INTEGRATING
A TACTICAL HARVEST-SCHEDULING MODEL
WITH A
LOG SORT-YARD LOCATION MODEL.

by

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ABSTRACT

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Keywords: facility location, log sort-yard location problem, forest products supply chain, harvest-scheduling model.

Failure to sort logs prior to their transportation to a mill can result in a loss of value in the forest products supply chain—for unsorted, higher value logs can be used in a low-value product where lower valued logs would otherwise suffice. To capture this lost value, a log sort-yard facility is used in the forest products supply chain. The sort-yard is located between multiple forest locations (supplies) and multiple mills (demands) and functions to grade, scale, buck and sort logs before they are trans-shipped to mills where the demand for their value is highest.

The problem of selecting the location of a sort-yard has been modeled by other researchers, but prior models have assumed that the locations of both log supplies and mills were fixed. In reality, the locations of log supplies are not fixed, but are selected using a multi-period, tactical harvest-scheduling model. The objective of this work is to formulate, test, and evaluate a model that simultaneously selects the location of cut-blocks and the location of a sort-yard over time.

This prototype model was tested on a small, toy data-set. Three scenarios were evaluated: a no sort-yard scenario, a fixed sort-yard scenario, and a scenario allowing the sort-yard to change location over time. Results revealed that the selection of cut blocks was highly sensitive to the changes in the scenarios, and that the approach of simultaneous optimization can lead to improved planning in the forest products supply chain.

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1. Introduction

1.1 Supply Chain Management

Supply chain management (SCM) is typically divided into three stages (Thomas and Griffin, 1996): the procurement of resources, the production of a product from these resources and the distribution of the completed product. Given these stages, a working definition of SCM would be:

> The simultaneous optimization of procurement, production and distribution, all the way from resource procurement to the consumption of a good by the final customer.

The complexity of supply chains requires that they be mapped; and the literature on this subject reveals two major types of supply chain maps (Haartveit *et al*., 2004): maps of divergent flows and maps of convergent flows. In a map of divergent flows, raw materials are manufactured into multiple end-products. In a map of convergent flows, multiple products are manufactured into a few end products (Haartveit *et al*., 2004).

Given the type of flow that characterizes a supply chain, optimization models are then developed to support decisions for each key operation within the supply chain. Hugos (2006) categorizes these key operations into four types of decision problems:

1. production scheduling,

2. inventory management,
3. location and
4. transportation

Production scheduling has been defined as the efficient allocation of resources over time for manufacturing goods (Rodammer and White, 1988). Production scheduling decisions address questions on the quantity and timing of the material in process within the supply chain. Production decisions also determine how many steps should be taken to produce a product and the sequence by which these steps should be taken (Graves, 1981).

Inventory management has the objective of ensuring the availability of products in the most timely and least-cost manner (CSCMP, 2011). Costs associated with inventory management include: replenishment cost, carrying cost, lost sales and system control costs (Silver, 1981). Replenishment costs are incurred whenever an action is required to replenish an inventory. These costs can either be fixed or dependent on lot size. Carrying costs are associated with holding an item in inventory. Carrying costs include: interest on loans used to purchase inventory, warehouse operational costs, insurance on inventory, and potential spoilage. Lost sales occur when the demand for a product exceeds the supply and include: the lost-sale cost, the cost of backordering and the loss of customer good will.

Location problems in the supply chain are concerned with selecting facilities that minimize the cost of transporting goods through all facility locations that are **fixed** within the supply chain, and with selecting facilities of lowest cost. Before any decision on the location of a facility can be made, candidate sites must be located, and costs for facility operations and service of customers must be determined (Owen and Daskin, 1998). A typical location problem requires data on a set of spatially distributed customers and a set of candidate facilities to serve the customers. Given these data, a location model is used to support decisions on which facilities to open and which customers to serve from each selected facility (Melo *et al*., 2009).

Transportation problems concern the finding of the least cost method of transporting goods through a set of locations that are given (i.e., rather than selected). One of the most well-researched transportation problems in operations research is the vehicle routing problem; the problem of assigning a minimal cost delivery route from a depot or depots to a set of different customers and then returning to the depot or depots (Laporte, 1992).

One of the major challenges in supply chain management is the overall design of an efficient supply chain. An efficient supply chain requires harmonization of activities in all organizations at every stage of the supply chain: i.e., in an efficient supply chain, decisions made at one stage should not be made in isolation from decisions made at other relevant stages in the supply chain.

1.2 Inefficiencies in Supply Chain Design of Forest Products

Although there has been important research into the supply chain of the forest products industry, the potential for improved profitability and performance has yet to be realized (Haartveit *et al*., 2004). Examples of how greater performances can be achieved have been identified and suggested by multiple scholars: e.g.,

1. Changing the drive behind management to a demand pull rather than a resource push on production (Haartveit *et al.,* 2004).
2. Better integration of the procurement and production stages of the forest products supply chain (D'Amours *et al*., 2008).
3. Managing for value creation, or value recovery, within the supply chain (Weigel *et al*., 2009).

These inefficiencies indicate that there is room for improving the relation between the procurement and the production stages of the forest products supply chain.

The objective of this thesis is to explore whether the integration of the tactical harvest-scheduling model and the log-sort locations model can be used to improve upon each of the three inefficiencies identified above. I shall first proceed with a literature review of both the tactical harvest-scheduling model and the log-sort locations models. This will be followed by and facilitate a detailed discussion of the specific objectives, significance and structure of my proposed work.

2. Literature Review

2.1 Sort-Yard Location Models

A log sort-yard is a temporary destination along a transport network where logs are graded, scaled, bucked, and sorted before being shipped to specialized manufacturing facilities. The motives for setting up a sort-yard vary, depending on who wishes to set up the yard. Dramm *et al*., (2004) list three distinct reasons for setting up sort yards: economic diversification, value recovery and risk reduction.

Economic diversification is an objective relevant to government-run sort-yards. Such sort-yards are chosen with the objective of diversifying rural economies by ensuring that a steady supply of suitable logs is made available for smaller mills directed at emerging markets of value-added products (Sunderman, 2003).

Value recovery is another objective in setting up a sort-yard. In this case, the central objective of a sort-yard is to ensure that the "right log" is sent to the "right mill":i.e., to prevent potentially high-value logs from being shipped and used where products requiring lower valued logs would suffice. Hence, sort-yards can play a key role in maximizing value recovery within the forest products supply chain.

Value recovery through sort-yards is especially relevant to land-owners with logs of diverse economic value. In such cases, sort-yards are used when detailed sorting of logs in the field is cost-prohibitive, or the cost of sorting at one mill and re-transporting sorted logs to another mill involves excessively high transportation cost. The location of the sort-yard is, therefore, selected to minimize the transportation costs incurred through the trans-shipment of logs from multiple forest locations to multiple mills.

Risk reduction through sort-yards is relevant to large, integrated, forest products firms desiring to even-out the inventory supply shortages caused by:

1. the operational difficulties of securing prompt access to particular log commodities directly from the forest; and
2. the stochastic nature of the wood market.

The buffer provided by a sort-yard against these uncertainties can be strategically important to the competitiveness of the firm.

The problem of examining where to locate a sort-yard requires information on timber supply, potential products, markets, industrial infrastructure, potential sort-yard locations and potential cut-block locations. The complexity and economic significance of this problem, therefore, justifies the development of a decision support model.

In operations research, the log sort-yard location problem can best be categorized as a facility location problem. Facility location models, in general, are used to select, from a set of candidate facilities, those which provide the lowest fixed cost and allow for the lowest transportation costs to multiple customers (Melo *et al*., 2009). Costs associated with facility location models include the cost of transporting goods to and from the facility, and the cost of constructing and operating the facility. The objective function is usually to minimize the sum of the fixed cost of the facility and the transportation costs of supplying multiple customers from the facility's location. Before any decision can be made, candidate sites for facilities must be located, and costs for facility operation and customer-service must be determined (Owen and Daskin, 1998).

The facility location problem has received great attention in operations research, and has evolved into multiple types (Daskin, 2003). Types of facility location models have been formulated to solve problems such as: Covering problems, median problems, center problems, fixed-charge location problems, and location allocation problems (Daskin, 2003).

Interestingly, the facility location model has been integrated with other models used to support decisions within the supply chain. For example, Shen (2000) and Shen *et al.* (2003) have integrated a facility location model with an inventory model. In addition, Perl (1983) and Perl and Daskin (1985) have also integrated a facility location model with vehicle routing model—such a model is relevant when a single truck is used to serve more than one customer from the selected facility.

Within the large family of facility location models, the log sort-yard location problem most closely resembles the multiple commodity multiple facility location model (Sessions and Paredes, 1987). In this model, first formulated by Geoffrion and Graves (1974), a set of plants produce a set of commodities, which are transported to a set of customers through one of a set of candidate distribution centres. This problem may be viewed as analogous to the sort-yard location, where there exists a set of cut-blocks that produce a set of log-types, which are transported to a set of mills through the selected location of a sort-yard.

Figure 1 conceptually illustrates the analogy between the multiple commodities multiple facilities location problem and the log sort-yard location problem.

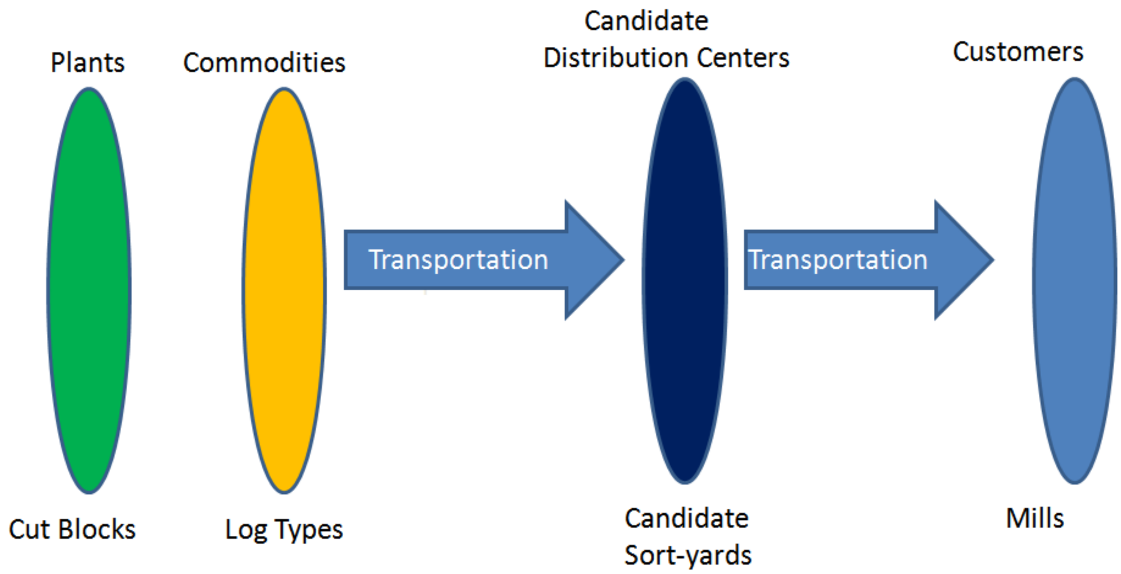

Figure 1: Multiple commodities multiple facilities location model as a sort-yard location model

In the multiple commodities multiple facilities location model, there is a set of factories which produce a set of commodities. These multiple commodities are then shipped to a set of customers with multiple demands for these commodities. The problem is to locate a distribution centre between the plants and the customers that minimizes the sum of transportation costs and fixed cost of the distribution centre while meeting all customer demands for the multiple commodities.

The log-sort-yard location model has not received much attention by researchers. In fact, only two distinct formulations for this problem exist in the literature. Sessions and Paredes (1987) were the first to formulate a model for this problem. Their objective function is to minimize the cost of sort-yard construction, operation and transportation. The formulation used one binary decision variable, one non-integer decision variable and two constraints. To overcome the computing slowness (the year was 1987), the prototype they developed had a two-stage heuristic for solving the problem. The first stage was used to solve the transportation problem of minimizing the hauling distance from multiple forest locations to the candidate sort-yards. The second stage used the results from stage one to select the location of the sort-yard.

Broad (1989) followed this work with a mixed integer linear programming (MILP) formulation of the log sort-yard location problem. As with Sessions and Paredes (1987), Broad's formulation had the initial flow of unsorted wood end at the sort-yard; after this, a second flow sorted wood proceeded from sort-yard to multiple mills. The objective of Broad's (1989) model was to minimize the sum of transportation and sort-yard costs while meeting customer demands. The model contained 12 linear constraints, one binary decision variable, and four non-integer decision variables.

Value recovery from a sort-yard was further studied by Sessions *et al*. (2005) using a case study of 340,000 ha on Vancouver Island, Sessions *et al*. (2005) collected data to evaluate whether it is more efficient to sort at a landing or at a sort-yard. The data were analyzed to estimate the probability of mis-sorting at the landing; *i.e.*, allocating and then transporting a log to a lower end-value, as distinct from its highest end-value. Using this probability, in addition to the costs of sorting and transporting logs, they concluded that it was most cost efficient to sort logs at the landing.

