and road networks. The third category includes problems that occur at wood mills. Note that this separation is not exclusive in the sense that, for example, a forest fire not only makes some forest sites inaccessible, but also a set of forest roads. Moreover, an unexpected event in a supply chain component typically generates disturbances for the other components. For example, if a loader at a forest site is working at a slower pace, this causes delay for the truck driver and then disrupts the timber reception plan at the wood mill.

This research has been carried out in partnership with FPInnovations, a non-

profit forest research centre dedicated to improving the Canadian forest industry through innovation. FPInnovations provided us with the case study presented in this paper. It is assumed that weekly transportation plans are developed to operate a fleet of homogeneous trucks in a supply chain with multiple products, multiple sources, and multiple destinations. Drivers are given a priority ranking based on specific criteria established by transportation companies, such as seniority, performance, or encouraging native workers in some regions. A higher priority ensures the driver a greater workload. Working hours are limited by regulatory constraints on the maximum number of consecutive driving hours and the minimum number of rest hours between successive shifts.

We assume a context in which every effort must be made to respect agreements with truckers on the working hours granted for each week. The rationale behind this goal is to keep truckers available for the forest industry in the face of competition for truckers with other industries such as oil and mining. In this context, one must observe as closely as possible the original plan agreed upon with the drivers, which limits possible changes to plans when unforeseen events occur. This paper presents methods that deal with this lack of flexibility and produce consistent alternative plans in reaction to real-time disruptions. This context and the proposed methods differ significantly from what can be found in the literature on similar problems in forestry and other sectors. The next section reviews this literature.

**TABLE 1** List of common unforeseen events.

Forest sites	Transportation	Wood mills
<ul style="list-style-type: none"> <li>• Truck at the wrong site</li> <li>• Loader not available</li> <li>• Changeover of loader grapples</li> <li>• Inventory inaccuracies</li> <li>• Pile of a product not accessible (behind a pile of another product)</li> <li>• Forest fires</li> </ul>	<ul style="list-style-type: none"> <li>• Road closure</li> <li>• Too many trucks inside the same cycle</li> <li>• Mandatory stop for weighing at checkpoints</li> <li>• Deficient forest road configurations (like sharp turns)</li> <li>• Road degradation, presence of a grader</li> <li>• Truck breakdown, misdirected truck, unforeseen stop by driver</li> <li>• Poor truck synchronization (some drive fast and some slow)</li> <li>• Weather conditions: heavy rain, thawing soils, poor visibility</li> <li>• Traffic jam or seasonal traffic increase (opening of the fishing or hunting seasons)</li> </ul>	<ul style="list-style-type: none"> <li>• Loader not available</li> <li>• Increase in demand</li> <li>• Queue for weighing at the mills</li> <li>• Changeover of loader grapples</li> <li>• Decrease in storage capacity</li> <li>• Decrease in demand</li> </ul>

## LITERATURE REVIEW

Construction of a transportation plan that satisfies demand at minimum cost while respecting availability and other operational constraints (such as synchronizing trucks with loaders and not exceeding their capacities) is known in the literature as the log-truck scheduling problem (LTSP). The LTSP can be seen as a vehicle routing problem with pick-up and delivery [4,5]. Most case studies in the literature that are relevant to this problem require that only a single vehicle serve each client only once. In forestry, this is not realistic because one vehicle cannot satisfy the entire demand of a wood mill. Rather, several visits are needed for each mill. This kind of problem is known as the vehicle routing problem with split deliveries [6,7]. In addition, certain constraints on delivery time windows must be respected. Variants of this problem have been addressed [8]. However, the approaches presented do not take into account the constraints of synchronization with loaders that are crucial to the problem presented in this work. These constraints appear in the LTSP, which was introduced in the context of optimizing forest industry transportation plans [9–11].

Optimization models and operations research methods are increasingly used to solve planning problems in the forest industry [2,3]. Among the most ambitious forest transportation optimization projects reported in the literature are the ASI-CAM project in Chile [12] and the EPO project in Finland [13]. The literature also contains contributions on logging truck routing and scheduling [14].

Recent technological advances have enabled the development of *intelligent transportation systems*. A review of these systems and the contribution of operations research to their development can be found in [15]. They are already in use for dispatching vehicles in real time in applications such as milk collection [16] or mail services [17]. There are also applications to cases where dispatching is relatively easier, such as emergency vehicle and taxi dispatching in urban environments where

it is not necessary, and usually is not even possible, to assign more than the next trip. The most frequent disturbances in these applications are the emergence of new demands during operations. However, the nature of the problems addressed in the context of this work is fundamentally different from the problems found in the literature because one must deal with changes not only in demand (e.g., arrival of a new request), but also in transportation network topology (e.g., road closure). The other major difference between real-time transportation problems in forestry and problems in urban environments is at the level of the supporting road network. Access to a forest site generally depends on a single forest road. It is usually impossible to find alternative ways to reach the same forest site, in contrast to urban areas, where the driver can access the same destination by an alternative route. This enables the dispatcher, in an urban context, to divert a vehicle from its initial destination to respond to a new request [18–21].

