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Research Consortium in e-Business in the Forest Products Industry (FOR@C)

Interuniversity research Center on Enterprise Networks, Logistics and transportation (CIRRELT),

Université Laval, Québec, Canada

Hierarchical Forest Management with Anticipation : an application to tactical-operational planning integration

Beaudoin, D[1,3,4], Frayret, J.-M.[2,3,4], LeBel, L[1,3,4]

[1]Faculté de foresterie et géomatique, Université Laval Québec, Canada

[2]École Polytechnique de Montréal, Québec, Canada

[3]Research Consortium in e-Business in the forest products industry (FOR@C),

[4]Centre Inter-Universitaire de Recherche sur le Réseaux d'Entreprise, Logistique et de Transport (CIRRELT).

Abstract

This paper examines the problem of harvest capacity planning at a tactical level in a context of procurement activities outsourced to independent contractors. Annual capacity planning allows planners to determine the number of contractors they need to hire per period throughout the year and to define the duration of their contracts. In practice, this process usually involves the analysis of historical data regarding the operational use of capacity and aggregated demand forecast, the output of which then serves to plan harvest operations. Although this form of hierarchical planning reduces the complexity of the task, the decomposition into sub-problems that must be successively resolved can lead to infeasibility or poor use of harvesting capacity. The specific problem addressed here resides in how one can consider the operational impact of harvesting decisions taken at the tactical level in order to ensure a plan's feasibility at the operational level. We present a tactical planning process using an anticipation function based on Schneeweiss' generic hierarchical coordination mechanism. The anticipation function corresponds to a sequencing and equipment transportation problem. We also present and test a mixed-integer model and a heuristic solution procedure to solve the anticipated problem. The anticipation approach we propose

appears to be a valid method to better integrate key operational-level decisions into tactical plans, especially with regards to the possibility of harvesting each block over several periods. The anticipation approach allows tactical planning to account for operational criteria.

Introduction

The use of mathematical models to deal with wood procurement problems dates back to the early 1960s. Since then, a large body of models has been developed to address various aspects of the wood procurement problem. Over the years, increased requirements from the industries, the general public and government for raw material, commodities, recreation, conservation and preservation have greatly increased the complexity of the resulting forest management planning problem (Weintraub and Davis 1996). Researchers have approached these increasingly complex problems with two lines of thinking: through the use of large monolithic models or by means of hierarchical decomposition.

On one side, Bitran and Tirupati (1993) and Schneeweiss (1999) identify limits in human cognition, mathematics, and computational power as an impediment to solving large-scale problems as a single entity. Along the same line, Bare and Field (1986) highlight "severe limitations" of monolithic models of very large dimension: (1) they are too poorly understood and too costly in terms of setup time, solution time and user skills to be of much value to present or future forest planning efforts; and (2) they do not adequately address the different, though related, problems of forest planning: strategic (allocation), tactical (scheduling), and operational (implementation) problems.

On the other hand, McNaughton *et al.* (2000) justify the use of a monolithic approach because of the consistency it allows the planner to achieve between the results of decision models defined at two hierarchical levels. While the authors present a large model that integrates both strategic and tactical aspects of forest harvesting, a fully-integrated, real-size problem remains yet to be solved. The primary reason of this limitation relates to the combinatorial nature and the resulting size of the problem. Even if a large model could be solved, the centralized approach to forest management planning does not properly represent the problem as encountered in practice. Indeed, centralized approaches do not take into account the fact that decisions at different levels often come from different persons. Furthermore, they do not consider that decisions are not taken at the same frequency nor time, but rather in a successive manner, sometimes spaced out by weeks or even months. As put by Weintraub and Davis (1996) the challenge is « to recognize and integrate different decision-makers who have different problems and objectives but are hopelessly bound together in a cumulative effect hierarchical problem ».

Hierarchical planning

Hierarchical production planning (HPP) aims to simplify complex planning problems. Hax and Meal (1975) introduced the idea of HPP by partitioning the decision process into sub-problems covering different time horizons. Information is aggregated and disaggregated through the various hierarchical levels. Hierarchical analysis refers to the organization of information for making decisions at different levels when the quality/accuracy of the decisions made at one level depends upon decisions or information at other levels (Boyland 2003). Levels may be defined temporally or spatially where the scope of the higher level fully encompasses the scope of the lower level (Haimes 1982).

In this context, Meal (1984) summarizes some of the advantages of the hierarchical planning approach: (1) it reduces problem complexity by separating them into sub-problems and aggregating data at higher decision levels; (2) it is easier to understand by providing a good organizational fit; and (3) it reduces uncertainty by postponing decisions as long as possible. In the context of forest management, Gunn (1996) points out that the use of a deterministic model on a rolling planning horizon and replanning represent a good heuristic procedure for dealing with forest management planning under uncertain conditions.

However, HPP has its drawbacks. Indeed, HPP involves solving a set of problems in a sequential manner. Such an approach can lead to sub-optimality, inconsistencies and even to infeasibility. The degree of sub-optimality depends upon the quality of the coordination scheme used to link together the decision levels. Inconsistencies may arise because of conflicting objectives at different planning levels, while infeasibility usually results from information aggregation (Gelders and Van Wassenhove 1981) and the loss of cohesion between models and reality. Zoryk-Schalla (2001) adds that « Mid-term planning uses less detailed and different information than short-term planning, because detailed data is not yet available at the time that mid-term planning decisions need to be made. Yet the mid-term decisions should be such that the short-term decisions can be taken in line with overall operational objectives ».

To justify the use of a monolithic model to overcome the lack of cohesion between the results at different levels of a hierarchical approach, McNaughton *et al.* (2000) refer to the paper of Daust and Nelson (1993). The authors provide an example of a problem where long-term harvest schedules were developed using aspatial, strata-based formulations and spatial block scheduling formulations. The sustained yields estimated by the spatial formulations were in all cases lower than those estimated by the aspatial formulations by a range of 2% to 29%. These results raise the critical question of how to obtain consistency between the results of decision models defined at two or more hierarchical levels. They conclude that for consistency, regulations governing the spatial distribution of harvest units should also be incorporated into the long-term planning process where sustainable harvest levels are calculated. This suggests that lower-level impacts anticipated during decision making at a higher level must be better modeled and assessed. Adequate procedures must be defined to create better links between levels.

