A Transportation-Scheduling System for Managing Silvicultural Projects

Jorge F. Valenzuela
H. Hakan Balci
Timothy McDonald
Auburn University
Alabama, USA

ABSTRACT

A silvicultural project encompasses tasks such as site-level planning, regeneration, harvest, and stand-tending treatments. An essential problem in managing silvicultural projects is to efficiently schedule the operations while considering project task due dates and costs of moving scarce resources to specific job locations. Transportation costs represent a significant portion of the total operating cost. The main difficulty in developing such a management system is finding an optimal transport schedule while handling complicated constraints, such as precedence and temporal relations among project tasks, project due dates, truck routing, weather, and other operational conditions. It is well known that finding an optimal solution to these types of problems involves high computational complexity. They are usually NP-hard. For this reason, we propose to use simulated annealing –a meta-heuristic optimization method– that interacts with a network simulation model of the system in which the precedence and temporal relations among project tasks and logistics are explicitly accounted for. The approach has been tested using data provided by a silvicultural contractor located in Alabama. The results obtained solving one instance of a small size problem with five worksites showed that the best solution could be found in less than four minutes using a personal computer with a processor Pentium III (1 GHz). A good solution for a larger problem with twenty worksites was found in thirty minutes. Also a resource analysis is performed to evaluate the impact of each resource on the best solution.

Keywords: *Project management, silvicultural systems, forest operations, meta-heuristic, optimization, simulation.*

The author are, respectively, Assistant Professor, and PhD Student in the Department of Industrial and Systems Engineering, and Associate Professor, Department of Biosystems Engineering, Auburn University.

INTRODUCTION

Silviculture is defined as managing forest vegetation by controlling stand establishment, growth, composition, quality and structure for the full range of forest resource objectives [7]. This is a broad definition encompassing a multitude of concepts, all of which must be translated into manipulations of a given trait or characteristics to effect some change at a stand or sub-stand. The range of manipulations used on any given stand can vary considerably, but as the science of silviculture matures the complexity and number of entries into stands for management activities has tended to increase. At the same time, the need to reduce the cost of these activities has lead to specialized equipment and contractors to implement custom prescriptions efficiently across many locations. When the primary resource being manipulated is timber, cost of silvicultural operations is of particular importance and new ways are being sought to reduce the amount of input resources needed to establish and maintain maximum growth rate.

Forest landowners in the Southeast US, particularly large industrial forest product companies, often use silvicultural service providers as a means of implementing their management prescriptions. These providers can perform a broad spectrum of management activities at low cost, but, as in logging, there is always a need to further improve the efficiency of the operations. Service providers have turned to new technology in order to improve their cost effectiveness, in particular adapting techniques from precision agriculture to reduce chemical inputs. Adopting logistical strategies used successfully in other industries also holds the promise of improving operational efficiency. Providing silvicultural services typically implies performing numerous operations simultaneously across a large geographic area. These operations share equipment resources. For example, a crawler tractor might be used for road improvement work as well as in site preparation plowing. Scheduling the use of these limited resources has a large impact on the efficiency of the entire operation. Equipment must be dispatched to sites in a sequence that minimizes total moving costs, primarily a function of distance traveled, and that also accounts for temporal aspects of task completion. The scheduling process is further complicated by constraints on movement of the equipment and by external factors such as weather. Management and scheduling of these activities is currently done by people with experience in such matters, but as companies become larger and the number and complexity of jobs increases, silvicultural service providers are looking for improved methods of assigning resources to jobs in a manner that optimizes their operational efficiency.

the case that the resource unit has its own transportation (can move by itself), the assumption is also valid. Figure 1 shows an example of a transport schedule (a solution) for a forest project with 5 worksites, two identical units of the resource class 1, and one unit of resource class 2. Here, worksite 0 (W_0) is assumed to be a central worksite where maintenance activities can be performed. The figure shows that the first unit of resource class 2 is currently at worksite 0 and is scheduled to visit worksite 4 and then worksite 3.