The literature on forest transportation problems in real time is sparse. The only work that we are aware of is a decision support system called CADIS (Computer-Aided Dispatch) developed for a New Zealand forestry company that no longer exists [22]. For privacy reasons, few details were given about the system, but the results were reported to be “of high quality” [23]. Other decision support systems are on the market for forest transportation and may include modules for truck dispatching, but these modules are typically managed manually or using undocumented methods. It has been reported [14] that, despite the lack of data in this area, FLO (Forest and Logistics Optimization) is probably one of the most advanced tools in the forestry industry. The American company Trimble, which markets installations of onboard computers and communication systems, is selling FLO. No indication has been given of the possible presence of models or optimization methods in FLO to react to disruptions. Note also that in these systems, vehicle dispatching is done only after receiving a call from the driver at the end of

a delivery. Future trips can be planned in advance, but these plans are not communicated to drivers. In the event of unforeseen circumstances, they must be updated. However, some forestry companies have a different mode of operation because truckers need to receive their working schedule for the whole week. In the event of unforeseen circumstances, flexibility decreases in this case because those responsible for the plan must try their best to follow the original plan that was agreed upon with the drivers. In the next section, we present methods that can be used in this particular context.

## METHODOLOGY

The starting point of the proposed approach is a pre-defined weekly transportation plan that can be derived manually or through an optimization method. This transportation plan is composed of a set of routes for each truck driver. Note that some routes in this set may be identical, but different truck drivers may operate them. As mentioned above, there is a priority ranking of truck drivers, and therefore the routes must be further distinguished by driver. A route is then defined as a sequence of empty and full trips performed by a particular truck driver. A route also includes loading and unloading operations, as well as waiting and resting between successive shifts. Time is discretized into a set of equal intervals, and the duration of a transportation operation is expressed as a multiple of these intervals. The loading and unloading durations are approximately equal, and hence their duration can be used as a discretization step. Demand and supply are expressed as full truckloads because the fleet is homogeneous. To model the problem of selecting the best route for each truck while respecting operational constraints, let us first define the input parameters of the model:

$F$  = Set of forest sites,  
 $M$  = Set of mills,  
 $P$  = Set of wood products,  
 $T$  = Set of trucks,

$R$  = Set of feasible routes,  
 $I$  = Set of time intervals,  
 $c_r$  = Cost of route  $r$ ,  
 $c$  = Unmet demand penalty,  
 $d_{mp}$  = Demand for product  $p$  at mill  $m$ ,  
 $s_{fp}$  = Quantity of product  $p$  available at forest site  $f$ ,  
 $n_{fmp}$  = Quantity of product  $p$  delivered from forest site  $f$  to mill  $m$  on route  $r$ ,  
 $n_{fi}$  = Number of loaders available over time interval  $i$  at forest site  $f$ ,  
 $n_{mi}$  = Number of loaders available over time interval  $i$  at mill  $m$ ,  
 $L_{rfi} = 1$  if route  $r$  includes a loading operation at forest site  $f$  over time interval  $i$ , 0 otherwise,  
 $U_{rmi} = 1$  if route  $r$  includes an unloading operation at mill  $m$  over time interval  $i$ , 0 otherwise.

The decision variables of the model are defined as follows:

$x_{fmp}$  = Quantity of product  $p$  delivered from forest site  $f$  to mill  $m$ ,  
 $\delta_{mp}$  = Quantity of unsatisfied demand of product  $p$  at mill  $m$ ,  
 $y_r = 1$  if route  $r$  is selected, 0 otherwise.

The mathematical model is inspired by the work reported in [11] that dealt with tactical (annual) transportation planning problems. The model was adapted for an operational (weekly) problem as follows:

$$\begin{aligned}
 & \text{Subject to} \quad \text{Min} \sum_{r \in R} c_r y_r + \sum_{m \in M} \sum_{p \in P} c \delta_{mp} \quad (1) \\
 & \sum_{f \in F} x_{fmp} + \delta_{mp} = d_{mp}, \forall m \in M, p \in P \quad (2) \\
 & \sum_{m \in M} x_{fmp} \leq s_{fp}, \forall f \in F, p \in P \quad (3) \\
 & \sum_{r \in R} n_{fmp} y_r \geq x_{fmp}, \forall f \in F, m \in M, p \in P \quad (4) \\
 & \sum_{r \in R} L_{rfi} y_r \leq n_{fi}, \forall f \in F, i \in I \quad (5) \\
 & \sum_{r \in R} U_{rmi} y_r \leq n_{mi}, \forall m \in M, i \in I \quad (6) \\
 & \sum_{r \in R} y_r \leq |I| \quad (7)
 \end{aligned}$$