In order to address this issue, Schneeweiss (2003) proposes a general hierarchical framework which aims to bring consistency between hierarchical levels while respecting the distributed nature of planning problems. This framework also allows for the explicit consideration of the impact at a given level of decisions taken at a lower-level through the use of anticipation mechanisms. Schneeweiss and Zimmer (2004) conducted an extensive quantitative analysis of operational coordination mechanisms in the context of hierarchical planning. They concluded that the use of anticipation mechanisms results in significant improvement over the pure top-down hierarchical process.

This paper applies Schneeweiss' framework to a large-scale forest procurement planning problem. The main contributions of this paper include: (1) a description of the wood procurement problem hierarchical decomposition; (2) a hierarchical integration mechanism of the problem; (3) an anticipation model for the sequencing and equipment transportation problem; and (4) a heuristic procedure for the anticipation operational model.

The remainder of this paper follows the following format: The first section describes the applicability of Schneeweiss' framework to wood procurement planning, followed by a description of a hierarchical coordination mechanism and its relationship to the tactical wood procurement planning process. Then follows a sequencing and equipment transportation cost-anticipation model along with a heuristic solution procedure, and a performance evaluation of the heuristic solution procedure. Finally, a discussion on the search for optimality and prospective remarks conclude this paper.

Application to wood procurement planning

In wood procurement planning problems, one of the objectives pursued by tactical level planning involves setting the required production capacities. Although forest companies plan and manage forest operations, they often sub-contract the execution of these operations. Capacity setting thus allows companies to identify how many contractors to hire throughout the year, to specify working periods, and to define the length of the contracts binding the contractors to the forest company. Consequently, from the forest company's point of view, capacity setting does not involve immobilizing large amounts of its own resources to purchase equipment.

Beaudoin *et al.* (in press) present a mixed-integer programming model which aims at supporting the wood procurement tactical decisions of a multi-facility company. This model allows for wood exchange between companies. Furthermore, the material flow through the supply chain is driven by both a demand to satisfy (Pull strategy) and a market mechanism (Push strategy), enabling the planner to take into consideration both wood freshness and the notion of quality related to the age of harvested timber. This tactical model does not explicitly address the capacity setting decision. Rather, it suggests that once planners select a plan for implementation from a set of candidate plans, harvesting capacity requirements can be evaluated in regard to the production targets per period proposed. However, targets set by aggregated production plans at the tactical level constrain operational planning. Unfortunately, infeasibility may occur for a couple of reasons. First, harvesting decisions at the tactical level depend on aggregated capacity figures. Also, set up times (moving equipment from a block to another), lot sizing (net capacity requirements depend on the volume harvested on a block each time harvesting occurs) and harvest block sequencing decisions all stem from operational level decisions.

Therefore, the problem resides in how to adequately consider the impact of future operational harvesting decisions on the tactical level, and how to ensure that a tactical plan remains feasible at an operational level. The next section outlines the theoretical background exploited to propose a solution to this problem.

Generic hierarchical coordination mechanism

As previously explained, coordination mechanisms are required in order to overcome the main problems of HPP. In order to do so, Schneeweiss' general hierarchical framework proposes a not so pure top-down approach that takes into account the implication of cascaded decisions in a hierarchical planning context. Figure 1 depicts the structure of the hierarchical planning system referred to as a Tactical-Operational Distributed Decision Making (DDM) system.

INSERT FIGURE 1

The tactical-operational DDM system involves a two-level decision model, respectively the top and base-level decisions. A decision model *M* is defined by its system of criteria *C* (i.e., objective function) and its decision field *A* (i.e., set of constraints). The tactical model corresponds to $M^T = M^T\left(C^T, A^T\right)$ and $M^B = M^B\left(C^B, A^B\right)$ represents the operational model. Information status and the time at which decisions must be made remain important, so I_{t0}^T and I_{t1}^B denote the respective information status at t_0 and $t_1 \geq t_0$. Coordination between the tactical and operational levels proposed by the author is achieved by *reactive implicit anticipation,* meaning that only part of the operational level is anticipated as a bottom-up influence and an *instruction* as a top-down signal. Before decision making occurs at the tactical level, the decision-maker anticipates the base-level's decision reaction to a potential tactical decision (i.e. IN) through an anticipation function AF(IN). In turn, by integrating the output of this function in his decision process, the decision-maker can be influenced. This process is called reactive anticipation because the anticipation is assessed through a function that provides an estimate of how the base-level would react if submitted to such an instruction (i.e. the potential tactical decision). More specifically, AF(IN) is determined through the use of an anticipation base-model $\hat{M}^B = \hat{M}^B\left(\hat{C}^B, \hat{A}^B, \hat{I}^B\right)$. The top criterion C^T can thus be broken down into two criteria, C^{TT} and C^{TB}. The former represents the private criterion which corresponds to the objective function of the tactical problem, while the latter represents the top-down criterion which corresponds to the objective function of the operational model. The top-down criterion is the part of the top-criterion which explicitly takes into account the operational level and depends on the anticipation function. For further details on

Schneeweiss' hierarchical coordination mechanism, the readers are referred to Schneeweiss (2003).

We address a twofold challenge in applying such a framework to the specific context of tactical wood procurement planning. First, we consider the integration of the anticipation model influence into the top-level decision model, and second, the design of the anticipation model. The next section addresses both.

Tactical wood procurement planning

In a wood procurement context, tactical planning integrates harvesting, transportation and inventory (standing, roadside and log yards) decisions over the next year. The main purposes of tactical planning include setting production targets and required production capacities per period.

Tactical planning process

While wood procurement planning has grown in complexity, the industry still plans with limited mathematical programming supports. Such an intuitive and manual process typically leads to two shortcomings: (1) the inability to consider alternative plans for implementation due to the prohibitive amount of time required to develop a plan; and (2) the difficulty of assessing the performance of plans subjected to stochastic conditions. In Beaudoin *et al.* (in press), the authors propose a tactical planning process to overcome these two shortcomings. Figure 2 maps this planning process onto Schneeweiss' framework.