2.2 Tactical Harvest-Scheduling Models

In planning the harvest of a forest, a long-term, sustainable harvest-flow is first determined through a strategic harvest-scheduling model. Strategic forest planning models are typically linear programming models (Martell *et al.*, 1998) and their objective is to maximize volume, or the net present value of timber harvested, subject to constraints ensuring the long-term, even-flow, of harvestable wood from the forest. Beginning in the early 1970's, a host of LP models was developed: e.g., MAXMILLION (Ware and Clutter, 1971), Timber RAM (Navon, 1971) and FORPLAN (Stuart and Johnson, 1985).

Although advances have been made in incorporating spatial resolution, and therefore locational planning, into LP models (Mealey *et al*., 1982), the problem confronted by all LP approaches with regard to spatial planning is that the decision variables (representing the harvest period and harvest quantity assigned to a block or stand-type) are continuous; hence, a mapped schedule (*i.e*., spatial solution) cannot be produced using a linear programming model.

The objective of the tactical harvest-scheduling model is to allocate the sustainable flow of wood determined by the linear programming model. The allocation occurs over a shorter time horizon (typically 10 to 20 years) and the harvest is broken into discrete periods. In the tactical planning model, the forest is divided into cut-blocks, and the objective is to select a set of cut-blocks to harvest over time such that the net present value of the harvest is maximized, while the net present cost of the road network required to harvest the blocks is minimized. Although, as we shall see, the tactical model has expanded to include a multitude of diverse constraints and objectives, when one speaks of the "basic" tactical harvest-scheduling problem, it is typically defined as we have done so above (Murray, 1999).

In order to produce spatially explicit solutions, the tactical harvest-scheduling model is often formulated as an integer programming model. The many tactical models formulated in the literature can be divided into two broad categories, based on the different algorithmic approaches used for generating integer solutions (Shan *et al*., 2009):i) exact solution methods and ii) heuristic solution methods. The appeal of exact methods, such as branch and bound or dynamic programming, is that their solutions are demonstrably optimal. The disadvantage is that problem size acutely limits computing a solution in a reasonable period of time and for this reason the harvest-scheduling has been characterized as NP-hard (Weintraub *et al*., 1995): *i.e*., the computing time required to find exact optimal solutions increases exponentially with the addition of decision variables to the problem instance (Wolsey, 1998).

The appeal of metaheuristic algorithms (e.g., simulated annealing, genetic algorithms, tabu search) is that they can provide solutions to very large, realistically sized problem instances in reasonable periods of computing time; but the cost of such speed is that the solutions generated are not necessarily optimal, nor is their proximity to the optimum known (Reeves, 1993).

We divide our review of the literature on the tactical harvest-scheduling model based on these two categories.

2.2.1 Exact Solution Methods to the Tactical Harvest-Scheduling Model

Kirby *et al*. (1986) and Jones *et al*. (1986) were the first to formulate and apply an integer programming model of the tactical harvest scheduling problem. Kirby *et al*. (1986) found that optimizing roads and cut-blocks simultaneously generated savings of up to 43% over optimizing them separately. They also concluded that the branch and bound algorithm used was capable of solving problems of only modest size.

After the initial formulation by Kirby *et al*. (1986), the trend in research was to develop more complicated models that better reflected real world planning problems. These developments took the form of increasingly complex spatial constraints that were added in order to satisfy ecological objectives in tactical forest planning. Specifically, these spatial constraints were clear-cut opening size, wildlife habitat and aquatic ecosystem protection.

The first objective addressed in expanding the tactical planning model was the formulation of adjacency constraints. An adjacency constraint prevents the solution from containing two adjacent cut-blocks scheduled to be cut within a given period of time. The objective of this constraint is to prevent the cut-block sizes from becoming so large that they violate hydrological, habitat or visual quality objectives (Martell *et al*., 1998).

Torres-Rojo and Broadie (1990) were the first to formulate an integer model that incorporates adjacency constraints. Adjacency constraints were then formulated in two distinct ways (Murray, 1999): i) the Unit Restricted Model (URM), and ii) the Area Restricted Model (ARM).In the URM, each polygon represents the borders of a possible harvest opening, while in the ARM, each harvest opening can be composed of more than one polygon. Research on different URM formulations was conducted by Jones *et al*. (1991), Weintraub *et al*. (1994), Murray and Church (1996), Snyder and ReVelle (1997), Guignard *et al*. (1998) and McDill *et al*. (2002). Research on the URM formulation was conducted by McDill *et al*. (2002) and Crowe *et al*. (2003). Goycoolea *et al*. (2005) have since evaluated the multiple formulation techniques used in URM of the tactical harvest-scheduling problem.

While multiple formulations of adjacency constraints were designed and explored, other models were formulated to question the efficacy of adjacency constraints. Carter *et al*. (1997) used an integer programming model to evaluate the degree to which adjacency constraints can conflict with certain wildlife habitat objectives. Barrett *et al*. (1998) evaluated the economic and fragmentation effects of adjacency constraints using an integer programming model.

The concern with meeting ecological objectives through means other than adjacency constraints spawned a host of new tactical planning models, with increasingly complex spatial constraints—often tested on small (or toy) data sets. For example, Barahona *et al*. (1992) pursued the simultaneous objectives of habitat dispersion and harvest-scheduling in a tactical planning model. Hof and Joyce (1993) also formulated a model to optimize timber management and wildlife habitat simultaneously. Rowse and Center (1997) formulated an integer programming model to optimize both a tactical timber-harvest schedule and satisfy optimal water-run-off objectives. Yoshimoto and Broadie (1994) formulated a model to evaluate the short- and long-term impacts of spatial restrictions on harvest scheduling with reference to riparian zone objectives. Bevers *et al*. (1996) addressed the difficult problem of planning a schedule of harvests that constrain storm-flow levels. Hof and Bevers (2000) incorporated spatially defined sediment level objectives into a tactical harvest scheduling model.

Integer models eventually expanded to planning not only for the habitat of particular species, or particular aquatic areas, but also for spatial pattern of seral patches across the landscape. Spatially explicit old growth objectives were incorporated into a tactical harvest-scheduling model by Toth *et al*. (2007). Yu *et al*. (2007) formulated a tactical planning model to schedule harvests while simultaneously leaving behind a patchwork of age-classes to emulate ‘natural’ disturbance patterns. Weintraub and Wilkstom (2008) also used integer programming to schedule harvesting activities while meeting long-term landscape pattern objectives.

2.2.2 Metaheuristic Solution Models of the Tactical Harvest-Scheduling Model

The second approach used to solving integer models of the harvest scheduling problem has been through the application of metaheuristic algorithms. O'Hara *et al.* (1989) were the first to use a heuristic approach, Monte Carlo integer programming, to solve the tactical harvest scheduling problem with adjacency constraints. Nelson and Broadie (1990) also used Monte Carlo integer programming to solve a similar tactical harvest scheduling model; they also evaluated their solutions against exact optima and found their heuristic solutions to be within 85%.

Simulated annealing was first used by Lockwood and Moore (1993) to solve the tactical harvest scheduling problem with adjacency constraints. Shortly after this research, the question of which metaheuristic algorithm is best suited to solving the tactical harvest-scheduling model was pursued for over a decade by multiple authors. Murray and Church (1995) compared the ability of Monte Carlo integer programming, hill-climbing, simulated annealing and tabu search to approach the optimal solution for two problem instances. Both tabu search and simulated annealing consistently were found to produce superior solutions.Pukkala *et al*. (2005) compared six metaheuristic algorithms in solving the tactical harvest-scheduling model. Bettinger *et al*. (2002) compared eight metaheuristic algorithms to solve models with increasingly difficult habitat constraints.

Eventually, the inquiry into which metaheuristic was best suited to solving the tactical harvest-scheduling model was changed into the inquiry of how best to tune the given metaheuristic's multiple search parameters (Thompson *et al*. 2009, Garcia-Gonzalo *et al.* 2012). Richards and Gunn (2003) performed an in-depth study on refining and tuning the tabu-search parameters in order to solve the harvest scheduling problem. Crowe and Nelson (2005) compared the solutions produced using simulated annealing to their exact optima and found that solution quality decreased as problem size increased.

Metaheuristic research on the tactical harvest-scheduling problem also expanded to solve problems with increasingly complex spatial constraints to satisfy multiple ecological objectives. Bettinger *et al*. (1998) used a metaheuristic algorithm to plan a harvest-schedule while controlling forest watershed effects. Bettinger *et al.* (1999) also used a metaheuristic search algorithm to optimize a harvest-schedule and elk habitat. Ohman and Eriksson (1998) used simulated annealing to plan for harvest schedules and contiguous patches of old growth.

The research using metaheuristic models also expanded to incorporate spatial objectives aimed at designing a landscape of multiple seral patches. Liu *et al*. (2000) used simulated annealing to schedule forest harvesting to meet multiple objectives, including spatially defined age-class patches. Kurtilla (2001) developed a method to evaluate the landscape impact of a solution and used this metric in the objective function of his harvest-scheduling model.

Baskent and Jordan (2002) used a metaheuristic algorithm to solve the tactical harvest scheduling problem that spatially emulates a 'natural' forest structure in order to emulate natural disturbance patterns. Caro *et al*. (2003) used a tabu search metaheuristic to solve a model designed to plan for both adjacency constraints and a controlled dispersal of old growth patches.Venema *et al*. (2005) used a metaheuristic to schedule harvests at the landscape scale and to satisfy a diversity of 'landscape ecology metrics'. Ohman and Lamas (2005) used simulated annealing to schedule harvests and reduce forest fragmentation. Zeng *et al.* (2007) developed a heuristic optimization model aimed at reducing the risk of wind damage. Bettinger *et al.* (2007) used a tabu-search metaheuristic algorithm to solve a "landscape design" problem through using a multi-objective simulated annealing model.

2.2.3 Observations on Literature Review

This review of both exact and metaheuristic approaches to modeling the tactical harvest-scheduling model reveals three major trends:

1. the incorporation of increasingly complex spatial planning methods;
2. the formulation of models designed to satisfy an increasing demand for the incorporation of ecological objectives into harvest-scheduling; and
3. a general indifference to formulating innovative models that would complement or enhance decisions made at the short-term, operational planning level. This indifference may be characteristic of the perspective in forest planning, noted earlier, which has been oriented towards a supply-push, rather than a demand-pull.

3. Objective, Significance, and Structure of this Thesis

3.1 Objective

The objective of this thesis is to explore whether the integration of the tactical harvest-scheduling model and the log-sort locations model can be used to improve upon each of the three inefficiencies identified in section 1.2. We can observe from the literature review that such integration would constitute an innovation not only in modeling the tactical harvest-scheduling model, but also the log sort-yard location problem.

3.2 Significance

Innovation is fine, but what significant contribution could this integration make to improve the effectiveness of the forest products supply chain? We will confront this question of significance by answering how our integrated model could effectively address the three areas of improvement needed in the forest products supply chain (as identified above, in section 1.2). The three areas of improvement will be addressed separately.

3.2.1 Changing the drive behind management to a demand pull rather than a resource push on production

An integration of the harvest-scheduling model with the log-sort-yard location model would lead to a tactical level cut-block allocation made in consideration of each of the mills' locations and demands. Even if the fixed costs of a sort-yard were prohibitively high, and no sort-yard were selected, the integrated model would still produce solutions where cut-block locations were made in consideration of demand and demand-location. This is significant because, as noted in the literature review, the "basic" objective function of the harvest-scheduling problem has been to maximize net present value (*i.e.,* the difference between the discounted revenue from the harvest and the discounted cost of building the required road network, and the shipping and handling costs); and to the best of our knowledge, no other tactical level harvest-scheduling model has taken into account multiple mill locations with multiple commodity demands when allocating cut-blocks.

Hence, the integrated model shifts the managerial perspective on tactical planning, from an exclusively supply-push perspective, to a demand-pull perspective; *i.e.*, the integrated model allows the locations of mill demand to reach back, in effect, from the operational planning level, to the tactical planning level, and influence cut-block location such that the commodities demanded by mills can be procured in a more efficient manner.

3.2.2 Better integration of the procurement and production stages of the forest products supply chain

A sort-yard can be used to reduce the risk of a mill not having access to a given log-type in a timely manner. The costs associated with this risk are lost sales and lost customer goodwill. In this respect, a sort-yard functions as an inventory management tool and there by facilitates a better integration of the procurement and production stages of the forest products supply chain.

Our integrated model is designed to select simultaneously the optimal locations of cut-blocks and sort-yards. Because of the simultaneous optimization, decision-makers can use this model to more fully explore the feasibility of establishing a sort-yard. Hence, insofar as this model can be used to increase the chances of finding a feasible sort-yard location, it makes a significant contribution to the opportunity of strengthening the integration of the procurement and production stages of the forest products supply chain.