$$y_r \in \{0, 1\}, \forall r \in R \quad (8)$$

$$x_{fmp} \in \mathbb{R}^+ \forall f \in F, m \in M, p \in P \quad (9)$$

$$\delta_{mp} \in \mathbb{R}^+ \forall m \in M, p \in P \quad (10)$$

The objective function (1) minimizes both the costs associated with the routes and the penalty incurred if the demand is not satisfied. The cost of a route is the sum of the costs of all the activities that constitute this route. This cost depends also on the priority ranking of the truck driver. The penalty cost is chosen to be large enough to ensure that demand is satisfied whenever possible. Constraints (2) and (3) aim at satisfying the demand while not exceeding the available supply. Constraint (4) ensures that products are delivered only if the corresponding routes are selected. Constraints (5) and (6) ensure that the number of trucks using a loader over any time interval is less than or equal to the number of available loaders at this interval. Constraint (7) limits the number of selected routes to the number of available trucks. Constraint (8) ensures that the route selection variables are binary, and constraints (9) and (10) ensure the non-negativity of the flow variables and the unmet demand variables respectively.

The number of routes that can be produced is generally large. The work reported in [11] uses column generation to solve this model iteratively by considering only the subset of routes that have

the potential to improve the objective function. After the model has been solved, the results are formatted to define weekly transportation plans for each truck driver and work schedules for each loader operator at wood mills and at forest sites. This approach makes it possible to define agreements with truckers on the workload that is granted to them for each week. In this particular context, one must try to respect the original plan agreed upon with the truckers because the forest industry is competing with oil and mining companies to attract these drivers.

When an unforeseen event becomes known, the model is not solved again from scratch. Rather, heuristic methods are used to define new routes that satisfy the model constraints based on the actual solution. The consequences of an unforeseen event are ultimately a combination of cancelled and/or delayed trips. Hence, the first step in this research was to develop recourse strategies for these two elementary disruptions, with the aim to build on these simple events to develop strategies for more complex disruptions.

### Cancelled Trips

As mentioned earlier, it is desirable to limit the number of changes to the original transportation plan. To achieve this, the system tries to reschedule the cancelled trip within the same week in such a way that a loader is free at the truck arrival time both at the forest site and at the mill. If

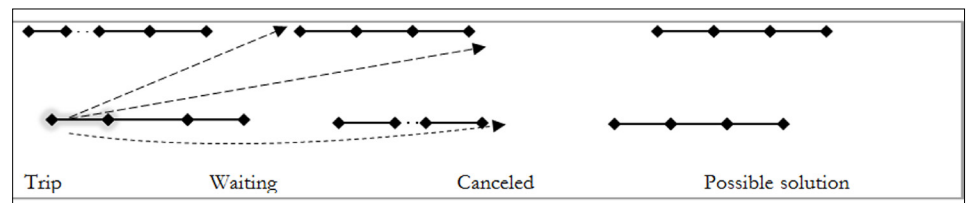


Fig. 1 - Initial solution.

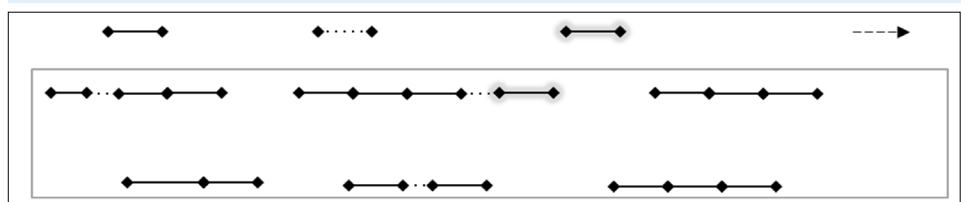


Fig. 2 - New solution.

this is possible, no other trips will be impacted or changed.

Figure 1 represents an excerpt from a transportation plan obtained by solving the mathematical model above. Each line represents the schedule of one truck and is composed of a set of shifts. Each shift contains a set of trips that may be interrupted by some waiting. Let us assume that the first trip of the second truck is cancelled. The cancelled trip can be rescheduled at the beginning or end of any shift of the same truck or of another truck, as long as the regulations on maximum driving hours and minimum rest time are met. To avoid impacting the other trucks' plans, the truck chosen to operate this trip may have to wait for the loader to be free before being loaded or unloaded. Efforts are made to minimize this waiting time as much as possible. Figure 2 shows one possible solution in which the cancelled trip was assigned to the first truck at the end of its second shift.