INSERT FIGURE 2

The top-level decision model (M^T) incorporates several components (a scenario generator, a tactical wood procurement planning model, and a rule-based simulator). The base-level decision model corresponds to all decisions that must be made at the operational level. This includes sequencing and equipment transportation decisions, the detailed allocation of products to blocks, the selection of bucking patterns for each block, etc. Finally, the anticipation model of the operational level incorporates only the operational decisions that most influence the tactical level. In brief, these decisions concern sequencing and equipment transportation, for which, the cost-anticipation model will be explained in the next section. Together, the top-level and the anticipation of the base-level decision models depicted in Figure 2 constitute a multi-criteria decision-making process to support a decision-maker in selecting a tactical plan to implement.

Integration of the anticipation and the top level decision models

The overall tactical planning process starts by creating a predefined number of scenarios S (defined by the planner) based on randomly generated values for the uncertain parameters, for each period considered in the model (Scenario generator). For each scenario $s \in S$, the planner determine the optimal plan a_s^T (referred to as a candidate plan) by solving a deterministic mixed-integer program (Tactical wood procurement planning model). Each candidate plan a_s^T then comes under further analysis. First, the planner simulates each candidate plan a_s^T within different scenarios (Ruled-based simulator). This analysis provides information on the private criteria C_s^{TT} of the top level. Next, each candidate plan a_s^T is submitted as an instruction $IN(a_s^T)$ to the anticipation model ($\hat{M}^B$) in order to anticipate the sequencing and equipment transportation cost $AF(IN)$, as well as other information on the top-down criteria C_s^{TB}, such as the feasibility of the candidate plan a_s^T. In each of these analyses, the planner gathers statistics in order to help resolve the resulting multi-criteria tactical decision problem. For further details on the tactical planning process discussed above and its components, we refer the reader to Beaudoin *et al.* (in press).

Operational anticipation

The anticipation offers a means through which the decision-maker takes into account the impact of his decisions on a lower level. The modeling decisions taken at the design stage of the anticipation model impact the quality of the information it provides. The anticipation operational model shares a modeling relationship with both the tactical $\left(M^{T}\right)$ and operational $\left(M^{B}\right)$ models. Its design involves a process of analysis and deduction (Figure 3).

INSERT FIGURE 3

We define hierarchical levels while in the design stage of such a hierarchical production planning system. For each level, we identify management objectives. The objectives at each level must line up with the overall objective of the organization. The goal pursued by the tactical level should dictate the constituents of the anticipation model, all the while representing an "accurate enough" assessment of the influence of the operational decision level. In order to do so, the decision-maker must first at the tactical level identify the components of the operational decision level that most influence his decisions. In practice, in order to avoid having to anticipate operational decisions, foresters define decision rules to simplify the planning process. For example, they largely use the rule of no-preemption of blocks during harvesting (i.e., never partially harvest blocks). Such a rule reduces the need to anticipate the cost of transporting harvesting equipment between blocks, because it results in a cost reduction at the operational level due to less transportation of equipment. This also simplifies the scheduling problem. However, it limits the flexibility offered at the tactical level by eliminating the possibility of harvesting only part of a block. Furthermore, not allowing preemption (i.e., ability to harvest a block over several periods) contributes at a tactical level to poor capacity deployment which can translate into (1) increased inventory of unneeded products, (2) shortages of needed products, (3) value loss through fibre degradation and (4) lost sales opportunities. In other words, not allowing preemption accords more importance to equipment transportation cost than to costs related to inventories imbalances, value loss and lost sales opportunities.

Consequently, a system analysis is required to identify the operational features that have the most impact on the tactical level. Adequate criteria to anticipate must hence be identified based on the objectives of the operational and tactical decisions levels. These criteria do not have to cover the entire operational problem.

In the example mentioned above, because blocks are harvested entirely, harvesting decisions take the form of binary variables. In the tactical wood procurement model proposed in Beaudoin *et al.* (in press), these decisions appear as continuous variables, which implicitly allows foresters to grasp the benefits of harvest block preemption. However, this practice results in an increase in the number of equipment transportations between blocks. Although limitations can be imposed on the number of periods over which harvesting can occur on a given block and the number of blocks on which harvesting can occur during a given period, such a practice exerts a definite impact on a machine's available production time. It thus becomes necessary to take this factor, as well as its cost, into account for the selection of a tactical plan. More specifically, when the decision-maker considers a candidate tactical plan, he needs to consider both its feasibility with regard to harvesting capacity and the equipment transportation cost involved in implementing the proposed harvest targets. These two criteria reflect the impact of tactical decisions on the operational level.

Consequently, the anticipation model we have designed is not intended for the detailed planning of operational activities, which involves detailed stem bucking pattern selection, among others. Hence, we anticipate only part of the operational level in order to assess the most strictly relevant information for the tactical decision-maker. Thus, in the context of the problem on hand, the anticipation model aims to minimize the total equipment transportation cost in implementing the tactical candidate plan. Ignoring harvest cost in the anticipation model will not translate into a schedule that groups machines to certain blocks for the sake of reducing the equipment transportation cost for two reasons. First, at a tactical level, harvest costs are already accounted for per type of machine in a specific block and at a given period. The resulting tactical candidate plan thus already provides information related to harvest capacity utilisation per type of machine and period. In hierarchical planning, tactical decisions are forwarded to the operational level for their implementation. Consequently, at the operational level, the planner does not reassess the type of machine assigned to each block and the periods over which harvesting will occur. Secondly, for a given machine harvesting a given block, seasonal or monthly harvest cost variations can be observed and have also been accounted for in the development of the tactical candidate plans. At the operational level, the timing of the harvest within the time frame covered by a tactical period does not impact the cost of the activity.

In general, the analysis of the features of the operational decision level allows the decision process designer to identify those having the most impact on the information needed to address the decision problem. Consequently, depending on the required information, other operational criteria may be accounted for in the anticipated problem.

Sequencing and equipment transportation cost-anticipation model

This section proposes a specific anticipation model of a firm's sequencing and equipment transportation cost-anticipation model ($\hat{M}^B$). First, we introduce data sets, followed by the parameters and variables used to formulate the model. Finally, we present the model formulation.