3.2.3 Managing for value creation, or value recovery, within the supply chain.

Based on our review of the sort-yard location problem, the role of a sort-yard in value-recovery is obvious—its purpose is to ensure that each log is transported to a mill where its highest value will be captured.

What is less obvious is that the integration of a tactical harvest-scheduling model with a log sort-yard location model moves the planning, and therefore managing, of value recovery to an earlier stage in the planning process. In effect, the integrated model moves the objective of value recovery to the tactical planning stage of the procurement process and thereby removes the isolation of decisions made at this stage with regard to the objective of value recovery.

This is important because, in the traditional hierarchical planning approach employed in forestry, decisions made at the operational level are constrained by the cut-block and road allocation decisions made at the tactical level. Hence, the value recovery decisions made at the operational level are constrained by decisions made at the tactical level. But, as noted above, in an efficient supply chain, decisions made at one stage of the supply chain which can influence decisions made at a later stage in the supply chain, should not, if possible, be made in isolation from one another. This model removes the isolation of tactical level planning for value recovery from the operational level planning, and therefore makes a significant contribution to planning for value recovery.

3.3 Structure of Thesis

The formulation of the integrated model is presented and explained in Section 4. Next, a description of the toy data set on which the model is tested is described in Section 5. In Section 6, the results of applying the model to different scenarios are presented. In Section 7, I discuss the strengths and weaknesses of this model with respect to the objective of improving the forest products supply chain. In Section 8, I offer my conclusions and suggestion for further research.

4. Methods

4.1 Formulation of the Integrated Model

The formulation of the integrated tactical harvest-scheduling model and the log sort-yard location model is derived from the multiple commodities multiple facilities location model, formulated by Geoffrion and Graves (1974). The major changes include:

1. the addition of a dummy sort-yard to accommodate shipping unsorted wood, should the alternative of no sort-yard be selected; and
2. the integration of this model with a tactical harvest-scheduling model.

Sets and Indices

K, k = set and index for candidate cut-blocks.

N_k = set of cut-blocks adjacent to cut-block k

L, l = set and index for log-types.

J, j = set and index for candidate sort-yard locations.

I, i, = set and index for mills.

T, t = set and index for time period (each period is 5 years).

Parameters

D_{ljit} = demand for log-type *l* at customer *i* from yard *j* in term *t* (m^3 per period).

S_{lkjt} = Supply of log-type *l* at harvest site *k*, available through sort yard *j*, in period *t* (m^3)

C_{lkjit} = unit cost of harvesting and shipping log-type *l* between harvest site *k*, sort yard *j* and to mill *i* in term *t* (\$ per m^3).

f_{jt} = the fixed cost of building sort-yard *j* in term *t* (\$).

u_{ktj} = fixed cost of road construction and maintenance to access cut-block *k* in term t, from sort-yard j(\$).

R_{ljkit} = Revenue from delivering log-type *l,* from block *k*, sort yard *j*, to mill *i,* in term *t.* (\$ per m^3).

V_{jmin} = Lower limit for throughput of wood at sort-yard *j* (m^3).

V_{jmax} = Upper limit for throughput of wood at sort-yard *j* (m^3).

Bl_t = Lower limit for percent deviation from D_{lit} in period *t* (%).

Bu_t = Upper limit for percent deviation from D_{lit} in period *t* (%).

Decision Variables

x_{jt} = 1 if sort yard *j* is selected in period *t,* 0 otherwise.

y_{ijt} = 1 if the demand of mill *i,* is serviced by sort yard *j,* in period *t*, 0 otherwise.

z_{kjt} = 1 if cut-block *k* is harvested in period *t* and shipped through sort-yard *j*, 0 otherwise.

w_{lkjit} = the quantity of log type *l* shipped between harvest site *k*, facility *j* to mill *I*, in period *t* (m^3).

Equations (1) to (13) form the base model used in this analysis. For certain scenarios explored, equations (14) and (15) were added.

The objective function is to maximize the total revenue minus the fixed cost of building sort-yard *j*, the fixed cost of accessing cut-block *k*, and the transportation and handling cost of shipping log-type *l* from cut-block *k* through sort-yard *j* to mill *i* in period *t*.

$$Maximize \sum_{t\in T}\sum_{l\in L}\sum_{k\in K}\sum_{j\in J}\sum_{i\in I} R_{lkjit}w_{lkjit} - \sum_{t\in T}\sum_{j\in J} f_{jt}x_{jt} - \sum_{t\in T}\sum_{j\in J}\sum_{k\in K} z_{kjt}u_{ktj} - \sum_{l\in L}\sum_{k\in K}\sum_{j\in J}\sum_{i\in I}\sum_{t\in T} c_{lkjit}w_{lkjit} \qquad [1]$$

Subject to:

The volume shipped from each block cannot exceed its supply: *i.e.*, the total volume shipped to all mills, through all sort-yards *j*, of each log type *l*, in each period *t,* from each cut-block *k*, cannot exceed the supply of log type *l*, existing on cut-block *k*, in period *t*.

$$\sum_{j\in J}\sum_{i\in I} w_{lkjit} \le z_{kjt}S_{lkjt}\ \forall l = 1,\dots,L;\ k = 1,\dots,K;\ t = 1,\dots,T \qquad [2]$$

The total volume shipped from all cut-blocks, *k*, through all sort-yards, *j*, cannot exceed or fall short of the upper and lower volume-bounds allocated to each mill, *i*, for each log type, *l*, for each period, *t*. That is*,* the amount shipped cannot exceed each mill's strategically allocated and sustainable demand.

$$\sum_{k\in K}\sum_{j\in J} w_{lkjit}Bl_t \leq \sum_{j\in J} D_{ljit}\, y_{ijt} \leq \sum_{k\in K}\sum_{j\in J} w_{lkjit}Bu_t\ \forall l = 1, \dots, L; \qquad [3]$$

$$i = 1, \dots, I;\ t = 1, \dots, T$$

One candidate sort-yard must be selected in each period (this includes the dummy variable where no sort-yard is selected).This constraint also means that it is possible to explore the effects of moving the sort-yard location between tactical planning periods. This may be feasible in situations where the fixed cost of establishing a sort-yard is small relative to the value of the logs shipped (e.g., when sort-yards can be established on recently harvested cut-blocks).

$$\sum_{j\in J} x_{jt} = 1 \qquad \forall t = 1, \dots, T \qquad [4]$$

The total volume of all log types, *l*, sent to all mills, *i*, flowing through a selected sort-yard in each period must be within an upper and lower limit.

$$V_{min}x_{jt} \leq \sum_{i\in I}\sum_{l\in L} D_{ljit}y_{ijt} \leq V_{max}x_{jt} \qquad \forall\, j = 1, \dots, J; t = 1, \dots, T \qquad [5]$$

Each mill, in each period, must be served by one sort-yard.

$$\sum_{j\in J} y_{ijt} = 1 \qquad \forall i = 1, \dots, I; t = 1, \dots, T \qquad [6]$$

If cut-block *k* is harvested in period *t*, then the entire supply of log types, *l*, available through sort-yard *j* must be transported to the mills. Note the supplies, s_{lkjt}, transported to mills will differ, depending on whether a real or a dummy sort-yard, j, has been selected.

$$\sum_{i \in I} w_{lkjit} = s_{lkjt} x_{jt} \quad \forall \ l = 1, \ldots, L;\ k = 1, \ldots, K;\ j = 1, \ldots, J;\ t = 1, \ldots, T \qquad [7]$$

Each cut-block may only be harvested once

$$\sum_{j \in J} \sum_{t \in T} z_{kjt} \leq 1 \qquad \forall k = 1, \ldots, K \qquad [8]$$

If a cut block is harvested, an adjacent block may not be harvested in the same period or the next period.

$$\sum_{k' \in N_k} z_{kjt} + \sum_{k' \in N_k} z_{k'jt} \sum_{k' \in N_k} z_{k'jt+1} \leq 1 \qquad \forall t = 1, \ldots, T; k = 1, \ldots, K; \qquad [9]$$

$j = 1, \ldots, J$

The decision to build sort-yard *j* in period *t* is binary:

$$x_{jt} \in \{0, 1\} \qquad \forall j = 1, \ldots, J;\ \ t = 1, \ldots, T \qquad [10]$$

The decision to supply mill *i* from sort-yard *j* in period *t* is binary:

$$y_{ijt} \in \{0, 1\} \qquad \forall i = 1, \dots, I; \;\; j = 1, \dots, J; \;\; t = 1, \dots, T \qquad [11]$$

The decision to cut block *k* in period *t* and ship it through sort-yard *j* is binary:

$$z_{kjt} \in \{0, 1\} \qquad \forall k = 1, \dots, K; \;\; j = 1, \dots, J; \;\; t = 1, \dots, T \qquad [12]$$

The flow of wood cannot be negative:

$$w_{lkjit} \geq 0 \qquad \forall l = 1, \dots, L; \;\; k = 1, \dots, K; \;\; j = 1, \dots, J; \;\; i = 1, \dots, I; \qquad [13]$$

$$t \;= 1, \dots, T$$

Only one sort-yard may be used across all periods:

$$\sum_{j \in J} x_{jt} \leq 1 \qquad \forall t = 1, \dots, T \qquad [14]$$

If a sort-yard is built on a cut-block, the cut-block must be harvested in the same period or a previous period.

$$x_{jt} \leq \sum_{j} \sum_{t<T} z_{kjt} \qquad \forall \; t = 1, \dots, T; \;\; j = 1, \dots, 4 \qquad [15]$$

This formulation requires a large number of binary decision variables. For example, assume this formulation were used on a problem instance with 100 candidate cut-blocks, 10 candidate sort-yards, three periods and three mills. This is a relatively small problem size compared to what is found in the real world. However, the number of binary variables would equal; x_{jt} = 30, y_{ijt} = 90, and z_{kjt} = 3,000, for a total of 3,120 for the problem instance. For this reason, we chose to test this prototype model using a small data-set.

4.2 Software and Hardware

For this analysis the CPLEX 12.1 solver was used. In order to decrease solution times, this solver allows for substantial manipulation of the branch and bound algorithm. However, the creators of CPLEX acknowledge that there are few rules for speeding up the branch and bound algorithm on MIP models. Some methods will speed up certain models while slowing down others (Maximal(a) 2012).

The software used in formulating this model in a manner readable by CPLEX was MPL 4.2, created by Maximal Software in Arlington, Virginia. MPL uses an algebraic modeling language that allows the modeler to create optimization models using equations (Maximal(b) 2012). The algebraic model is used as the basis for creating a problem matrix, which is read directly into the solver. Data can be entered into the model directly through the main file, or separately through referencing sparse-files, data-files or spreadsheets (Maximal(b) 2012).

In the case of this research, this model was built with all of the data entered into the main-file. The model, expressed in MPL can be found in Appendix 1.

The model was solved using an Intel® Core™ 2 CPU, 6320 @ 1.86 GHz, 2.00 GB of RAM.

5. Description of Data Set

5.1 Spatial Distribution of Data

The spatial layout of the data-set used to test this model is illustrated in Figure 2. It consists of 100 candidate cut-blocks, nine candidate sort-yards, a dummy sort yard, three mills and a transportation network.

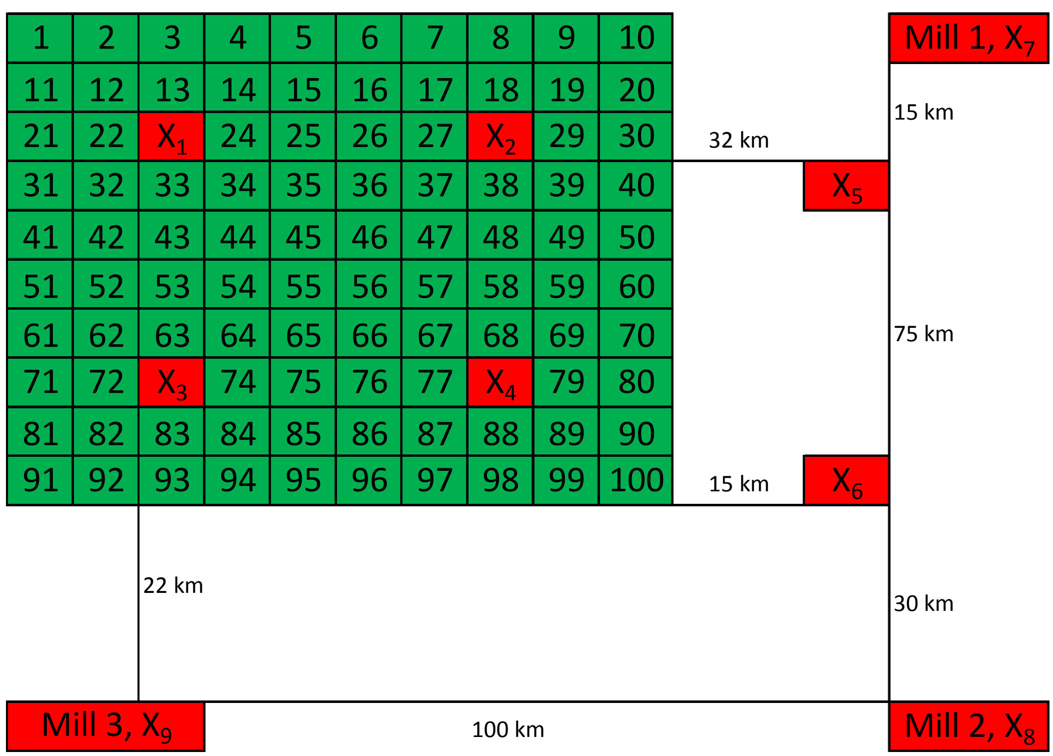

Figure 2: Spatial design of the data-set

There are nine candidate sort-yards (coloured red): four of the cut-blocks are treated as candidate sort-yards; two candidate sort-yards are located along the road to the mills; and there is one candidate sort-yard at each of the three mills. There is also a dummy sort-yard used to allow for the option of transporting unsorted wood directly to the mills.