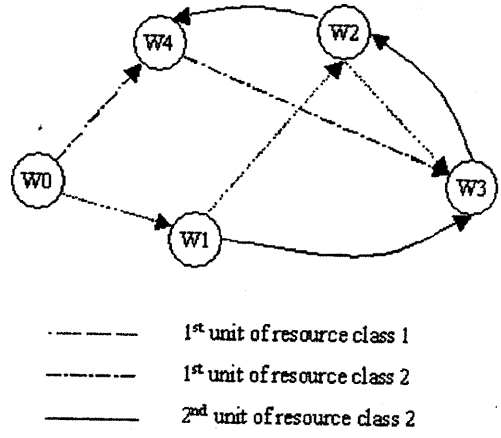


Figure 1. A solution for a multi-project problem.

Mathematical Model

We assume that the silvicultural multi-project consists of N spatially dispersed worksites. Each worksite is considered one project. The quantity d_{ij} is the distance between worksites i and j. At each worksite i (i=0, ...,N-1), a set of M_i tasks need to be performed. The set of tasks to be performed at worksite i is denoted by $\{t_{1i}, t_{2i}, \ldots\}$. The task precedence relationships, resource requirements, and execution times of the tasks are all part of a project description, which we denote by $\mathbf{W}=[W_0,..,W_i,..,W_{N-1}]$. The due dates of the projects are denoted by $\mathbf{D}=[D_0,..,D_i,..,D_{N-1}]$. Figure 2 presents a hypothetical example of a project description outlining the tasks to be performed at worksite 1, project description W_1. The figure shows the precedence relationships, duration, and resource requirement of each activity. The available resource classes, quantities, and initial positions of each of the resource units are part of the transport description, which we denote by $\mathbf{T} = [T_1,\ldots,T_j,\ldots,T_R]$ (R resource classes.)

The mathematical model for minimizing project durations can be written as follows:

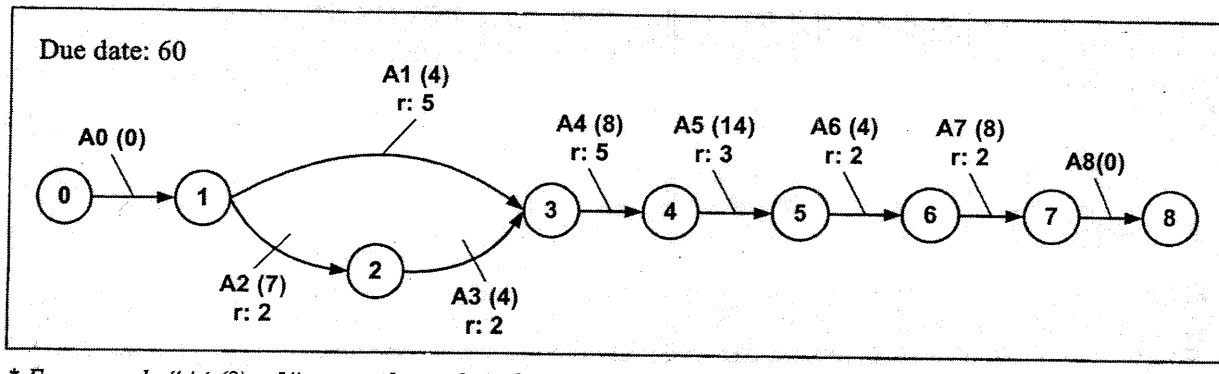
Min z

Subject to $\mathbf{C} = \mathbf{F}(\mathbf{X}; \mathbf{W},\mathbf{T})$; $\mathbf{C} \leq \mathbf{1}z$; $\mathbf{C} \leq \mathbf{D}$

Where $\mathbf{C}$ is a vector in which entry i is the completion time of project i. $\mathbf{F}(.)$ is a function that evaluates the completion time of each project given the descriptions of the projects and transport, and the solution $\mathbf{X}$. The vector $\mathbf{1}$ denotes a vector with all entries equal to 1, i.e. $\mathbf{1}$=[1, 1,...,1].