Sets

I : The set of harvesting blocks $\left(i = 1,\ldots,\widetilde{I}\right)$

M : The set of machines $\left(m = 1,\ldots,\widetilde{M}\right)$

R_t : The set of rounds within period t $\left(r = 1,\ldots,\widetilde{R}_t\right)$

T : The set of periods $\left(t = 1,\ldots,\widetilde{T}\right)$

In HPP, two temporal features define each level: the time horizon and the period. The time horizon defines the interval over which the decisions extend, while the period represents the interval of time after which the decisions come under reconsideration. The higher the level, the longer the horizon and the period. Since the set production targets originating from the tactical level serve at the operational level, two definitions of period are required. In the remainder of this paper, the term *period* refers to a tactical period, while *round* refers to the sequence of machine-block allocations over time such that each *period* includes several *rounds*.

Parameters

I_m^S: Start block of machine m at the beginning of the planning horizon.

V_{it}: Volume to be harvested on block i during period t.

D_{mt}: Capacity of machine m during period t.

α: Acceptable difference in total volume harvested by each machines.

δ: Portion of lowbed (flat deck trailer) total time not available for equipment transportation.

L: Total lowbed capacity during period t.

T_{mijt}: Required time to move machine m from block i to block j during period t.

C_{mijt}: Cost to move machine m from block i to block j during period t.

P_{mit}: Productivity of machine m on block i during period t.

N_{jrt}: Maximum number of machines on block j during round r of period t.

Decision variables

Figure 4 summarizes decision variables and their relationships with one another.

INSERT FIGURE 4

x_{mirt}: Time spent by machine m harvesting on block i during round r of period t.

$$y_{mijrt} : \begin{cases} 1, \text{if machine } m \text{ moves from block } i \text{ to block } j \text{ during round } r \text{ of period } t. \\ 0, \text{otherwise} \end{cases}$$

Model

[1] $$\text{Min} \sum_{m \in M} \sum_{i \in I} \sum_{j \in I} \sum_{t \in T} \left(C_{mijt} \sum_{r \in R_t} y_{mijrt} \right)$$

Subject To:

Capacity constraints

[2] $$\sum_{j \in I} \sum_{r \in R_t} x_{mjrt} + \sum_{i \in I} \sum_{j \in I} \left(T_{mijt} \sum_{r \in R_t} y_{mijrt} \right) \leq D_{mt} \quad \forall m \in M, \forall t \in T$$

[3] $$\sum_{m \in M} \sum_{i \in I} \sum_{j \in I} \left(T_{mijt} \sum_{r \in R_t} y_{mijrt} \right) \leq (1 - \delta) L \quad \forall t \in T$$

[4] $$\sum_{m \in M} \sum_{i \in I} y_{mijrt} \leq N_{jrt} \quad \forall j \in I, \forall r \in R_t, \forall t \in T$$

Supply constraints

[5] $$\sum_{m \in M} \left(P_{mit} \sum_{r \in R_t} x_{mirt} \right) = V_{it} \quad \forall i \in I, \forall t \in T$$

[6] $$\sum_{i \in I} \left(P_{mit} \sum_{r \in R_t} x_{mirt} \right) \geq \frac{(1 - \alpha) \sum_{i \in I} V_{it}}{\widetilde{M}} \quad \forall m \in M, \forall t \in T$$

[7] $$x_{mjrt} \leq \min \left\{ D_{mt}, \frac{V_{jt}}{P_{mjt}} \right\} \sum_{i \in I} y_{mijrt}$$
$$\forall m \in M, \forall j \in I, \forall r \in R_t, \forall t \in T$$

Flow constraints

[8] $$\sum_{i \in I} \sum_{j \in I} y_{mijrt} \leq 1 \quad \forall m \in M, \forall r \in R_t, \forall t \in T$$

[9] $$y_{mij11} = 0 \quad \forall m \in M, \forall i \in I, \forall j \in I$$
$$\text{where} \quad i \neq I_m^S$$

$$[10.1] \quad \sum_{i \in I} y_{mi\varepsilon rt} = \sum_{j \in I} y_{m\varepsilon j(r+1)t} \quad \forall m \in M, \forall \varepsilon \in I, \forall r < \widetilde{R}_t, \forall t \in T$$

$$[10.2] \quad \sum_{i \in I} y_{mi\varepsilon \widetilde{R}_t t} = \sum_{j \in I} y_{m\varepsilon j1(t+1)} \quad \forall m \in M, \forall \varepsilon \in I, \forall t < \widetilde{T}$$

Non-negativity constraints

$$[11] \quad x_{mirt} \geq 0 \quad \forall m \in M, \forall i \in I, \forall r \in R_t, \forall t \in T$$

$$[12] \quad y_{mijrt} \in \{0,1\} \quad \forall m \in M, \forall i \in I, \forall j \in I, \forall r \in R_t, \forall t \in T$$

Objective function

The objective function aims to minimize the total anticipated equipment transportation cost. Companies incur equipment transportation costs whenever they must use a lowbed to move equipment from one block to another. In the case where subsequent blocks lie close to one another, operators may drive the machines without incurring extra costs, although moving time must be taken into account.

Constraints

Capacity constraints

Equations [2] and [3] represent, respectively, machine and lowbed capacities. The planner must consider individual machine's capacities in order to determine a sequence of blocks to harvest and to synchronize the timing of their displacements. Equation [2] also ensures that time spent harvesting and moving does not exceed the machine's available time. For the lowbed, aggregated capacity is considered rather than individual capacity since no lowbed scheduling is attempted (eq. [3]). Due to the operational limitations imposed by the harvesting blocks' size as well as safety reasons, equation [4] limits the number of machines on a block at any given time.

Supply constraints

The starting point for the anticipated problem involves a list of targeted volumes to be harvested per block for every period considered. Equation [5] ensures that equipment spends enough time on the blocks to reach these targets. Equation [6] allows for a relatively uniform distribution of the workload between contractors. Equation [7] outlines the setup forcing constraint: if there exists any positive production for machine *m* on block *j* at round *r* of period *t*, a setup is enforced (transport machine *m* to block *j*). In order to strengthen the formulation, we limit the production by both the maximum possible production time with the available capacity and the maximum time to harvest the targeted volume on the block.