To describe the algorithm developed in this research to find all possible solutions, the following notation has been used:

- $Start_s^t$  = Start time of shift  $s$  of truck  $t$ ,
- $End_s^t$  = End time of shift  $s$  of truck  $t$ ,
- $Max$  = Maximum consecutive driving hours,
- $Min$  = Minimum rest hours between two shifts,
- $L_{ij} = 0$  if the loader is free at site (forest site or mill)  $j$  over time interval  $i$ ,
- $Max$  otherwise (this prevents choosing time intervals initially assigned to other trucks),
- $Del_s^t$  = Last delivery point of shift  $s$  of truck  $t$ ,
- $b_t$  = Home base of truck  $t$ ,
- $d_{i1i2}$  = Distance between two sites  $i_1$  and  $i_2$ ,
- $f^*$  = Impacted forest site,
- $m^*$  = Impacted wood mill,
- $\alpha_s^t$  = Waiting time at impacted forest site,
- $\beta_s^t$  = Waiting time at impacted mill.

The following algorithm identifies all the solutions that assign the cancelled trip to a truck at the end of one of its shifts while respecting the constraints on driving

```

for every truck  $t$  do
  for every shift  $s$  of truck  $t$  do
    for  $\alpha_s^t$  in  $\{0, 1, \dots\}$  do
       $\theta_1 \leftarrow End_s^t + d_{del_s^t f^*} + \alpha_s^t$  (the truck arrives at the impacted forest site and waits  $\alpha_s^t$  time units)
      if ( $\theta_1 - Start_s^t < Max$  and  $Start_{s+1}^t - \theta_1 \geq Min$ ) do
        for  $\beta_s^t$  in  $\{0, 1, \dots\}$  do
           $\theta_2 \leftarrow \theta_1 + L_{f^* \theta_1} + d_{f^* m^*} + \beta_s^t$  (the truck is loaded, arrives at the mill, and waits  $\beta_s^t$  time units)
           $\theta_3 \leftarrow \theta_2 + L_{m^* \theta_2} + d_{m^* b_t}$  (the truck is unloaded and goes back to its base)
          if ( $\theta_3 - Start_s^t \leq Max$  and  $Start_{s+1}^t - \theta_3 \geq Min$ ) do
            store the solution
            break
          end if
        end for
      end if
    end for
  end for
end for
end for
end for

```

and rest time.

For solutions that assign the cancelled trip to a truck before the start of one of its shifts, the same algorithm is used, but instead of beginning at the end of a shift, it begins at the start of a shift and moves backward to find a solution.

Because in the original transportation plan, the wood allocation was made from the impacted site to the impacted mill (optimally), it is desirable to keep the same allocation. To do this, it is necessary to ensure that this trip will take place. Knowing the distance that separates the two sites, all that remains is to find a truck that could reach the forest site during a time interval when the loader at this site is free and that could reach the mill during a time interval when the loader at the mill is also free. The first step is to verify whether one of the trucks used in the current week could make the trip at the end of one of its shifts or before the start of one of its shifts. If the tool can find several solutions using only initially planned trucks, the user has the choice among three decision criteria to determine the trucker who will perform this trip. The user may choose to allocate this trip to the trucker who lost the cancelled trip if that truck forms part of the found solutions. The second decision criterion proposed is the priority of the drivers, and the third criterion is the cost of the solution. The impact of these criteria on the solution is studied in the results section.

If no solution is found using existing trucks, other strategies are available to the user. The first is to extend the opening hours of the wood mill to receive the delivery. Similarly, such an extension might reveal several potential solutions, and the user should select a decision criterion as above. Another option is to check whether the transportation company could provide an additional truck to perform the trip. If so, the tool provides a preferential ranking of bases or starting points if several additional trucks are available. It is also possible to combine adding a truck to extending working hours.

Some events may make it impossible to keep the initial wood allocation, meaning that the product being transported in the impacted trip must be delivered from another forest site. In this case, the other sites where there is a surplus of this product are ranked according to the distance separating them from the destination wood mill. The impacted site is then replaced by the top-ranked forest site, and the process described above is repeated. After the final solution has been selected, the initial plans for loaders and trucks are updated.

This user interaction and the multitude of available options may seem cumbersome, but this was intentional. Indeed, the experience accumulated by FPInnovations staff showed them that their partners prefer to have control over their decision process. Certainly, the aim of this



work was to support the users in making decisions, but they wanted to be able to choose the solution that best suited their needs among a small set of choices, rather than having to deal with one imposed “optimal” solution.

### Delayed Trips

The second elementary event considered here is a delay in trip completion, which can be caused by various events such as degradation of forest roads, reduced visibility, or traffic jams. When such a delay is observed, the truck arrives at a wood mill or at a forest site in a different time slot than the one to which it was allocated in the initial transport plan. It may therefore occupy a time interval that was initially granted to another truck. The latter is then obliged to wait for the loader to become free and will in turn experience some delay relative to its initial plan. Any truck that joins the queue will also undergo delay. Similarly, the future trips of each of these trucks will also be automatically delayed. Hence, the delay propagates throughout the logistics system. In the case of a trip planned for the end of a loader’s working day, this propagation of delay could lead to deliveries arriving after the closing time of the corresponding mill. To forestall this, we capture this propagation, anticipate late arrivals (after closing time), and react in real time.