The roads outside the forest are also displayed in Figure 2. The length of each road segment is shown beside each road. Roads inside the forest are not shown, but it is assumed that transportation is only possible between adjacent blocks. Since each stand is 100 ha in size, each road segment within the forest is 1 km in length. Adjacent blocks are defined as those which share an arc, not a point. For example, block 1 would have blocks 2 and 11 as adjacent blocks, but not block 12.

In this data set, transportation costs are measured in $\$/m^3/km$, and were calculated from the method described in Martin (1971). This calculation provided transportation costs for a $50m^3$ truck load of $\$0.12/m^3/km$ in the forest, and $\$0.07/m^3/km$ on the highway. It assumed that there were roads from every bock to every adjacent block, and that transportation would take place along the shortest path.

5.2 Inventory and Log-Values in Data Set

Five different stand-types were used in the data-set. These stand-types are:

1. high quality hardwood,
2. low quality hardwood,
3. high quality mixed-wood,
4. low Quality Mixed-wood and

5. coniferous.

The spatial distribution of the five stand-types is illustrated in Figure 3.

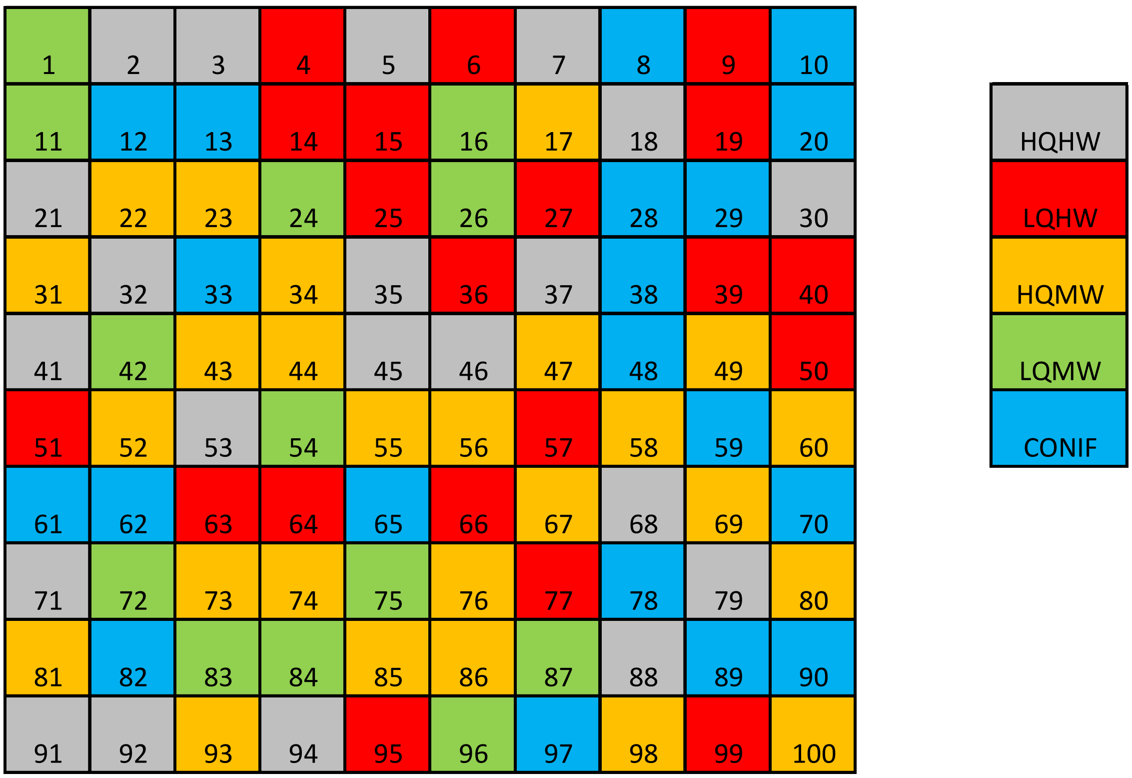

Figure 3: Spatial distribution of the five stand-types within the forest

The forest inventory was designed to represent a mixed-wood forest from which seven sorted log-types and two unsorted log-types are available. The sorted log-types, and the estimated revenue generated from selling these logs to the "right mill" are presented in Table 1. These prices were obtained from the Maine Forest Service (Maine, 2010).

Table 1: Revenue from selling the seven sorted log-types

Sorted Log	Revenue ($/m^3)
Telephone Pole	300
High Quality Softwood Saw-Log	190
Low Quality Softwood Saw-Log	150
Hardwood Veneer	450
High Quality Hardwood Saw-Log	300
Low Quality Hardwood Saw-Log	210
Pallet Wood	65

Within each stand-type, volumes and constituent proportions of log-types were assigned randomly, but within limits typical of each stand-type. Table 2 presents the maximum and minimum volumes for each log-type found within each stand-type.

Table 2: Maximum and minimum volumes for each log-type in each stand-type.

		Volume Limits for each Stand-Type (m^3/ha)				
Log-Type	Limit	HQHW	LQHW	HQMW	LQMW	CONIF
Telephone Pole	Maximum	15	5	35	5	50
Telephone Pole	Minimum	0	0	20	0	35
HQ Soft Saw	Maximum	0	0	55	30	15
HQ Soft Saw	Minimum	0	0	30	10	0
LQ Soft Saw	Maximum	15	10	55	10	65
LQ Soft Saw	Minimum	0	0	30	0	0
HW Veneer	Maximum	25	15	55	30	0
HW Veneer	Minimum	10	5	30	10	0
HQ Hard Saw	Maximum	55	50	30	30	0
HQ Hard Saw	Minimum	30	25	15	10	0
LQ Hard Saw	Maximum	55	50	30	50	20
LQ Hard Saw	Minimum	30	25	55	20	0
Pallet Wood	Maximum	25	25	10	25	15
Pallet Wood	Minimum	10	10	0	10	5
Maximum Volume (m^3/ha)		190	155	270	180	165
Minimum Volume (m^3/ha)		80	65	180	60	40
Average Volume (m^3/ha)		135	110	225	120	102.5

Calculating the value of each mixed-wood assortment was performed by multiplying the value of a log-type by its proportion in the mixed-wood assortment. For example, assume an assortment of mixed-wood can be broken down into 30% high-quality hardwood saw-logs, 30% low-quality hardwood saw-logs, 10% hardwood veneer and 30% pallet-wood. If this wood were sorted and transported to a mill, where its highest value is captured, the calculation of its value would be performed as presented in Table 3.

Table 3: Calculation for the value of sorted wood.

Log types found in mixed wood	Proportion in mixed wood	Value of log	Contribution of log to value
High Q Hardwood Saw	0.3	$300.00	$90.00
Low Q Hardwood Saw	0.3	$210.00	$63.00
Hardwood Veneer	0.1	$450.00	$45.00
Pallet Wood	0.3	$65.00	$19.50
		Sorted Value($/m^3) =	$217.50

If the same mixed-wood were shipped to a mill *unsorted*, its value would be determined by the mill's demand for the individual log-types. If a log-type cannot be processed to its highest end-product, then it will be used for a lower quality product. Table 4 shows the value of this same assortment of mixed-wood when shipped un-sorted to a mill demanding only high quality hardwood saw-logs and pallet wood. In this case, the veneer logs are being used to produce high quality saw-logs and the low quality saw-logs are being used to produce pallet wood. From the data used in this example, the difference between the sorted value (see Table 3) and the unsorted value (see Table 4) represents a potential value loss of $58.50 per m^3.

Table 4: Sample calculation for the value of an un-sorted mixed-wood assortment

Log types found in mixed wood	Proportion in mixed wood	Is there demand at this mill?	Utilised value of log	Contribution of log to value
High Q Hardwood Saw	0.3	Yes	$300.00	$90.00
Low Q Hardwood Saw	0.3	No	$65.00	$19.50
Hardwood Veneer	0.1	No	$300.00	$30.00
Pallet Wood	0.3	Yes	$65.00	$19.50
			Un-sorted Value($/m^3) =	$159.00

5.3 Mill demand

The data set included three mills. Each mill has a demand that differs from the other mills. Demand did not change for each mill between periods. The demand for each mill for each log type can be seen in Table 5.

Table 5: Mill demand in 100s of meters cubed

Log-Type	Mill 1	Mill 2	Mill 3
Tpol	160	0	0
SSw2	125	50	100
HSw1	0	150	100
HSw2	150	0	115
Veneer	0	0	175
Pallet	50	70	75
SSw1	50	70	12.5
HMw	200	220	465
SMw	285	170	112.5

6. Results

The results were produced by applying the model to the data-set using three different scenarios over three terms of 5 years each (t = 3), and are presented below.

6.1 Scenario 1: No Sort-Yard Allowed

Our intention in running a scenario where the model was constrained from selecting a sort-yard was to observe whether the resulting allocation of blocks would make intuitive sense; *i.e.*, if no sort-yard were selected, then one would expect to see an allocation where the logs assigned to meet each mill's demand would be found in blocks clustered around or nearby the mills to which they have been assigned for transportation.

The harvest schedule for the first Scenario, the no sort-yard scenario is presented in Figure 4.

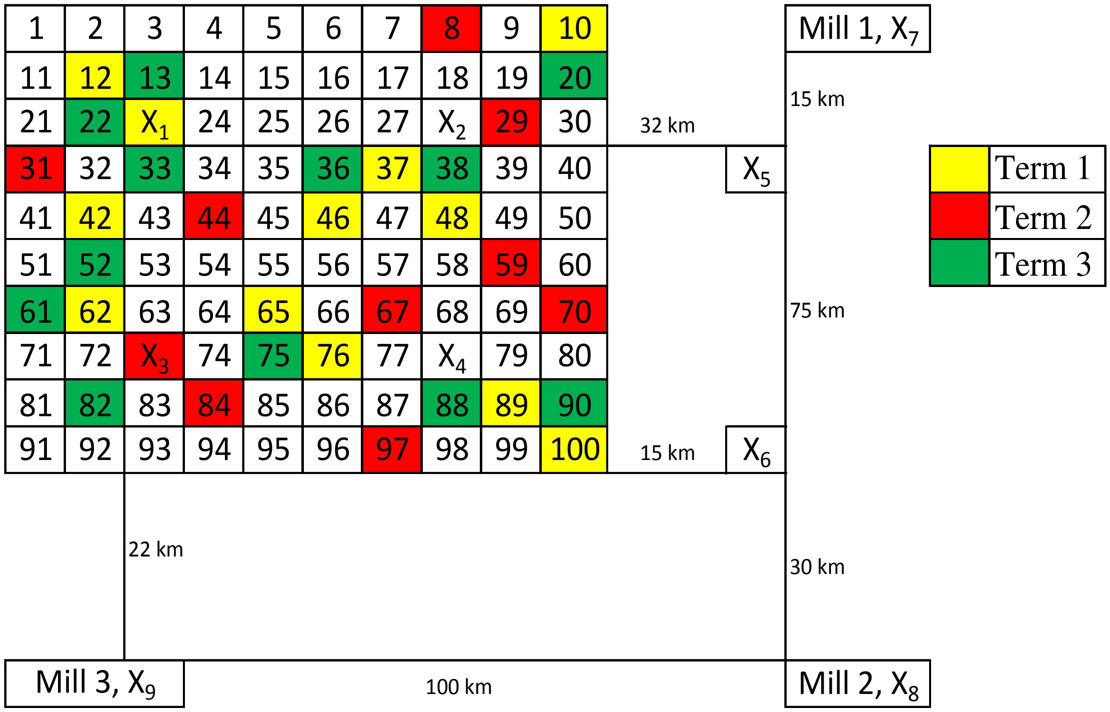

Figure 4: Harvest schedule for Scenario 1, where no sort-yard was selected

When the harvest-schedule in Figure 4 is observed, it is difficult to distinguish a pattern to the allocation (except that the adjacency constraints were followed.) This is because Figure 4 does not illustrate where the wood from these blocks is to be used. Therefore, we turn to Figure 5, which shows where each block harvested has its wood shipped.