Flow constraints

Since a machine cannot work on more than one block at a time, equation [8] serves to render it indivisible. Also, the location of the machines at the beginning of the planning horizon will have an impact on their subsequent destinations as the model will aim to minimize equipment transportation cost which relates to moving distances. Equation [9] identifies the initial location of the equipment. Finally, equations [10.1] and [10.2] represent intra- and inter-period flow conservation constraints and ensure that equipment can be moved from a block only if driven or delivered there previously.

The sequencing and equipment transportation cost-anticipation problem yields a large-scale mixed-integer linear problem. Binary variables correspond to moving decisions and continuous variables describe harvesting time.

Heuristic procedure

The problem at hand corresponds to a scheduling problem with sequence-dependent setup times, one of the most difficult types of scheduling problems. A one-machine sequence-dependent setup scheduling problem is equivalent to a traveling-salesman problem (TSP) and is NP-hard (Pinedo 1995). Sequence-dependent setup scheduling of a multi-machine and multi-production stage system creates an even greater challenge. Parallel machines scheduling problem (PMSP) date back to the late 1950's (McNaughton 1959 and Hu 1961). Cheng and Sin (1990) provided a state-of-the-art of scheduling approaches until 1990 on parallel machines scheduling. More recently Mokotoff (2001) complemented the review with new developments on PMSP.

The problem is solvable by using a commercial solver directly with a limited number of periods. In view of the difficulty of finding the optimal solution to a real-size problem, a simple heuristic procedure has been developed to solve the sequencing problem.

Heuristic solution procedure

A heuristic solution procedure was proposed in an attempt to find a good quality solution in a reasonable amount of time. The proposed heuristic stems from time decomposition. The time decomposition method consists in dividing a large time horizon into several smaller periods where scheduling problems can be solved efficiently (Wu and Ierapetritou 2003). The heuristic makes use of the solution procedure depicted in Figure 5.

INSERT FIGURE 5

For a given original problem, the solution procedure begins by initializing sub-problem *p* to zero. The procedure solves a series of *n* sub-problems sequentially where *n* corresponds to the number of periods in the original tactical problem. Using results from the actual sub-problem *p*, constraints are propagated to *p+1* in order to ensure that the ending location of a machine becomes its starting position for the next sub-problem.

Heuristic

Three heuristics underwent testing for the sequencing and equipment transportation cost-anticipation problem. The main differences between these heuristics reside in the planning horizon covered by the sub-problems and the nature of the decision variables. Hereafter, we present only the best performing heuristic. For further details on the two other heuristics and their performance evaluations, we refer the reader to Beaudoin *et al.* (2005).

The multi-period sequencing and equipment transportation cost-anticipation problem is decomposed by partitioning the planning horizon into *n* overlapping, dependent sub-problems. Let $\bar{t}$ represent the current period considered into sub-problem *p*, $p = 1,2,...,n$, where *n* corresponds to the number of periods considered in the original problem. Let t_p represent the first period considered into sub-problem *p*. The range of periods assigned to sub-problem *p* corresponds to $\{t_p, t_p + 1\}$. For each sub-problem, the first period considered corresponds to the current period, thus $t_p = p = \bar{t}$. Variables corresponding to moving decisions are of type integer. This formulation iteratively solves the sub-problems by considering the impact of the moving decisions for the subsequent period. This modification facilitates computations while considering future displacement needs. From the optimal solution of each sub-problem, only the solution of the current period $\bar{t}$ is used in the solution of the original problem. Sub-problems are solved to optimality using the model previously presented (equations [1]-[12]).

Heuristic performance evaluation

Two computational experiments were conducted to evaluate the performance of the heuristic. Through these experiments, we compared solutions found with the heuristic with those obtained through: (1) direct solving of small instances of test problems; and (2) lower bound calculation obtained by Lagrangean relaxation with a subgradient optimization scheme. Direct solving used standard branch-and-bound technique.

For the computational experiments, we considered three harvesting systems, each composed of a processor and a forwarder. No possibility exists of using extra systems, as capacity determination occurs at the tactical level. Within the tactical planning process, the planner gathers statistics regarding plans' feasibility. Meanwhile, in order to evaluate the performance of the heuristic in term of its ability to find solutions close to optimality, we set harvesting and lowbed capacities in order to avoid any infeasibility.

All computations were performed with CPLEX 9.1 on a 1.27 GHz Pentium 3 personal computer with 1.83 GB of RAM to solve the mixed-integer problems directly and through the heuristic solution procedure. The mathematical model is implemented in the Optimization Problem Language (OPL) of Ilog and the heuristic solution procedure as well as the Lagrangian relaxation in OPLscript.

For the first experiment, we developed 30 small instances of test problems with the number of periods and the number of blocks to be harvested per period randomly selected from uniform distribution [1, 6] and [0, 5], respectively. We also developed the levels of harvesting to occur on the identified blocks from a uniform distribution [2000, 6000]. The solutions found by solving the mixed-integer program presented previously served to benchmark the solution found by the heuristic. Let C_H and C_{MIP} represent the costs found by the heuristic and the mixed-integer program, respectively. Table 1 summarizes the performance of the heuristic.

INSERT TABLE 1

The average required time to solve the test problems to optimality equates to 89.7 minutes, the minimum time, 1.4 minutes, and the maximum, over 240 minutes - the time limit imposed to CPLEX for the experiment. The average time to solve the same test problems with the heuristic equates to 3.3 minutes, the minimum time, only 0.1 minute, and the maximum time, 6.0 minutes. The average cost deviation is 1.8%, the minimum deviation, 0.0%, and the maximum deviation, 4.8%. Table 1 clearly indicates that the heuristic can find reasonably good solutions in a short period of time. Finding the optimal solution by directly solving the mixed-integer program, however, remains impractical. Several of the small instances of test problems exceeded the time limit of four hours.

For the second experiment, we developed 30 test problems in a similar fashion with the number of periods and the number of blocks to be harvested per period randomly selected from uniform distribution [6, 26] and [3, 6], respectively. We also determined the levels of harvesting to occur on the identified blocks from a uniform distribution [2000, 6000]. We computed Lower bounds through Lagrangean relaxation with a subgradient optimization scheme. The Lagrange relaxation reformulation of the original problem dualizes the inter-period flow balancing constraint [10.2] in the objective function [1]. A complete description of the lower bound evaluation procedure appears in the Appendix.