First, the transportation plan is updated to reflect delay propagation using the following algorithm, where  $TP$  is defined as the set of impacted trips. In the beginning, this set includes the current (delayed) trip in addition to all the following trips of this truck that are planned for the current shift. The algorithm works as follows:

1. If  $TP \neq \emptyset$ , sort the trips according to their arrival times at a loader and go to 2; else, stop.
2. If the first truck arrives when a loader is free, update the loader and this truck plan and go to 1; else, go to 3.
3. If the truck arrives during a time interval initially planned for another truck, add one time slot to this truck

time arrival for all current shift trips, add them to  $TP$ , and go to 1; else, go to 4.

4. If the truck arrives after business hours, store it as a late arrival and go to 1.

If the proposed tool predicts a delivery after business hours, it offers the user the option to extend the business hours to receive this delivery. If such an extension is impossible, this trip is considered as cancelled. The trip then ends up as a case of the first elementary unexpected event (cancelled trip), and the corresponding strategies are used.

### Loader Breakdown

When a loader breakdown occurs, it is assumed that an estimate of failure duration is available. With this information, the user specifies the maximum acceptable waiting time of a truck at this loader. If, for example, a truck were planned to arrive at this loader a few minutes before the estimated time for completion of a repair, it would be better to accept delay for this trip instead of cancelling it. Note again that this may not be the “optimal” solution, but this particular context favours simple adjustments over complete re-optimization of the transportation plan.

Once the waiting time threshold has been defined, all trips heading to the broken-down loader are separated into delayed trips and cancelled trips (to be rescheduled). The first step is to deal with delayed trips because they can lead by propagation to the cancellation of other trips, as explained above. These are added to the list of cancelled trips and are processed by the corresponding strategies. The processing order of these trips is that of the priorities of the truck drivers that operate each trip. This is justified by the fact that the earlier a trip is processed, the greater will be the probability of rescheduling it in the same week. This ensures the maximum volume of work as agreed upon with the priority drivers. Again, the solution may not be optimal in terms of costs, but it is more acceptable to drivers and dispatchers. This method can be sum-

marized as follows:

1. Go to the impacted loader plan and extract the trips related to the breakdown duration. The loader plan consists of a set of tuples “truck, product, origin/destination of product” for each time interval. These give information about the trips.
2. Given the waiting time threshold, separate these trips into trips to cancel ( $TC$ ) and trips to incur delay ( $TD$ ).
3. Use the delay method to update the plan. Add trips arriving after business hours to  $TC$ .
4. Order  $TC$  by truck driver priority.
5. For every trip in  $TC$ , use the cancelled trips method.
6. Update the plan.

Other disturbances can also be represented as loader failures. A forest fire or forest road closure undermines access to one or more forest sites and hence to the products there. Failure of a loader at a forest site leads exactly to the same result. Similarly, several unexpected events resemble each other in terms of their consequences, and the strategies presented in this section remain valid for dealing with them. For this reason, the proposed approach has been illustrated with loader breakdowns only.

## RESULTS

FPIInnovations provided a weekly planning problem based on real data. This problem is solved using an optimization method to obtain the transportation plan. In the week under study, the number of available trucks was 62, but the solution obtained by the optimization method used only 50 trucks to satisfy the demand. It was assumed that the user had recourse to some of the unused trucks to operate some trips if the initial transportation plan were disrupted due to an unforeseen event. As mentioned above, the fleet of trucks was homogeneous, but there was a priority ranking of drivers. There were 4 wood mills, 59 forest sites, and 12 different products. Total demand was 542 full

A.M. and/or end them after 7 P.M. Initially, loader schedules at forest sites were not restricted, but the optimization method, by minimizing transportation costs, also minimized loader operating hours. There are models in the literature that consider loader scheduling explicitly, as in [10]. Loading and unloading times were estimated at 20 minutes for this case study. Therefore, 20-minute steps were used to discretize the planning horizon. The trip duration between forest sites and wood mills ranged from 1.5 to 4.5 hours and depended on whether the trucks were loaded. The approximate driving cost was around \$100 per hour, and the waiting cost was about \$75 per hour. The difference between loaded and empty driving costs was captured in the duration of these trips. The maximal driving time per shift was 14 hours, and the minimal rest time between shifts was 10 hours.

The first step was to test how the tool reacted to single-trip cancellations and delays. When a trip must be rescheduled, the user is provided with different decision criteria. In current practice, there is no standard recourse used to react to unforeseen events. Therefore, it is impossible to predict user behaviour when choosing among the options offered by the tool. Moreover, this behaviour and the available options may vary depending on usage context. For example, the efficiency of adding a new truck depends on when the truck becomes available, as well as on the price charged by the truck owner. Hence, several scenarios were developed to examine how the different options impacted the resulting solutions and to achieve a proof-of-concept of the ideas presented in this paper. To reschedule a trip with respect to the regulations on driving and rest time, the following scenarios were defined:

- Scenario 1: Try to assign the trip to one of the existing trucks. If two or more solutions are found, the trip is assigned to the least costly truck. This is a classical scenario in which the main objective is to minimize costs. This scenario will be used as a reference for comparison with the results of the

other scenarios.