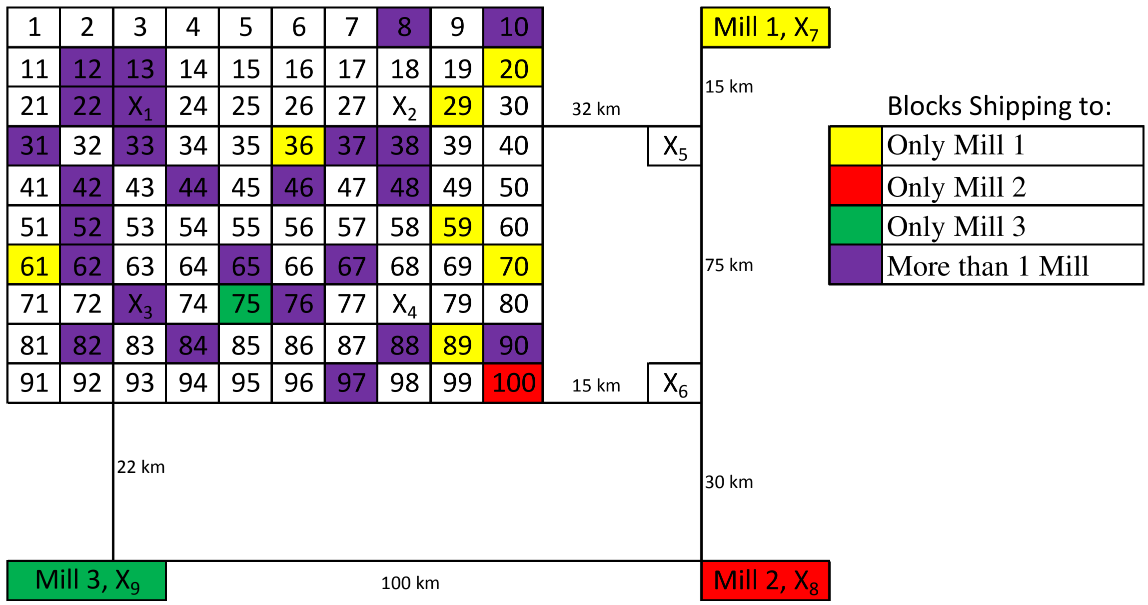

Figure 5: Transportation of wood to mills in Scenario 1.

Again, like Figure 4, there is no distinguishable pattern to the wood allocation illustrated in Figure 5. Some of the blocks send their wood to the closest mill, yet others, such as blocks 52 and 61 do not.

Given these results, I speculated that the wood allocation in Figure 5 does not show a distinguishable pattern because the solution is a compromise resulting from the conflicting objectives of maximizing both revenue and minimizing transportation costs. In other words, even though the logs from the harvested stands are transported to the mills unsorted, and the mills have demands for unsorted log types (*i.e.*, when the index j in the demand parameter D_{ljit} represents a dummy variable) the diversity of stands, and therefore diversity of log values within the stands, disposes each mill to preferring unsorted wood from some stands, where unsorted value is higher, than in other stands, where unsorted value is lower—even when an extra transportation cost is entailed.

Hence, in order to test our initial speculation, that, *ceteris paribus*, unsorted wood would tend to be allocated in clusters of stands located nearby the mills to which they were to be delivered, we designed a second scenario, Scenario 1b. In this scenario, the objective function was altered such that there would be no incentive to capture extra value – even in unsorted wood.

6.2 Scenario 1b: No Sort-Yard Allowed and No Reward for Value Captured

In Scenario 1b, we retained the constraint against selecting a sort-yard and altered the objective function such that each mills' demand for unsorted wood was to be based solely on minimizing transportation and harvest-unit access costs. In other words, the objective function became:

$$Minimize \sum_{t\in T}\sum_{i\in I}\sum_{k\in K}\sum_{j\in J}\sum_{i\in I} c_{lkjit}w_{lkjit} + \sum_{j\in J} f_{jt}x_{jt} + \sum_{k\in K} z_{kjt}u_{kjt} \qquad [16]$$

The alteration of the objective function in Scenario 1b is intended to produce an allocation that is blind to value and is focused only on meeting volume demands and minimizing transportation costs.

The resulting harvest-schedule for Scenario 1b is shown in Figure 6.

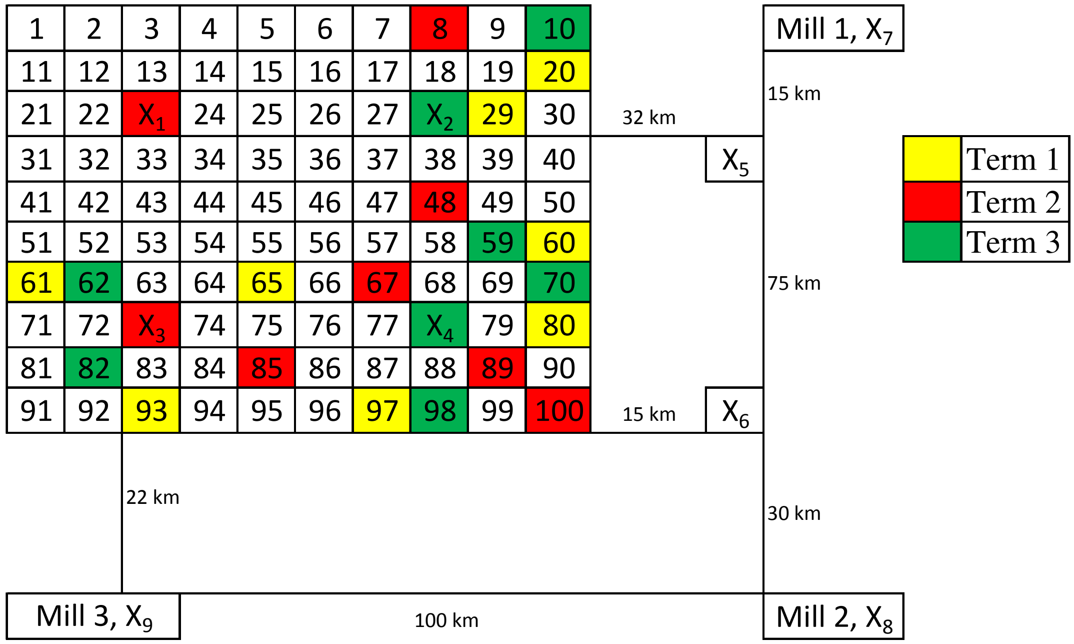

Figure 6: Harvest schedule for Scenario 1b with minimize cost objective function.

In Figure 6, we finally observe a distinct pattern, where cut-blocks are selected near the highways leading to each mill. This minimizes the transportation costs and the fixed costs of entering each block. The pattern is more evident when the allocation of wood to mills is mapped in Figure 7. Here it is clear that each mill is procuring its wood from the blocks closest to it.

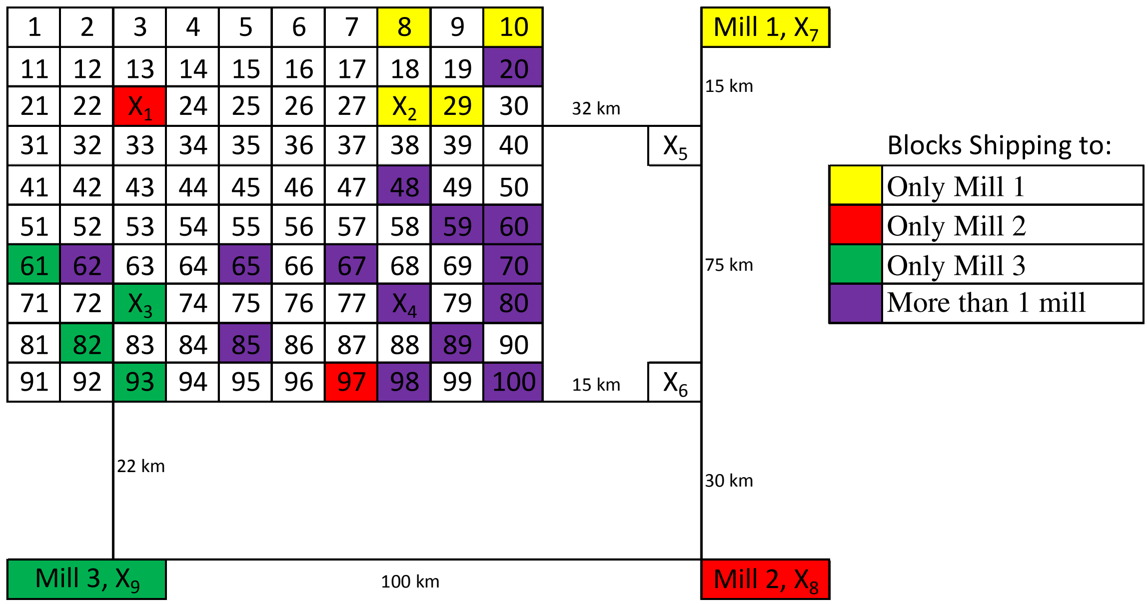

Figure 7: Wood allocation for Scenario 1b with the minimize cost objective function.

The output from Scenario 1 and 1b were also compared in terms of their value lost. In Scenario 1, the value lost averaged \$9.59 per m^3 of wood, and for Scenario 1b the value lost averaged \$25.69 per m^3.

The results from Scenarios 1 and 1b illustrate that the allocation of cut-blocks can be highly sensitive to changes in trade-offs that can occur between the conflicting objectives of minimizing transportation costs and maximizing revenue. This trade-off, of course, also occurs in regular harvest-scheduling models (where the objective is to maximize revenue and minimize road-building costs). The important difference between our integrated model and a standard harvest-scheduling model is that, when the transportation costs are high relative to the harvest-revenues from logs, instead of a total road network that is minimized, the integrated model minimizes transportation costs by allocating wood as closely as possible to its point of demand.

6.3 Scenario 2: One Permanent Sort-Yard is Selected

The harvest schedule for Scenario 2 (where a permanent sort-yard is selected) is illustrated in Figure 8.

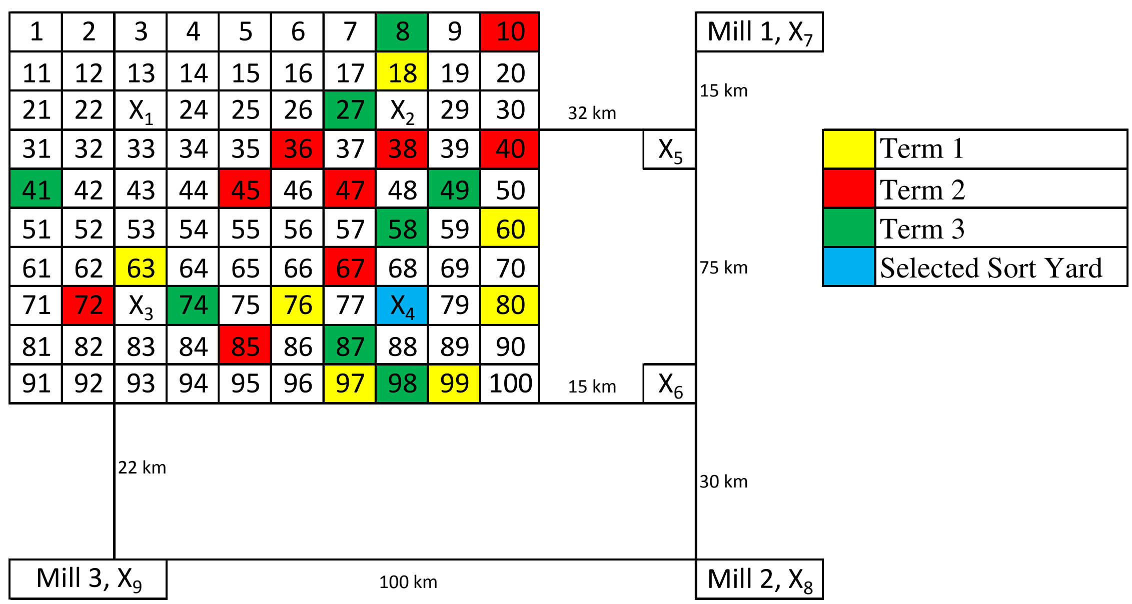

Figure 8: Harvest schedule for Scenario 2, where one permanent sort-yard is selected.

In this scenario, the candidate sort-yard, X_4, is selected. Here we observe that many, but not all, of the cut-blocks selected are clustered tightly around the selected sort-yard as the solution balances meeting each mill's demand while minimizing transportation costs. We can also observe that the adjacency constraints, in several instances, limit this clustering to different periods.