Let C_H and C_{LB} represent the costs found by the heuristic and the computed lower bound respectively. Table 2 summarizes the performance of the heuristic.

INSERT TABLE 2

The average time to solve the problems with the heuristic equates 33.1 minutes, the minimum time, 12.6 minutes, and the maximum time, 53.7 minutes. The average cost deviation, 6.1%, the minimum deviation, 1.6%, and the maximum deviation, 11.5%.

Anticipation and limits of optimality

The anticipation approach proposed in this paper involves a two-step procedure because top-level instructions are introduced as constraints in the anticipation model of the operational level. The results of this anticipation then re-enter the tactical multi-criteria decision problem. Because these results represent an anticipation of what operational planning would resemble if each of the candidate tactical plans were implemented, the need for an optimal solution becomes unnecessary for two reasons. The first relates to the status of information. More specifically, when operational planning occurs, the information required to produce a plan may differ from the available information when conducting tactical planning. Any optimal solution of the anticipation decision model thus likely becomes sub-optimal. The second reason involves the time framework differential of tactical and operational planning. Operational planning occurs indeed several times within one tactical period. The resulting plan implemented at execution time thus represents the concatenation of many partial operational plans (the first periods between two planning cycles). Consequently, even the optimal solution of the anticipation model would not fully represent the operational planning dynamics with its ability to recover from perturbations. This becomes even more complicated when the operational planning horizon covers more than one tactical planning cycle (i.e., periods) for which tactical decisions have not yet been made. Figure 6 illustrates the interactions and time framework differential of these planning levels.

INSERT FIGURE 6

Consequently, in the context of hierarchical planning with anticipation, the search for an optimal anticipation decision seems rather irrelevant. It seems more important to consider the anticipation not as an optimization problem but rather as an information gathering process to help evaluate how decisions that are taken at one level impact lower levels' ability to reach the set production targets. Although proven useful in the solution approach proposed in this paper, it raises other questions such as how to evaluate the level of quality of an anticipation and how to improve this quality over time.

Conclusion

Wood procurement planning remains by nature a complex process. HPP is known for reducing problem complexity by partitioning the problem into sub-problems that are solved in a sequential manner. Such approach can lead to sub-optimality, inconsistencies and even to infeasibility. We have seen how Schneeweiss' modeling framework, making use of anticipation, can operate in the context of tactical wood procurement planning in order to lessen the shortcomings of HPP while respecting the distributed nature of the planning problem. Indeed, this approach provides the flexibility needed to include several key decisions taken at one level but having the potential to greatly influence a plan at a different level. We present a multi-dimension modeling approach employing tactical harvest planning with preemption and operational sequencing and equipment transportation. The approach can also serve to anticipate other operational features. The approach can be used advantageously in planning at higher levels incorporating a broad range of problems.

A firm's sequencing and equipment transportation cost-anticipation problem has been presented as a mixed-integer model. This anticipation model is not intended for the actual planning of operational activities. We anticipated part of the operational level in order to gather information relevant to the decision-maker at a tactical level. This information reveals its value in a tactical planning process in the evaluation of the impact of tactical decisions on the operational level.

The sequencing and equipment transportation cost-anticipation model remains solvable with a commercial solver if considering a limited number of periods. In view of the difficulty and the relevance of finding the optimal solution to this problem, we have also tested a heuristic solution procedure based on time decomposition. The performance of the heuristic solution procedure has been evaluated by comparisons with computed lower bounds obtained through Lagrangean relaxation. The computational results show that the total equipment transportation cost averages 6.1% above the lower bound.

The search for an optimal anticipation decision seems rather irrelevant in the light of limitations imposed by the information asymmetry and the asynchronous planning in the various planning levels. To lessen the shortcomings resulting from the information asymmetry, uncertainty could be accounted for in the anticipated operational model instead of using the presented deterministic approach. Simulating the implementation of each candidate tactical plan over a determined number of uncertain operational scenarios could provide more valuable information to the decision-maker seeking to select a candidate tactical plan for implementation.

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Appendix

Lagrangean relaxation consists in absorbing (dualizing) the bounding constraints into the objective function and in solving the resulting problem. In the Lagrange relaxation reformulation of the original problem, the inter-period flow balancing constraint [10.2] is dualized in the objective function [1] with dual multipliers $\lambda_{m\varepsilon t}$ unrestricted in sign.

[13] $$\text{Min} \sum_{m\in M}\sum_{i\in I}\sum_{j\in I}\sum_{t\in T}\left(C_{mijt}\sum_{r\in R_t} y_{mijrt}\right) + \sum_{m\in M}\sum_{\varepsilon\in I}\sum_{t=1}^{\tilde{T}-1}\lambda_{m\varepsilon t}\left(\sum_{j\in I} y_{m\varepsilon j1(t+1)} - \sum_{i\in I} y_{mi\varepsilon\tilde{R}_t t}\right)$$

After rearranging the terms in the objective function, the Lagrange problem becomes:

[14] $$\text{Min} \sum_{m\in M}\sum_{i\in I}\sum_{j\in I}\sum_{t\in T}\left(C_{mijt}\sum_{r\in R_t} y_{mijrt}\right) + \sum_{m\in M}\sum_{\varepsilon\in I}\sum_{t=2}^{\tilde{T}}\lambda_{m\varepsilon(t-1)}\left(\sum_{j\in I} y_{m\varepsilon j1t}\right) - \sum_{m\in M}\sum_{\varepsilon\in I}\sum_{t=1}^{\tilde{T}-1}\lambda_{m\varepsilon t}\left(\sum_{i\in I} y_{mi\varepsilon\tilde{R}_t t}\right)$$

s.t. [2]-[10.1], [11]-[12].

The Lagrange problem decomposes into separate sub-problems for each period *t*:

For *t=1*:

[15] $$\text{Min} \sum_{m\in M}\sum_{i\in I}\sum_{j\in I}\left(C_{mijt}\sum_{r\in R_t} y_{mijr1}\right) - \sum_{m\in M}\sum_{\varepsilon\in I}\lambda_{m\varepsilon 1}\left(\sum_{i\in I} y_{mi\varepsilon\tilde{R}_t 1}\right)$$

s.t. [2]-[10.1], [11]-[12].