Solution Approach

The solution approach consists of two main components, a network simulation model and a search heuristic. The simulation model is used to evaluate the function $\mathbf{F}$, i.e. the completion time of the projects. The purpose of the search heuristic component is to select a good solution $\mathbf{X}$, and is implemented using a Simulated Annealing (SA) algorithm. In the literature there are multiple applications of SA to forest management and planning. Öhman and Lämås [14] studied long-term planning of harvest activities considering biodiversity, recreation and new road planning. They concluded that the spatial dimension of the problem increased complexity, but that the SA



* *For example "A4 (8) r:5" means that task 4 of project A has a duration of 8 hours and requires resource class 5.*

Figure 2. Description of worksite/project W_1*

The scope of scheduling silvicultural tasks lies within what is called project scheduling under resource constraints, which has been extensively studied [6]. One of the simplest project scheduling approaches is the Critical Path Method (CPM) [17]. In this method, the set of tasks are represented as a network to denote the precedence relations among pairs of tasks. The goal in the CPM approach is to determine the smallest possible project completion time without violating the precedence relations of the tasks. The method assumes infinite availability of resources. A more realistic variant of the CPM is the Resource-Constrained Project Scheduling problem (RCPSP) [10]. Several approaches have been proposed to solve the RCPSP. Pritsker et al. [15] proposed one of the first mathematical formulations, a 0-1 linear programming model to solve the RCPSP. The formulation requires the definition of up to nT binary variables, where n is the number of activities and T is the number of time periods. The complexity of the model is $O(n^2+mT)$, where m is the number of resources. More 0-1 linear programming models can be found in [3, 11]. Although the RCPSP is more realistic, it still has some limitations. One of the drawbacks of the RCPSP formulation is that it assumes constant availabilities of the resources during the planning horizon, but it is common in practice that machines are scheduled for maintenance or they are required for other projects. Also, due dates cannot be considered within the RCPSP framework. The Generalized Resource-Constrained Project Scheduling Problem (GRCSP) [10] overcomes some of these limitations and has been successfully used in manufacturing applications [4]. Despite its high practical relevance, the GRCSP is still not a good model for use in scheduling silvicultural tasks since the method neglects transportation costs. There is also a large literature on transportation routing problems, which are modeled and solved with various approaches [8, 12]. The reader is referred to [5] for an overview of vehicle routing problems. However, these models do not implicitly account for the ordered sequence of tasks that may use these transportation resources.

This paper proposes a computer meta-heuristic model for scheduling simultaneously several silvicultural projects, each project consisting of an ordered sequence of tasks requiring the use of limited equipment resources. The model implicitly considers due dates of each project, the order and nature of steps to complete tasks, task-duration times, resource requirement constraints, task-precedence relationships, geographic location of the projects, transportation costs, and due date violation costs. The goal of the model is to allocate shared expensive assets and minimize transportation costs and completion time of the projects. The resulting optimization problem is a nontrivial generalization of the GRCSP. To solve meaningful problems, we have developed an optimization procedure consisting of a simulated annea (SA) [16] algorithm that interacts with a network sim tion model of the silvicultural multi-project system.

The paper has been organized as follows. In sectio we describe the proposed approach. In section 3, we scribe our experimental methodology and summarize merical and performance results. In section 4, a resou capacity sensitivity analysis is performed to evaluate impact of each resource on the best scheduling soluti

PROPOSED APPROACH

The problem of managing silvicultural projects can formulated as efficiently scheduling transportation a project tasks while considering project due dates a costs of moving resources to specific job locations. Sch uling transport among several competing locations a functions is critical in efficiently managing silvicultu projects. Transportation costs represent a signific portion of the total operating cost. Trucks are needed delivering timber to mills and for carrying machinery b tween worksites, which can be located anywhere withi large geographic area. A transportation management sy tem that allocates limited truck resources optimally amo competing interests and takes into account project d dates could increase the total operational efficiency o procurement entity.