6.4 Scenario 3: Allow for a Non-permanent Sort-Yard Location

The fixed cost of establishing a log sort-yard can be quite small compared to the establishment of a distribution centre in other industries. Given this low fixed cost, we inquired whether any transportation efficiency could be gained by allowing the sort-yard location to change between harvesting periods.

In Figure 9, we present the mapped harvest schedule for Scenario 3. Figure 9 reveals that sort-yard $X_4$is selected in term 1, and that the selected yard then moves to X_2, in term 2, before returning to X_4, in term 3. Figure 9 also reveals that selected cut-blocks are clustered around the selected sort-yard for each period. Finally, Figure 9 reveals that the cut-blocks are dispersed more widely across the forest than in Figure 8, where only one permanent yard is allowed.

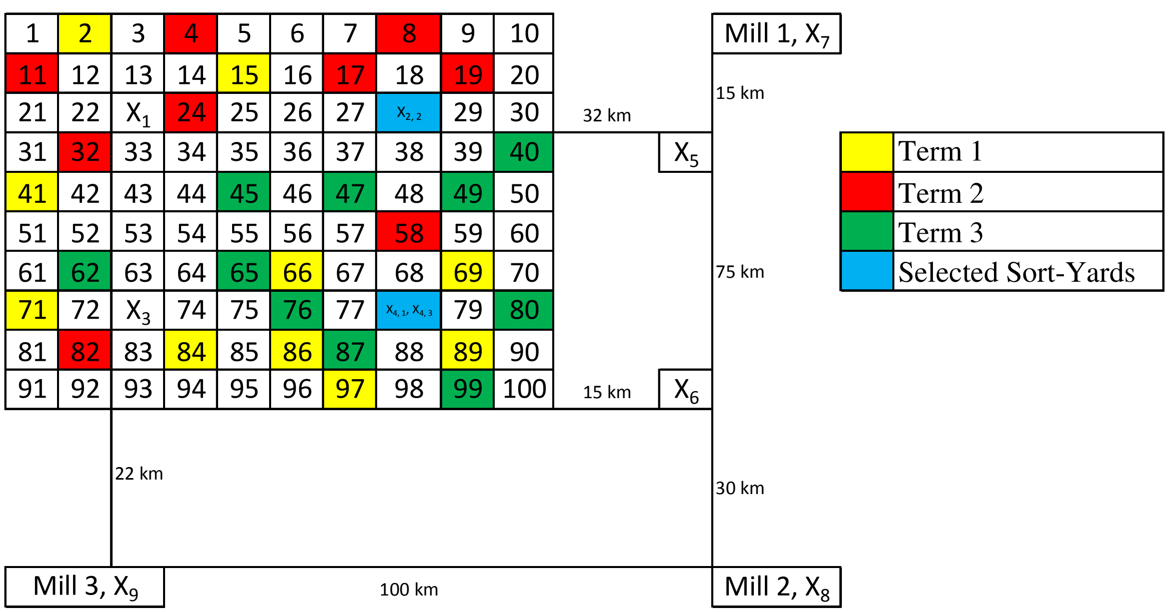

Figure 9: Harvest schedule for Scenario 3, where one sort yard can move between periods.

6.5 Values of Interest Compared between Scenarios

In comparing the non-spatial attributes of these scenarios, let us begin with their different objective functions, listed in Table 6.

Table 6: Objective function values for each scenario

Scenario	Name	Profit
1	no sort-yard	$91,874,800.00
1b	no sort (minimize cost)	$63,615,927.31
2	fixed sort-yard	$104,915,900.00
3	moveable sort-yard	$110,820,200.00

Table 5 indicates that Scenario 3 had the highest objective function value, closely edging out Scenario 2, which was constrained to a fixed sort-yard location. These scenarios also show that (for this data set) it is slightly more profitable to establish a sort-yard than not. Scenario 1, in which the most valuable mixed-wood stands were selected for unsorted delivery, has an objective function within 14% of Scenario 2's objective function.

From Table 5wemight be tempted to infer that (for this data set) the extra costs incurred by Scenario 3 (by moving the sort-yard and more broadly dispersing the harvest) were more than made up for by decreased transportation costs. Such an inference would be premature until the transportation costs per scenario are compared (see Table 7).

Table 7: Transportation costs for each scenario

Scenario	Name	Transportation Cost
1	no sort-yard	$2,270,600.00
1b	no sort (minimize cost)	$1,664,500.00
2	fixed sort-yard	$2,165,000.00
3	moveable sort-yard	$2,263,800.00

In Table 7, observe that Scenario 1 has the highest transportation cost, followed by Scenario 3, Scenario 2 and Scenario 1b. Note that Scenario 1, in which wood is transported directly to the mills, incurs the highest transportation costs. Why? I can only infer that Scenario 1 incurs a high transportation cost in order to harvest and transport the highest valued stands. In other words, since the wood delivered in Scenario 1 is unsorted, extra transportation costs are suffered in exchange for increased revenue.

The most surprising result in Table 7 is that the moveable sort-yard scenario (Scenario 3) has a higher transportation cost than the fixed sort-yard scenario (Scenario 2). This is surprising because Scenario 3 has a higher objective function value than Scenario 2, and both scenarios suffer a value-loss of zero, because they both have sort-yards. How, then, can Scenario 3 have higher transportation costs?

Looking more deeply at the results, it is found that the total volume harvested in Scenario 3 was slightly higher than the total volume harvested in Scenario 2. This higher harvest was allowed for by the V_{max} and V_{min} parameters used in equation [5] of the model. Therefore, when the transportation costs are viewed as $/m^3, it can be seen that transportation costs are nearly identical between the fixed and moveable sort-yard scenario. Transportation costs adjusted to average $/m^3 can be seen in Table 8.

Table 8: Transportation costs

Scenario	Name	Transportation Average per m^3
1	no sort-yard	$4.22
1b	no sort (minimize cost)	$3.80
2	fixed sort-yard	$4.13
3	moveable sort-yard	$4.14

These results indicate that, in this problem instance, moving the location of a sort-yard between periods does not decrease transportation costs.

7. Discussion

The major focus of this study was to formulate and test a tactical harvest-scheduling model that is integrated with a log-sort-yard location model. The purpose of this integration was to facilitate improved planning in the forest products supply chain in three ways:

1. **Value recovery**: An improved supply chain was intended by facilitating value recovery through the optimal location of a sort-yard.
2. **Shifting perspectives to demand pull**: It was intended that the supply chain be improved by shifting the perspective on cut-block allocation from a supply-push to a demand-pull. This was done by allocating cut-blocks such that transportation costs were minimized in supplying the demand locations from multiple mills for multiple commodities.
3. **Inventory management:** This model was designed to improve the supply chain by facilitating a reduced risk in inventory shortages and costs associated with these risks.

7.1 Realistic Value Recovery: Data Assumptions

As the formulation of the integrated model shows, an assumption is made that reliable data be available on the wood quality characteristics of standing timber. Is this assumption realistic? To answer this important question, a brief review of the relevant literature is first presented.

Reliable data on standing wood quality has greatly improved with the emergence and availability of Light Detection And Ranging (LiDAR) (van Leeuwen *et al*. 2011). LiDAR is an emerging technology which can directly measure the three dimensional structure of forest canopies using ground or airborne laser instruments. LiDAR data collected from the air has been widely used for the estimation of forest inventory attributes, such as crown width, length, height-to-first-living branch, and biomass and biomass change over time (Chasmer *et al*. 2006). The error for measuring the height of individual trees from airborne laser systems is typically less than1.0m (Persson *et al*., 2002). In a review paper evaluating the ability of LiDAR to assess standing wood and fibre quality, van Leeuwen *et al*. (2011), conclude that LiDAR can provide highly accurate information on individual-tree and stand-level forest structure. This conclusion is based two emerging techniques:

1. the integration of airborne and ground-based LiDAR systems (e.g., Hilker *et al*. 2010); and
2. advances in modeling wood fibre qualities from LiDAR data (e.g., Suarez-Minguez 2010).

The application of LiDAR data is currently expanding from the forest inventory problem to procurement problems at the operational planning level, where detailed economic values of standing timber are required (Dassot *et al*. (2011). There has been much research on this problem recently and advances are based the application of ground-based LiDAR systems. In these studies, tree values and log product yields were estimated using terrestrial LiDAR derived data and compared with estimates based on the harvester and manual stem profiles. For example, Murphy (2010) used ground-based LiDAR data to estimated stand value and log product yields to within 9% and 6% of actual values, respectively. Acuna *et al*. (2009) used LiDAR to estimate value recovery within 8% of actual harvester recovery for radiate pine in Australia. Murphy (2010) also demonstrated a larger-scale usefulness of LiDAR in generating an optimal allocation plan for bio-energy and log production based on data from using 4,000 stems from 16 forests. Finally, in a review article on the applicability of terrestrial based LiDAR scanners to forest planning, Dassot *et al*. (2011) observe that terrestrial-based LiDAR scanners should, but have not yet, become standard equipment in commercial forest management for two reasons:

1. the cost of the scanners currently prohibits their broader use (but prices are decreasing); and
2. the development of cheap and easy-to-use software is needed to make it possible to automatically extract information from incomplete data.

Hence, given the currently limited application of terrestrial-based LiDAR to collecting reliable economic information on standing timber, our assumption that such data would be readily available for our integrated model may be premature. Nonetheless, the precision of the estimates of standing timber values and the decreasing cost of the technology does make our prototype model relevant to a realistic future.

7.2 Realistic Value Recovery: Who Benefits?

The results showed that a superior objective function value occurred when a sort-yard was selected. This result was dependent of the parameters used in this particular data set. Dramm *et al*. (2004) observed that sort-yards are economically feasible only when there exists a diversity of higher valued logs. But, even when a diversity of logs exists, and an optimal sort-yard location is selected, the assumption that decision-makers will automatically choose to install a yard, and thereby capture the full values of the logs, must be examined.

Decision-makers may not agree to implement a solution which will increase value recovery because: a) there is a cost to establishing and running a yard; and b) not all mills necessarily benefit equally from a sort-yard. For example, a mill which demands low value logs will not benefit from a sort-yard; but a mill which requires high-value logs will benefit from a solution. A cost-benefit analysis performed by each mill may result in some mills willing to pay the cost of a yard with other mills not willing to pay.Another option is to share the savings or benefits fairly between collaborating actors.

Hence, the recovery of wood value, which is a major objective of this decision support model, depends on how the multiple mills agree to share the cost or benefit. On the one hand, if the multiple mills are owned by one firm, then there is no conflict in agreeing to pay for the cost of the sort-yard. On the other hand, if there are multiple independent owners of the mills, an agreement may not be reached-- unless a governmental agency agrees to pay for the cost of the sort-yard. For example, the log sort-yard in Vernon, B.C. is owned by the municipal government and it serves multiple, independent mills (Dramm *et al*., 2004).

Hence, the nature of the sort-yard location problem is complicated by the fact that the multiple mills may have interests which conflict. Therefore, it would be naïve to assume that the solutions generated by the model would be easy to implement.

7.3 Shifting to "demand pull": missing roads

Shifting the tactical planning perspective toward demand-pull requires that efficiencies are facilitated at the operational planning level. A major cost in operational planning is the construction of road networks; and yet, in this tactical model, road networks are not explicitly a part of the model's solution.

At the tactical level of planning, the primary approach to reducing the costs of building roads is to reduce the total length of roads needed to execute the harvest. Our prototype model can address this challenge in two possible ways.

The first possible approach would require the user to apply a weighted penalty, in the objective function, to: $\sum_{k \in K} z_{kjt} u_{ktj}$.

where:

z_{kjt} = 1 if cut-block k is harvested in term t and shipped through sort-yard j, 0 otherwise.

u_{ktj} = fixed cost of accessing cut-block k in term t, from sort-yard j($).

If the values used for u_{ktj} were based on distance, then applying large penalty values to this element of the objective function would result in blocks clustered more closely around the selected sort-yard. This approach, given a high enough penalty value, would reduce the total distance of roads needed to execute the harvest; but it is an inelegant solution, for it can easily result in a double-counting of road segments needed and it still does not produce an explicit road network.

A second approach to planning for reduced road building costs in this model would be to add new binary decision variables representing the construction or non-construction of road-link j in period k. This would be added to the objective function with a cost parameter and the standard set of road building constraints, found in other tactical planning models, would also be added to the model. The objective function would otherwise remain unchanged.

In Scenario 1b an observed result was the clustering of blocks around mills to minimize transportation costs. This observation needs an explanation. The clustering of blocks around a mill would only be a temporary phenomenon. If the model were extended to plan for an entire rotation, the entire forest would need to be accessed and this clustering result would not be evident. It is likely that testing this model over an entire rotation would result in a steady progression of cut-blocks starting at the access points to the forest and gradually spreading over time as road building costs are spread out incrementally. Although the entire forest would be harvested, the transportation and road building costs would still be minimized for the planning horizon.