- Scenario 2: Try to assign the trip to one of the existing trucks. If two or more solutions are found, the trip is assigned to the truck that has the highest priority.
- Scenario 3: Try to assign the trip to the impacted truck (the one that lost the trip).
- Scenario 4: Try to assign the trip to one of the existing trucks. If no solution is found, the mill opening time is extended to enable the truck with the highest priority to operate the trip.
- Scenario 5: Try to assign the trip to one of the existing trucks. If no solution is found, the mill opening time is extended to enable the least costly truck to operate the trip.
- Scenario 6: Try to assign the trip to the impacted truck. If no solution is found, the mill opening time is extended to enable this truck to operate the trip.
- Scenario 7: Use an additional truck to operate the trip.
- Scenario 8: Extend the mill opening time and use an additional truck to operate the trip.

Then one of the planned trips was cancelled, and the performance of the proposed tool under each of the eight scenarios was measured. This test was repeated for every trip of the weekly transportation plan under consideration. This approach tested the tool under a wide scope of experimental conditions, ranging from early cancellations that are generally easier to reschedule to late cancellations happening at the end of the week. Table 2 presents a summary of the results and compares the effectiveness of the proposed tool under

the various scenarios. The first step was to compare the average transportation costs generated by the solutions. Note that extending the mill opening time and using additional trucks generated extra costs that are not included in the results because they depend on how transportation is managed and who owns the trucks (for instance, penalties may be incurred if a trip is cancelled for some drivers). Only the routing costs are used in Table 2. The first scenario is used as a reference with regard to cost. The third column of Table 2 gives the percentage of cancelled trips that the tool was able to reschedule within the same week under the various scenarios. The last column shows the changes in usage rate for the truck fleet.

It can be seen that scenarios 2 and 3 yield solutions with the highest costs. This could have been easily predicted because the cost of solutions found for the highest-priority truck or for the impacted truck is at best equal to the least costly solution. However, the average cost in scenario 3 is slightly lower than that in scenario 2. This can be explained by the percentage of solutions found under these scenarios: a solution using the impacted truck (scenario 3) was found in only 2.58% of instances, whereas under scenario 2, a solution was found in 51.58% of instances. The latter included some high-cost solutions that affected the overall average cost. Scenarios 4, 5, and 6 included extension of the mill opening time. This improved tool performance with regard to the ability to reschedule trips. The percentage of solutions using existing trucks increased from 51.58% to 91.14%. Although extending the mill opening time generally made it possible to find less costly solutions, it also generated new solutions that could not

Scenario	% Cost Increase	% Trips Rescheduled	% Increase in Truck Usage
1	0.00	51.85	55
2	35.54	51.85	74
3	34.86	2.58	73
4	-5.77	91.14	51
5	5.23	91.14	58
6	-1.18	10.52	54
7	-14.70	88.75	-47
8	-15.29	97.60	-47



be found under the first three scenarios. However, these solutions could have high costs that negatively impacted the average cost (as can be observed under scenario 5).

Adding a new truck in scenario 7 yielded a rescheduling capacity of 88.75%, which is lower than in scenarios 4 and 5, where the mill opening time was extended. However, the model found better solutions with regards to cost. This reduction was even more substantial when adding a truck was combined with extending the mill opening time (scenario 8). However, one must keep in mind that this additional flexibility comes at a certain cost. Taking this extra cost into account, the user can decide whether or not to use these options. Note also that the rescheduling capacity of the tool never reached 100%. This was due to trips that were planned at the end of the final day of the week, because there was not enough time left to reschedule these trips within the same week.

The last column shows that overall truck usage was improved for all scenarios except for those where a new truck was added. These results could have been easily predicted; note that these solutions can be found only if reallocation is done in real time. Otherwise, these opportunities are lost. The proposed strategy of allocating trips at the end of or before the start of a shift makes it possible to use underutilized trucks, increasing their productive hours and their annual tonnage. This key indicator could help convince forest companies of the importance of using such tools.

To measure the impact of the tool on delayed trips, we developed a random number generator that selects an impacted trip and delay duration. In all the experiments, our tool anticipated at least one truck arrival after mill closing time. Under current practice, these trucks would have to wait until the morning to be unloaded, which disrupts the plan for the following day. The proposed approach therefore includes a way of avoiding unnecessary trips to points that are inaccessible during the time allowed. These trips are processed as cancelled trips, and because the cancella-

tions of all the trips in the transportation plan under study were considered in the first set of tests, the results are not reproduced here.