For $1 < t < \tilde{T}$:

[16] $$\text{Min} \sum_{m\in M}\sum_{i\in I}\sum_{j\in I}\left(C_{mijt}\sum_{r\in R_t} y_{mijrt}\right) + \sum_{m\in M}\sum_{\varepsilon\in I}\lambda_{m\varepsilon(t-1)}\left(\sum_{j\in I} y_{m\varepsilon j1t}\right) - \sum_{m\in M}\sum_{\varepsilon\in I}\lambda_{m\varepsilon t}\left(\sum_{i\in I} y_{mi\varepsilon\tilde{R}_t t}\right)$$

s.t. [2]-[8], [10.1], [11]-[12].

For $t = \tilde{T}$:

[17] Min $\sum_{m\in M}\sum_{i\in I}\sum_{j\in I}\left(C_{mij\widetilde{T}}\sum_{r\in R_{\widetilde{T}}} y_{mijr\widetilde{T}}\right)+\sum_{m\in M}\sum_{\varepsilon\in I}\lambda_{m\varepsilon(\widetilde{T}-1)}\left(\sum_{j\in I} y_{m\varepsilon j1\widetilde{T}}\right)$

s.t. [2]-[8], [10.1], [11]-[12].

The Lagrange problem is solved through several iterations and the Lagrange dual prices $\lambda_{m\varepsilon t}$ are updated by a standard subgradient optimization scheme formulated in [18].

[18] $\lambda_{m\varepsilon t}^{\phi+1}=\lambda_{m\varepsilon t}^{\phi}+S^{\phi}\left(\sum_{j\in I} y_{m\varepsilon j1(t+1)}^{\phi}-\sum_{i\in I} y_{mi\varepsilon\widetilde{R}_t t}^{\phi}\right) \quad \forall m\in M, \forall \varepsilon\in I, \forall t<\widetilde{T}$

Let $\lambda_{m\varepsilon t}^{\phi}$ be the dual prices at iteration *Φ* and let $\left(x_{mjt}^{\phi}, y_{mijrt}^{\phi}\right)$ be the optimal solution for the Lagrange problem at iteration *Φ*. The optimal objective value of [14] for the Lagrange problem at iteration *Φ* is $v\left(\lambda_{m\varepsilon t}^{\phi}\right)$. In the calculation of the step size *S* (eq. [19]), UB is the best-known upper bound for the original problem [1]-[12] and π is initially set to two and is decreased whenever $\left(x_{mjt}^{\phi}, y_{mijrt}^{\phi}\right)$ has failed to improve in a specified number of iterations. For further details on Lagrangean relaxation, we refer the reader to Fisher (1981).

[19] $S=\dfrac{\pi\left(UB-v\left(\lambda_{m\varepsilon t}^{\phi}\right)\right)}{\sum_{m\in M}\sum_{\varepsilon\in I}\sum_{t=1}^{\widetilde{T}-1}\left(\sum_{j\in I} y_{m\varepsilon j1(t+1)}^{\phi}-\sum_{i\in I} y_{mi\varepsilon\widetilde{R}_t t}^{\phi}\right)^2}$

For the calculation of the step size as defined by equation [19], UB to full size problems are provided by the heuristic and π is initially set to 2 and is decreased whenever no improvement occurred in the last 30 iterations. The stopping criterion for the subgradient optimization scheme was set to 200 iterations.

Table 1 Performance of the heuristic solution procedure compared with the optimal solutions found by branch and bound.

$\left(C_H - C_{MIP}\right)/C_{MIP} * 100\%$			Time required to find the heuristic solution in minutes			Time required to to solve the MIP in minutes		
Min	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**
0.0	4.8	1.8	0.1	6.0	3.3	1.4	240.0*	89.7

*The time required to find the optimal solution exceeds the time limit of 4 hours set for solving the MIP by CPLEX.

Table 2 Performance of the heuristic solution procedure compared with computed lower bounds.

$(C_H - C_{LB})/C_{LB} * 100\%$			Time required to find the heuristic solution in minutes		
Min	**Max**	**Mean**	**Min**	**Max**	**Mean**
1,6	11,5	6,1	12,6	53,7	33,1