The discounting of future road costs typically forces a tactical planning model to construct roads as far as possible into the future in order to maximize net present value. The result would is a harvest schedule that follows a steady progression from the access points deeper into the forest over time. Exceptions to this gradual progression do exist.

In the case of a highly variable forest, such as in this analysis, it may be necessary to travel a significant distance in order to procure the logs necessary to meet mill demand.

Hence, an expansion of this model to include road network planning would improve its ability to assist in efficient operational planning; and the current prototype model would have little difficulty in incorporating road-network planning.

7.4 Shifting to “demand pull”: the no sort-yard scenario

As we have noted several times, an economically feasible sort-yard requires a diversity of high-value logs in order to profit from capturing their value. Given this reality, an interesting question to ask is: can our model still be of use even when there is not a great diversity of logs (e.g. the boreal forest), and therefore no need for a sort-yard to capture value?

In effect, we are asking whether the novel perspective in tactical planning used in our model (i.e., cut-block and log-supply allocation made in consideration of multiple mills’ locations and demands) has any merit on its own, quite apart from the benefits of sort-yard location and the capturing of log values? The answer to this question is illustrated by the solution to Scenario 1b, where blocks were allocated to minimize total transportation cost, which was reduced greatly versus the transportation costs of the other scenarios.

In other words, by shifting our tactical planning model perspective from a traditional “supply-push” (where blocks are allocated to maximize the NPV of the harvest) to a “demand-pull”, we were able to produce a solution which reduces the realistic transportation costs incurred by supplying multiple mills from multiple cut-blocks. As explained previously, if the model were extended from three periods to an entire rotation the entire forest would eventually be cut. However, the discounting of future road construction would force the construction of roads into the future. This would lead to a harvest schedule beginning at access points to the forest and gradually spreading over time. Although the entire forest would be accessed road and transportation costs would still be minimized.

Hence, it can be concluded that the incorporation of a demand-pull perspective into tactical level planning may have merits on its own; *viz*., the reduction in total transportation costs.

7.5 Integrating procurement and production: Market uncertainties

One of the purposes of a sort-yard is to reduce the risk of inventory shortages and costs associated with these risks. But simply building a sort-yard does not guarantee that these risks will be avoided. For, among other things, inventory management requires planning for efficient replenishment in response to market uncertainties. How might this integrated model be used to meet this objective?

Efficient replenishment in response to market uncertainties would require an allocation of blocks (and resulting roads) that provide efficient access to the full diversity of commodities across time. In other words, the allocation should be made so that, at the operational level, access to any particular commodity (which may suddenly be in high demand) is delayed as little as possible.

This model does not currently incorporate such planning objectives; but if it is to be improved upon, the modeling required for tactical-level planning from a demanddriven perspective, then the extension of this model to incorporate inventory management objectives would be a valuable improvement to this model. In this area of improvement, the development of an explicit road network, over time, would be a necessary attribute of inventory management.

8. Conclusions

The objective of this research was to develop and evaluate a prototype model that integrates both a tactical harvest-scheduling model and a sort-yard location model. The significance of this innovation was evaluated based on the ability of the integrated model to facilitate an improvement in the forest products supply chain.

The formulation of this integrated model was based on a multiple commodity multiple facility location model. The integrated model was designed to simultaneously optimize: i) the selected location of a sort-yard; and ii) the allocation of cut-blocks in a tactical harvest-scheduling problem. The novel objective function of this model was to maximize the difference between total harvest revenue and the costs of road construction, maintenance and transporting logs from the cut blocks, through the selected sort-yard, and to the demand-locations of multiple mills.

The results of applying this model to a toy data-set showed that improved objective function values can be achieved by using a sort-yard to increase harvest-revenue by redirecting logs to demand-locations where their value is most highly captured. The scenarios in which the model was tested also showed that cut-block allocation was highly sensitive to the changes in the emphasis in the objective function, from maximizing revenue, to minimizing transportations costs. The results also showed that, depending on the scenario, allocated cut- blocks were clustered around the selected sort-yard, or clustered nearby the mills to which their logs were allocated, in order to minimize transport costs. Although this result would differ if the model were run on a full rotation, it shows that transportation costs are being minimized through this model.

It can be concluded that the integrated model developed in this research has the ability to facilitate improvements in forest products supply chain. This conclusion is based on the integrated model's potential: i) to shift the planning perspective from supply-push to demand-pull; ii) to better integrate the production and procurement stages of the supply chain; and iii) to manage for value recovery.

This conclusion is qualified by a major assumption underlying this prototype model; namely, that reliable data on standing timber value needed by this model is actually available. Reviews of the literature on this assumption showed that the results of combining air- and ground-based LiDAR to estimate standing timber value with reliable accuracy is possible, but not broadly used at present. Hence, the assumption on the availability of the reliable timber-value data is realistic, but premature.

The direction for future research based on the work of this thesis is clear. Improved integration of the procurement and production stages of the supply chain requires that this model be expanded to include principles of inventory modeling, coupled with explicit road network planning, in order to facilitate efficient log replenishment in response to the stochastic nature of the wood products market.

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APPENDIX I

MPL FILE

In the MPL file, Mills Eastwood, Wayne and JoseyWales refer to Mills 1, 2 and 3 in the analysis. Sort yards Alpha, Beta, Gamma, Delta, Epsilon, Zeta, Eastwood, Wayne, JoseyWales, and No refer to sort yards 1 through 10, with Alpha-Delta being the 4 internal sort-yards and No being the dummy sort yard. The sort-yards that share names with mills are located at these mills.

A note on the adjacency constraints: Each block has between 2, 3or 4 adjacent blocks, as the adjacencies cover one period removed this leads to between 4, 6 or 8 linear constraints for each block. The adjacency constraints are formulated as cliques, each clique contains two blocks shipped through all ten sort yards in two periods, or Y_{ijt} = 40 for each linear constraint. Consequently, the adjacency constraints are quite large, and to include the entire list would require 86 pages of type 6 font. Due to the size of the adjacency constraints, only the adjacency constraints for one block (block 12) are included. Adjacencies for all other blocks can be constructed according to the pattern shown for Block 12.

For the complete data-set and model, please contact the author.

Files included here are:

The Main MPL File. When the scenarios were run, the data was written into the main code. This was done to prevent MPL from corrupting data read in from data files or sparse files (A problem that happens on occasion with this program). However, the main file included in this appendix is set up for using data files or sparse files for ease of display.