In the methodology section, it was explained that many events have the same consequences on the transportation plan as a loader breakdown. Therefore, the loader breakdown example was used here to measure tool performance for more complex disruptions. One loader was chosen randomly, and the impacted trips were chosen depending on its breakdown occurrence time and duration. The duration times were also randomly generated. The first half of the trips were cancelled and the second half delayed. Recall that delay can generate extra cancelled trips. Hence, three test settings were defined and referred to as:

- Light: the breakdown duration ranges from one to two hours.
- Moderate: The breakdown duration ranges from three to five hours.
- Severe: The breakdown duration ranges from six hours to thirteen hours, which is the number of working hours in a day. In fact, it attains 13 hours only if the loader goes down exactly as it starts the day. On average, the duration of severe breakdowns remains between six and seven hours.

Note that when the loader is down for one hour, three trips are impacted on average. In fact, the loading or unloading time is approximately equal to twenty minutes. Therefore, three trucks will be unable to load or unload their shipments during a one-hour breakdown.

The occurrence time of breakdowns was chosen to be at the beginning or in the middle of the week. Breakdowns on the last day of the week were not studied because it is known that the impacted trips cannot be rescheduled within the same week. For a real application, the tool can easily handle a rolling horizon, which means trying to reschedule trips within the following seven days rather than in the same week. Note also that the same random numbers were used for all scenarios

to achieve a fair comparison.

Because breakdowns involve rescheduling a set of trips rather than only one trip as in the first tests, scenarios 3 and 6 were modified. When a solution using the impacted truck was not available, the highest-priority truck was used instead. A new scenario was also added:

- Scenario 9: Try to assign each trip to its initial truck. If the trip cannot be rescheduled, use an extra truck.

Table 3 presents the results for the various instances. The average cost under scenario 1 is used as a reference. The costs used in Table 3 are the costs per trip. This measure was used because the number of trips rescheduled varied in each scenario. The results using the impacted trucks were approximately equal to those using the higher-priority trucks (scenario 2 versus scenario 3, or scenario 5 versus scenario 6). This outcome can be explained by the fact that when no solution was found using the impacted truck, the trip was assigned to the highest-priority truck. Scenarios 7 and 8 gave exactly the same results. This means that extending the mill opening time did not improve the solutions obtained when using extra trucks. The absence of impacted trips late in the week may explain that phenomenon. Using extra trucks only for unassigned trips (scenario 9) generated additional costs that attained about 74% with the “Severe” setting. This enabled rescheduling all the trips, but at a higher cost. As shown by the results of scenarios 7 and 8, one may conclude that it is always better to assign all the trips to extra trucks. However, these costs do not include the extra fees for adding a new truck or the penalties incurred if the agreement made with the drivers regarding workload volume is not respected.

Extending the mill opening time produced interesting results. Comparing scenarios 1 and 4, it is clear that extending the mill opening time increased cost. The difference can be explained by the fact that extending the mill opening time generates new solutions that can be costly, but makes it possible to improve rescheduling

**TABLE 3 Results for one loader breakdown.**

Breakdown Category	Light		Moderate		Severe	
	% Cost Increase	% Trips Rescheduled	% Cost Increase	% Trips Rescheduled	% Cost Increase	% Trips Rescheduled
1	0.00	61.67	0.00	57.33	0.00	56.67
2	88.32	61.67	81.73	57.33	73.08	56.67
3	88.71	61.67	81.98	57.33	73.24	56.67
4	5.57	89.35	21.89	86.67	28.75	80.29
5	52.48	89.35	71.73	86.67	80.68	80.29
6	51.18	89.35	70.82	86.67	80.00	80.29
7	-2.78	100.00	12.15	100.00	18.37	100.00
8	-2.78	100.00	12.15	100.00	18.37	100.00
9	16.12	100.00	38.60	100.00	73.95	100.00

performance. This raises the question of finding the right trade-off between satisfying demand and minimizing costs. Furthermore, comparing scenarios 2 and 3 to scenarios 5 and 6 respectively shows that even if extending the mill opening time increases the number of rescheduled trips, it also reduces cost, except with the “Severe” setting. Therefore, in scenario 4, we can conclude that improving the solutions found in scenario 1 was not enough to offset the high costs of the new scheduled trips.

As for rescheduling capacity, it was better than in the single-trip cancellation tests (Table 2). This can be explained by the fact that trips very late in the week were discarded from the tests involving breakdowns. Note also that increasing the breakdown duration decreased rescheduling capacity for the first six scenarios. In the last scenarios, there were enough trucks to operate the impacted trips and also enough time to reschedule the trips within the same week.

Compared to current practice, the proposed tool makes it possible to increase overall fleet efficiency through quicker response, resulting in less lost time and reduced truck costs over the long term. However, the results show that only

56% to 62% of the trips could be rescheduled under the first three scenarios, which do not include extending the mill opening time and using additional trucks. The density of the loader plans, which contain only 15% free time intervals, can explain this phenomenon. Two additional case studies were used to confirm this explanation. These case studies, which are denoted as Case 2 and Case 3, considered the same supply chain, but demand was decreased to reduce the density of the loader plans. The demand was decreased by 15% in Case 2 and by 25% in Case 3. The free time intervals now constituted 28% and 37% of the new loader plans in Cases 2 and 3 respectively. Case 1 refers to the initial case study analyzed above. The “Moderate” test setting was used to compare these three case studies. For ease of comparison, Table 4 also reproduces the results of Case 1.