Figure 1 Tactical-Operational DDM system

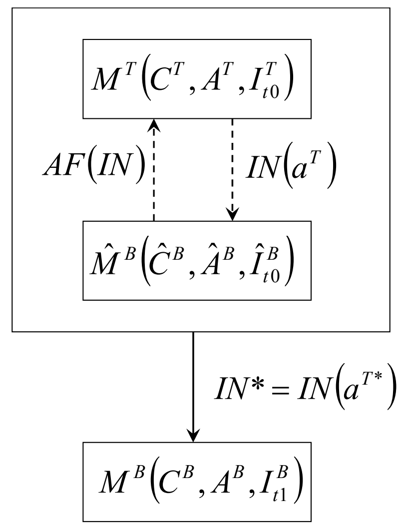

Figure 2 Tactical planning process

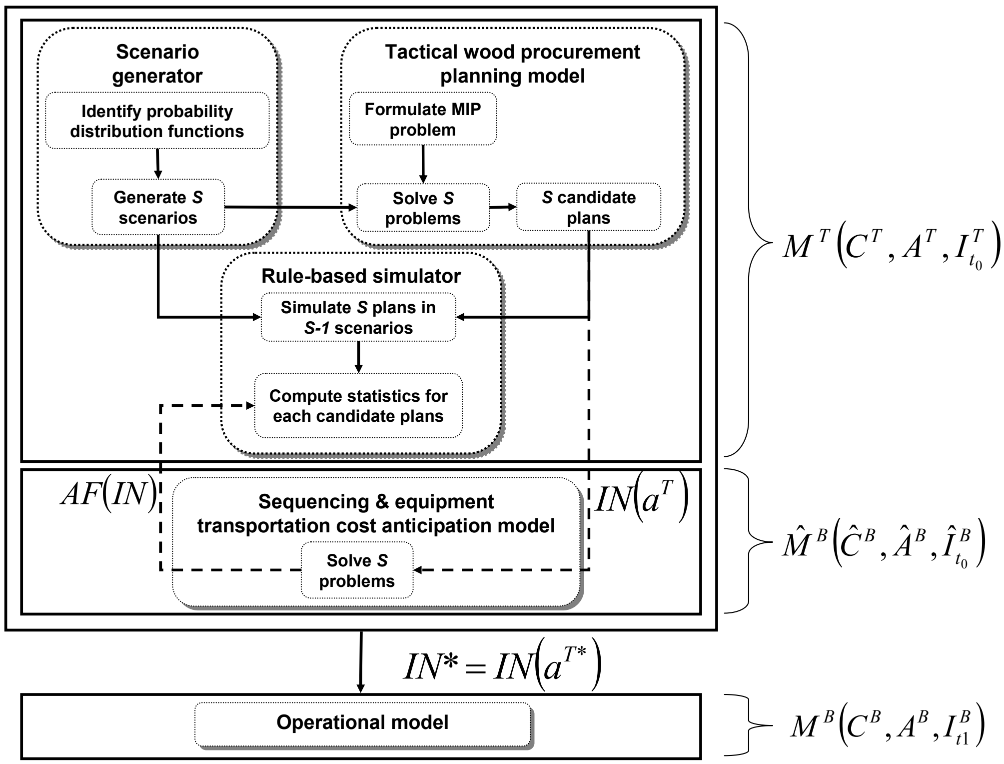

Figure 3 Design relationship

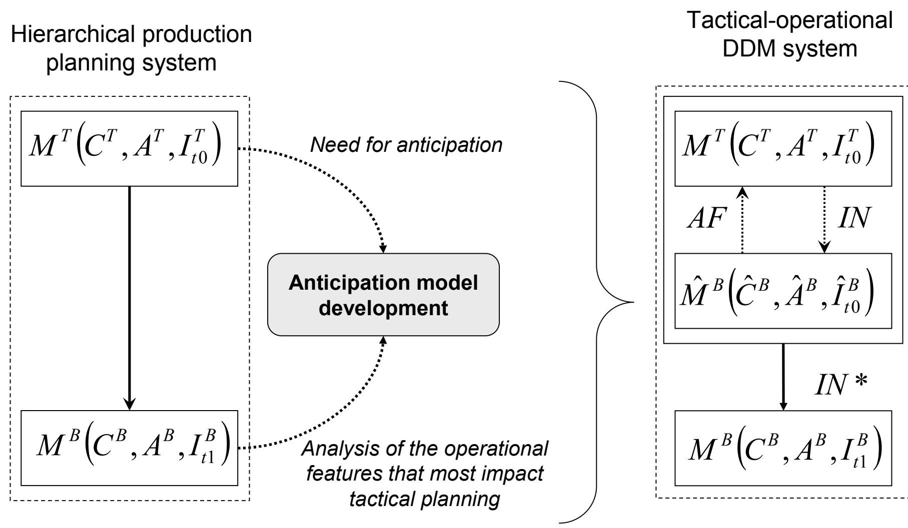

Figure 4 Sequencing and equipment transportation problem

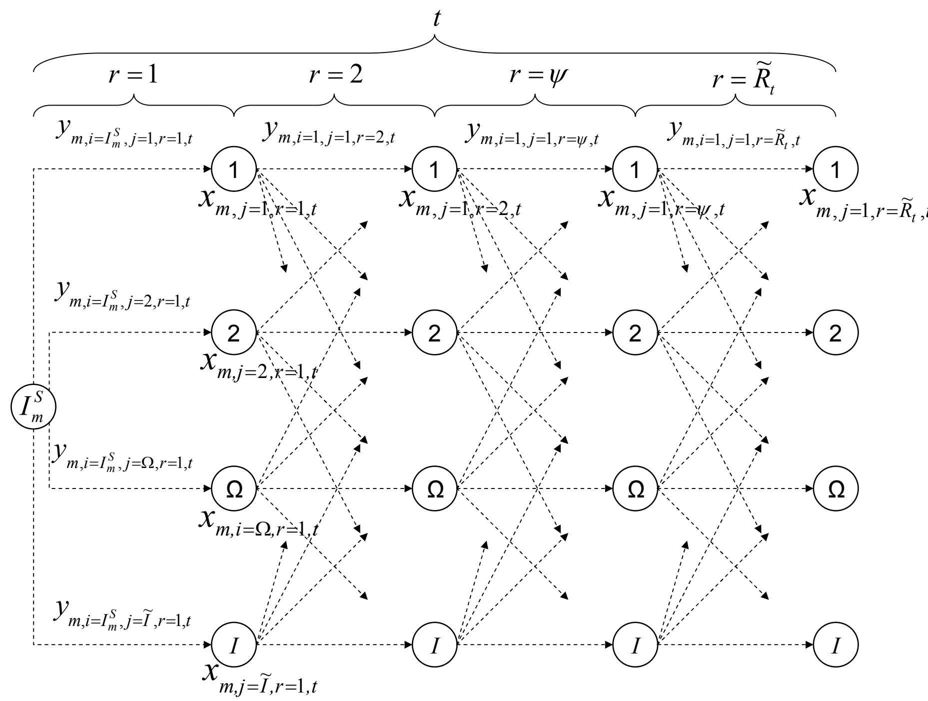

Figure 5 Flow chart of the heuristic solution procedure

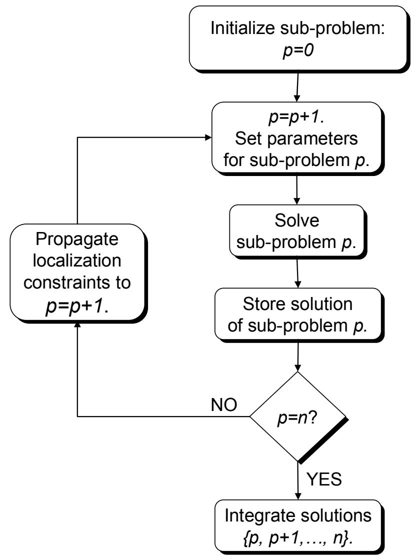

Figure 6 Rolling planning horizon in hierarchical planning