Main MPL File:

```
TITLE
        SortYard_SEPTEMBER

INDEX
        Period := (1, 2, 3);
        Block := (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65,
        66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97,
        98, 99, 100);
        Mill := (Eastwood, Wayne, JoseyWales);
        SortYard := (No, Eastwood, Wayne, JoseyWales, Alpha, Beta, Gamma, Delta, Epsilon, Zeta);
        LogType := (Tpol, SSw2, HSw1, HSw2, Veneer, Pallet, SSw1, HMw, SMw);

DATA
        D[Mill, SortYard, LogType]        := DATAFILE("Demand4SY.dat");
        S[Block, SortYard, LogType]       := SPARSEFILE("Supply4SY.dat");
        F[SortYard]                       := (0, 10000, 10000, 10000, 10000, 10000, 10000, 10000, 10000, 10000);
        R[Block, Mill, LogType]           := SPARSEFILE("Revenue4SY.dat");
        TC[Block, SortYard, Mill]         := SPARSEFILE("TransCost4SY.dat");
        RC[Block] := (300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300,
        300, 300, 300, 300, 300,300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300,
        300, 300, 300, 300, 300, 300, 300, 300, 300, 300,300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300,
        300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300, 300,300, 300, 300, 300, 300, 300, 300, 300, 300,
        300, 300, 300, 300, 300, 300, 300);
        VL[Block, Mill, LogType] := SPARSEFILE("ValueLost4SY.dat");
        Vmin[SortYard] := (10, 10, 10, 10, 10, 10, 10, 10, 10, 10);
        Vmax[SortYard] := (10000000, 10000000, 10000000, 10000000, 10000000, 10000000, 10000000, 10000000, 10000000,
        10000000);

VARIABLES
        Y[Mill, SortYard, Period];
        X[SortYard, Period];
        W[Period, Block, Mill, SortYard, LogType];
        Z[Period, Block, SortYard];

MACROS
        TotalRevenue          := SUM(Block, Mill, LogType, SortYard, Period: W * R * 1);
        FixedCost := SUM(SortYard, Period: X * F);
        ValueLost             := SUM(Period, Block, SortYard, LogType, Mill: W * VL);
        RoadCost              := SUM(Block, Period, SortYard: Z * RC * 1);
        ShipCost   := SUM(Block, Period, LogType, SortYard, Mill: (W * TC * 1));
        TotalCost  :=RoadCost + ShipCost + FixedCost;
        RevenueMinusCost    :=(TotalRevenue - TotalCost);
        TotalHarv1            := SUM(Period = 1, Block, Mill, SortYard, LogType: W);
        TotalHarv2            := SUM(Period = 2, Block, Mill, SortYard, LogType: W);
        TotalHarv3            := SUM(Period = 3, Block, Mill, SortYard, LogType: W);
```

```
MODEL
        ! [1]
         MAX (TotalRevenue - TotalCost);
        ! [16]
        ! MIN TotalCost;
SUBJECT TO

        ! [2]
        BlockTriggerFlow[SortYard, Block, Period, LogType]:
                SUM(Mill: W) - (S * Z) = 0;

        ! [3a]
        MillDemand[Mill, LogType, Period, SortYard]:
                SUM(Block: W * 0.8) - (D * Y) <= 0;

        ! [3b]
        MillDemand[Mill, LogType, Period, SortYard]:
                SUM(Block: W * 1) - (D * Y) >= 0;

        ! [4]
        OnlyOneSortYard[Period] :
                SUM(SortYard: X) = 1;

        ! [5a]
        LinkingConstraintLOWER[SortYard, Period] :
                SUM(Mill, LogType: Y * D) >= (X * Vmin);

        ! [5b]
        LinkingConstraintUPPER[SortYard, Period] :
                SUM(Mill, LogType: Y * D) <= (X * Vmax);
        ! [6]
        GLimits[Period, Mill]:
                SUM(SortYard: Y) = 1;

        ! [7]
        BlockSupply[Block, SortYard, LogType, Period]:
                SUM(Mill: W) - ( S * X ) <= 0;

        ! [8]
        CutOnce[Block]:
                SUM(Period, SortYard: Z) <= 1;

        ! [9] Adjacency constraints: (Block 12 only)
!Term 1-2,  block +1
Z[1, 12, Alpha] + Z[1, 12, Beta] + Z[1, 12, Gamma] +Z[1, 12, Delta] + Z[1, 12, Epsilon] + Z[1, 12, Zeta] + Z[1, 12, Eastwood] +
Z[1, 12, Wayne] + Z[1, 12, JoseyWales] + Z[1, 12, No] + Z[1, 13, Alpha] + Z[1, 13, Beta] + Z[1, 13, Gamma] + Z[1, 13, Delta] +
Z[1, 13, Epsilon]  + Z[1, 13, Zeta] + Z[1, 13, Eastwood]  + Z[1, 13, Wayne] + Z[1, 13, JoseyWales] + Z[1, 13, No] + Z[2, 13, Alpha]
+ Z[2, 13, Beta] + Z[2, 13, Gamma] + Z[2, 13, Delta] + Z[2, 13, Epsilon] + Z[2, 13, Zeta] + Z[2, 13, Eastwood] + Z[2, 13, Wayne] +
Z[2, 13, JoseyWales] + Z[2, 13, No] <= 1;
!Term 2-3,  block +1
Z[2, 12, Alpha] + Z[2, 12, Beta] + Z[2, 12, Gamma] +Z[2, 12, Delta] + Z[2, 12, Epsilon] + Z[2, 12, Zeta] + Z[2, 12, Eastwood] +
Z[2, 12, Wayne] + Z[2, 12, JoseyWales] + Z[2, 12, No] + Z[2, 13, Alpha] + Z[2, 13, Beta] + Z[2, 13, Gamma] + Z[2, 13, Delta] +
Z[2, 13, Epsilon]  + Z[2, 13, Zeta] + Z[2, 13, Eastwood]  + Z[2, 13, Wayne] + Z[2, 13, JoseyWales] + Z[2, 13, No] + Z[3, 13, Alpha]
+ Z[3, 13, Beta] + Z[3, 13, Gamma] + Z[3, 13, Delta] + Z[3, 13, Epsilon] + Z[3, 13, Zeta] + Z[3, 13, Eastwood] + Z[3, 13, Wayne] +
Z[3, 13, JoseyWales] + Z[3, 13, No] <= 1;
!Term 1-2, block -1
Z[1, 12, Alpha] + Z[1, 12, Beta] + Z[1, 12, Gamma] +Z[1, 12, Delta] + Z[1, 12, Epsilon] + Z[1, 12, Zeta] + Z[1, 12, Eastwood] +
Z[1, 12, Wayne] + Z[1, 12, JoseyWales] + Z[1, 12, No] + Z[1, 11, Alpha] + Z[1, 11, Beta] + Z[1, 11, Gamma] + Z[1, 11, Delta] +
Z[1, 11, Epsilon]  + Z[1, 11, Zeta] + Z[1, 11, Eastwood]  + Z[1, 11, Wayne] + Z[1, 11, JoseyWales] + Z[1, 11, No] + Z[2, 11, Alpha]
+ Z[2, 11, Beta] + Z[2, 11, Gamma] + Z[2, 11, Delta] + Z[2, 11, Epsilon] + Z[2, 11, Zeta] + Z[2, 11, Eastwood] + Z[2, 11, Wayne] +
Z[2, 11, JoseyWales] + Z[2, 11, No] <= 1;
!Term 2-3, block -1
Z[2, 12, Alpha] + Z[2, 12, Beta] + Z[2, 12, Gamma] +Z[2, 12, Delta] + Z[2, 12, Epsilon] + Z[2, 12, Zeta] + Z[2, 12, Eastwood] +
Z[2, 12, Wayne] + Z[2, 12, JoseyWales] + Z[2, 12, No] + Z[2, 11, Alpha] + Z[2, 11, Beta] + Z[2, 11, Gamma] + Z[2, 11, Delta] +
Z[2, 11, Epsilon]  + Z[2, 11, Zeta] + Z[2, 11, Eastwood]  + Z[2, 11, Wayne] + Z[2, 11, JoseyWales] + Z[2, 11, No] + Z[3, 11, Alpha]
+ Z[3, 11, Beta] + Z[3, 11, Gamma] + Z[3, 11, Delta] + Z[3, 11, Epsilon] + Z[3, 11, Zeta] + Z[3, 11, Eastwood] + Z[3, 11, Wayne] +
Z[3, 11, JoseyWales] + Z[3, 11, No] <= 1;
!Term 1-2, block +10
```

```
Z[1, 12, Alpha] + Z[1, 12, Beta] + Z[1, 12, Gamma] +Z[1, 12, Delta] + Z[1, 12, Epsilon] + Z[1, 12, Zeta] + Z[1, 12, Eastwood] +
Z[1, 12, Wayne] + Z[1, 12, JoseyWales] + Z[1, 12, No] + Z[1, 22, Alpha] + Z[1, 22, Beta] + Z[1, 22, Gamma] + Z[1, 22, Delta] +
Z[1, 22, Epsilon]  + Z[1, 22, Zeta] + Z[1, 22, Eastwood]  + Z[1, 22, Wayne] + Z[1, 22, JoseyWales] + Z[1, 22, No] + Z[2, 22, Alpha]
+ Z[2, 22, Beta] + Z[2, 22, Gamma] + Z[2, 22, Delta] + Z[2, 22, Epsilon] + Z[2, 22, Zeta] + Z[2, 22, Eastwood] + Z[2, 22, Wayne] +
Z[2, 22, JoseyWales] + Z[2, 22, No] <= 1;
!Term 2-3, block +10
Z[2, 12, Alpha] + Z[2, 12, Beta] + Z[2, 12, Gamma] +Z[2, 12, Delta] + Z[2, 12, Epsilon] + Z[2, 12, Zeta] + Z[2, 12, Eastwood] +
Z[2, 12, Wayne] + Z[2, 12, JoseyWales] + Z[2, 12, No] + Z[2, 22, Alpha] + Z[2, 22, Beta] + Z[2, 22, Gamma] + Z[2, 22, Delta] +
Z[2, 22, Epsilon]  + Z[2, 22, Zeta] + Z[2, 22, Eastwood]  + Z[2, 22, Wayne] + Z[2, 22, JoseyWales] + Z[2, 22, No] + Z[3, 22, Alpha]
+ Z[3, 22, Beta] + Z[3, 22, Gamma] + Z[3, 22, Delta] + Z[3, 22, Epsilon] + Z[3, 22, Zeta] + Z[3, 22, Eastwood] + Z[3, 22, Wayne] +
Z[3, 22, JoseyWales] + Z[3, 22, No] <= 1;
!Term 1-2, block -10
Z[1, 12, Alpha] + Z[1, 12, Beta] + Z[1, 12, Gamma] +Z[1, 12, Delta] + Z[1, 12, Epsilon] + Z[1, 12, Zeta] + Z[1, 12, Eastwood] +
Z[1, 12, Wayne] + Z[1, 12, JoseyWales] + Z[1, 12, No] + Z[1, 2, Alpha] + Z[1, 2, Beta] + Z[1, 2, Gamma] + Z[1, 2, Delta] + Z[1, 2,
Epsilon]  + Z[1, 2, Zeta] + Z[1, 2, Eastwood]  + Z[1, 2, Wayne] + Z[1, 2, JoseyWales] + Z[1, 2, No] + Z[2, 2, Alpha] + Z[2, 2, Beta]
+ Z[2, 2, Gamma] + Z[2, 2, Delta] + Z[2, 2, Epsilon] + Z[2, 2, Zeta] + Z[2, 2, Eastwood] + Z[2, 2, Wayne] + Z[2, 2, JoseyWales] +
Z[2, 2, No] <= 1;
!Term 2-3, block -10
Z[2, 12, Alpha] + Z[2, 12, Beta] + Z[2, 12, Gamma] +Z[2, 12, Delta] + Z[2, 12, Epsilon] + Z[2, 12, Zeta] + Z[2, 12, Eastwood] +
Z[2, 12, Wayne] + Z[2, 12, JoseyWales] + Z[2, 12, No] + Z[2, 2, Alpha] + Z[2, 2, Beta] + Z[2, 2, Gamma] + Z[2, 2, Delta] + Z[2, 2,
Epsilon]  + Z[2, 2, Zeta] + Z[2, 2, Eastwood]  + Z[2, 2, Wayne] + Z[2, 2, JoseyWales] + Z[2, 2, No] + Z[3, 2, Alpha] + Z[3, 2, Beta]
+ Z[3, 2, Gamma] + Z[3, 2, Delta] + Z[3, 2, Epsilon] + Z[3, 2, Zeta] + Z[3, 2, Eastwood] + Z[3, 2, Wayne] + Z[3, 2, JoseyWales] +
Z[3, 2, No] <= 1;

! [14] Constraints allowing only one sort-yard

        !X[Alpha, 1] - X[Alpha, 2] = 0;
        !X[Alpha, 2] - X[Alpha, 3] = 0;

        !X[Beta, 1] - X[Beta, 2] = 0;
        !X[Beta, 2] - X[Beta, 3] = 0;

        !X[Gamma, 1] - X[Gamma, 2] = 0;
        ! X[Gamma, 2] - X[Gamma, 3] = 0;

        !X[Delta, 1] - X[Delta, 2] = 0;
        !X[Delta, 2] - X[Delta, 3] = 0;

        !X[Epsilon, 1] - X[Epsilon, 2] = 0;
        !X[Epsilon, 2] - X[Epsilon, 3] = 0;

        !X[Zeta, 1] - X[Zeta, 2] = 0;
        !X[Zeta, 2] - X[Zeta, 3] = 0;

        !X[Eastwood, 1] - X[Eastwood, 2] = 0;
        !X[Eastwood, 2] - X[Eastwood, 3] = 0;

        !X[Wayne, 1] - X[Wayne, 2] = 0;
        !X[Wayne, 2] - X[Wayne, 3] = 0;

        !X[JoseyWales, 1] - X[JoseyWales, 2] = 0;
        !X[JoseyWales, 2] - X[JoseyWales, 3] = 0;

! [15]  If Sort-Yard Then Block...
        X[Alpha, 1] - Z[1, 23, Alpha] <= 0;
        X[Alpha, 2] - Z[1, 23, Alpha] - Z[1, 23, Beta] - Z[1, 23, Gamma] - Z[1, 23, Delta] - Z[1, 23, Epsilon] - Z[1, 23, Zeta] -
        Z[1, 23, Eastwood] - Z[1, 23, Wayne] - Z[1, 23, JoseyWales] - Z[1, 23, No]- Z[2, 23, Alpha]  <= 0;
        X[Alpha, 3] - Z[1, 23, Alpha] - Z[1, 23, Beta] - Z[1, 23, Gamma] - Z[1, 23, Delta] - Z[1, 23, Epsilon] - Z[1, 23, Zeta] -
        Z[1, 23, Eastwood] - Z[1, 23, Wayne] - Z[1, 23, JoseyWales] - Z[1, 23, No]- Z[2, 23, Alpha]
         - Z[2, 23, Beta] - Z[2, 23, Gamma] - Z[2, 23, Delta] - Z[2, 23, Epsilon] - Z[2, 23, Zeta] - Z[2, 23, Eastwood] - Z[2, 23,
        Wayne] - Z[2, 23, JoseyWales] - Z[2, 23, No] - Z[3, 23, Alpha]  <= 0;

        X[Beta, 1] - Z[1, 28, Beta] <= 0;
        X[Beta, 2] - Z[1, 28, Alpha] - Z[1, 28, Beta] - Z[1, 28, Gamma] - Z[1, 28, Delta] - Z[1, 28, Epsilon] - Z[1, 28, Zeta] - Z[1,
        28, Eastwood] - Z[1, 28, Wayne] - Z[1, 28, JoseyWales] - Z[1, 28, No]- Z[2, 28, Beta]  <= 0;
        X[Beta, 3] - Z[1, 28, Alpha] - Z[1, 28, Beta] - Z[1, 28, Gamma] - Z[1, 28, Delta] - Z[1, 28, Epsilon] - Z[1, 28, Zeta] - Z[1,
        28, Eastwood] - Z[1, 28, Wayne] - Z[1, 28, JoseyWales] - Z[1, 28, No]- Z[2, 28, Alpha]
        - Z[2, 28, Beta] - Z[2, 28, Gamma] - Z[2, 28, Delta] - Z[2, 28, Epsilon] - Z[2, 28, Zeta] - Z[2, 28, Eastwood] - Z[2, 28,
        Wayne] - Z[2, 28, JoseyWales] - Z[2, 28, No] - Z[3, 28, Beta]  <= 0;
```

```
        X[Gamma, 1] - Z[1, 73, Gamma] <= 0;
        X[Gamma, 2] - Z[1, 73, Alpha] - Z[1, 73, Beta] - Z[1, 73, Gamma] - Z[1, 73, Delta] - Z[1, 73, Epsilon] - Z[1, 73, Zeta] -
        Z[1, 73, Eastwood] - Z[1, 73, Wayne] - Z[1, 73, JoseyWales] - Z[1, 73, No]- Z[2, 73, Gamma]  <= 0;
        X[Gamma, 3] - Z[1, 73, Alpha] - Z[1, 73, Beta] - Z[1, 73, Gamma] - Z[1, 73, Delta] - Z[1, 73, Epsilon] - Z[1, 73, Zeta] -
        Z[1, 73, Eastwood] - Z[1, 73, Wayne] - Z[1, 73, JoseyWales] - Z[1, 73, No]- Z[2, 73, Alpha]
        - Z[2, 73, Beta] - Z[2, 73, Gamma] - Z[2, 73, Delta] - Z[2, 73, Epsilon] - Z[2, 73, Zeta] - Z[2, 73, Eastwood] - Z[2, 73,
        Wayne] - Z[2, 73, JoseyWales] - Z[2, 73, No] - Z[3, 73, Gamma]  <= 0;

        X[Delta, 1] - Z[1, 78, Delta] <= 0;
        X[Delta, 2] - Z[1, 78, Alpha] - Z[1, 78, Beta] - Z[1, 78, Gamma] - Z[1, 78, Delta] - Z[1, 78, Epsilon] - Z[1, 78, Zeta] -
        Z[1, 78, Eastwood] - Z[1, 78, Wayne] - Z[1, 78, JoseyWales] - Z[1, 78, No]- Z[2, 78, Gamma]  <= 0;
        X[Delta, 3] - Z[1, 78, Alpha] - Z[1, 78, Beta] - Z[1, 78, Gamma] - Z[1, 78, Delta] - Z[1, 78, Epsilon] - Z[1, 78, Zeta] -
        Z[1, 78, Eastwood] - Z[1, 78, Wayne] - Z[1, 78, JoseyWales] - Z[1, 78, No]- Z[2, 78, Alpha]
        - Z[2, 78, Beta] - Z[2, 78, Gamma] - Z[2, 78, Delta] - Z[2, 78, Epsilon] - Z[2, 78, Zeta] - Z[2, 78, Eastwood] - Z[2, 78,
        Wayne] - Z[2, 78, JoseyWales] - Z[2, 78, No] - Z[3, 78, Delta]  <= 0;


BINARY
        ! [10]
        X[SortYard, Period];
        ! [11]
        Y[Mill, SortYard, Period];
        ! [12]
        Z[Period, Block, SortYard];

BOUNDS
        ! [13]
        W[Block, SortYard, LogType, Mill, Period] >= 0;

END
```