The rescheduling capacity in Cases 2 and 3 has increased as predicted. Moreover, scenario 2 is now quite different from scenario 3 (the same can be observed when comparing scenarios 5 and 6). This can be explained by the fact that the tool can find more solutions for the impacted trucks in Cases 2 and 3. Furthermore, the highest-priority trucks seem to generate

higher costs. The remaining results have similar characteristics to those obtained in Case 1.

One must keep in mind that the results presented in this section are averaged over a set of instances. In a real application, each case must be examined individually. For example, one might conclude from the results presented in this section that adding an extra truck always yields the best solution with regard to routing costs. However, for a single trip, this would not be the case if the home base of the available additional truck were far from the impacted sites. This is another reason for having many options available to users.

The tool aims to assist dispatchers in creating the best combinations of recourse strategies on the basis of cost, rescheduling capacity, and the nature of the unforeseen event. However, one key element of real-time decision support systems is computing time. The advantage of the heuristic methods presented here is that they can obtain a solution in a few seconds. Their drawback is that they do not always produce the optimal solution with regard to cost. However, the context under study in this paper favours adjustments to the transportation plan rather than complete re-optimization. Current

**TABLE 4 Comparison of case studies.**

Case	1		2		3	
	% Cost Increase	% Trips Rescheduled	% Cost Increase	% Trips Rescheduled	% Cost Increase	% Trips Rescheduled
1	0.00	57.33	0.00	94.56	0.00	100.00
2	81.73	57.33	98.65	94.56	86.27	100.00
3	81.98	57.33	95.38	94.56	46.11	100.00
4	21.89	86.67	-4.38	100.00	0.00	100.00
5	71.73	86.67	32.45	100.00	44.26	100.00
6	70.82	86.67	18.04	100.00	25.62	100.00
7	12.15	100.00	-6.99	100.00	0.00	100.00
8	12.15	100.00	-6.99	100.00	0.00	100.00
9	38.60	100.00	3.27	100.00	0.00	100.00

work includes developing mathematical models and exact methods to deal with contexts where the agreements defined with the truckers allow re-optimization of the disrupted transportation plan. This is the case, for example, when only one trip at a time is communicated to the drivers, instead of a weekly plan.

## CONCLUSIONS

The goal of the tool presented in this paper is to re-optimize a disrupted transportation plan in response to certain unforeseen events that may happen during trips between forest sites and wood mills. The inputs to the tool are a weekly plan (obtained manually or using an optimization method) and a set of unforeseen events. The testing prototype includes a generator of unforeseen events and implements heuristic methods used to reschedule trips depending on the type of unforeseen event. The results show that the tool can reschedule, for most of the tested instances, at least half the trips that could have been lost if no response was made in real time. This improves the overall usage rate of under-utilized trucks over the long term. The instances were derived from a real application and tested under generated unforeseen events. The approach developed here enabled the production of alternative solutions with little computing time. The cost of the solutions depended on the decision criteria considered. These included minimizing costs, increasing the workload of higher-priority trucks, or re-assigning lost trips to the impacted trucks. Recourse strategies tried to reschedule trips by using existing trucks, adding extra trucks, or extending the mill opening time. The last two options generated extra costs that varied depending on the supply chain configuration. The case study analysis, however, excluded these costs and compared the various solutions only on the basis of routing costs. The results showed that these two options made it possible to reschedule more trips, which avoided incurring penalty costs for unsatisfied demand. The user should then find a trade-off between satisfying demand and

minimizing average cost per truckload.

The utilization context considered in this paper is rather rigid in that truck drivers must be provided with weekly plans that the dispatcher must adhere to as much as possible. Better solutions can be found if the dispatcher is allowed to make more changes to the original plan. We are currently developing approaches to deal with different contexts, such as one in which only one trip at a time is communicated to drivers. In these contexts, the dispatcher waits until the driver finishes a trip before revealing the next trip. This context is more flexible and provides more recourse possibilities. Other contexts offer more flexibility by including trucks equipped with onboard loaders. These trucks are especially useful in the case of a truck breakdown. They can also be used in forest sites where only small volumes of wood are available, thus avoiding the use of a loader on these sites.

The unforeseen events have different characteristics at each occurrence. Some events are also interrelated. For example, degradation of a forest road could lead to its closure with a given probability. The aim of this paper is to present an approach for reacting to transportation disruptions. Collecting and validating relevant data and designing statistical processes that describe these interrelations are topics for future research that fit into the current development of Big Data in the forest sector. Indeed, more and more log trucks are equipped with onboard computers and communication technologies that can be used for this purpose.

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