Problem Description

A solution **X** to the transportation-scheduling proble consists of a set of routes for each of the resources th visit each project location such that all projects can b completed. A route specifies the sequence in which th resource will visit the worksites. For example, for a set projects consisting of four worksites and three resour units, a solution could be given by the set of routes X {(1, 4, 3, 2, 3), (2,1,4), (4,2,1)}. In this solution, resource is scheduled to start at worksite 1, then travel to worksi 4, and so on. In our formulation, we assume R differe classes of resources and that each class k (k=1,..,R) ha r_k identical units available. For example, four similar tra tors (three John Deere and one Allis Chalmers) may for the "resource class" tractor. Each tractor is then a re source unit. We assume that once an activity releases particular resource, the resource can start its travel to th next activity scheduled to use this resource unit. Th next activity can be located at the same or at a remot worksite. This assumption implies that if the resourc unit requires a truck, the truck will be available to trans port it. Notice, however, that a truck can also be modele as a resource unit and it can be requested by activities. I

approach could effectively generate optimal solutions. In another study [1], Baskent and Jordan used the SA approach to solve a new landscape management model. They tested their model on a 20,000 ha (987 stands) hypothetical test problem. The result showed that the SA meta-heuristic technique was capable of solving large-size stochastic problems with hard constraints.

The SA algorithm starts by generating an initial solution to the transportation-scheduling problem. In our approach, the initial solution can be either provided by the user or generated randomly. The simulation model is next used to evaluate the quality of this initial solution. The inputs to the simulation model are the data corresponding to the project descriptions and the transport sched ule for the resources (a solution). The simulation model outputs performance measures, such as completion times for the tasks and distances traveled by the resources. The SA algorithm searches for a better solution using the information provided by the simulation model and the current solution. We have implemented three neighbor operators to perturb the current solution. One operator generates a new solution by switching two worksites (randomly selected) of the current solution within a route of a specific unit. The second operator generates a new solution by switching two worksites between two different units of a same class. The units and the worksites are randomly selected. The third operator generates a new solution by moving one worksite from a unit to another unit of the same resource class. We use a random selection process to choose the operator to be applied at each neighborhood search. The search procedure uses the simulator every time that it needs to evaluate the performance of a new solution. An optimal or close to optimal solution is obtained by iteratively running this search procedure. Figure 3 shows a block diagram of the solution approach.

Simulated Annealing

Simulated Annealing [16] is one of the nature-insp heuristics that are applied to combinatorial optimiza problems. It was derived from statistical mechanics. algorithm, which was proposed by Kirkpatrick *et al.* is based on an analogy between annealing treatmen solids and solving combinatorial optimization proble Annealing is the physical process of heating a solid then cooling it down slowly until it crystallizes. At a gi temperature, the probability distribution of system e gies is determined by the Boltzmann's probability ec tion:

$$P(E) = \alpha e^{[-E/kT]}$$

where E is system energy, k is Boltzmann's constant, the temperature and $P(E)$ is the probability that the s tem is in a state with energy E. To simulate the evolut to thermal equilibrium of a solid for a fixed value of te perature T, Metropolis *et al.* [13] proposed a Monte Ca method, which generates sequences of the states of solid.

In the analogy between solving a combinatorial opti zation problem and the annealing process, the states the solid represent the feasible solutions of the optimi tion problem. The energies of the states correspond to values of the objective function computed for those so tions. The minimum energy state corresponds to the op mal solution of the problem and rapid quenching can viewed as local optimization. The basic steps of a SA gorithm are as follows:

Step 0: Create an initial solution. This is the first curre solution.

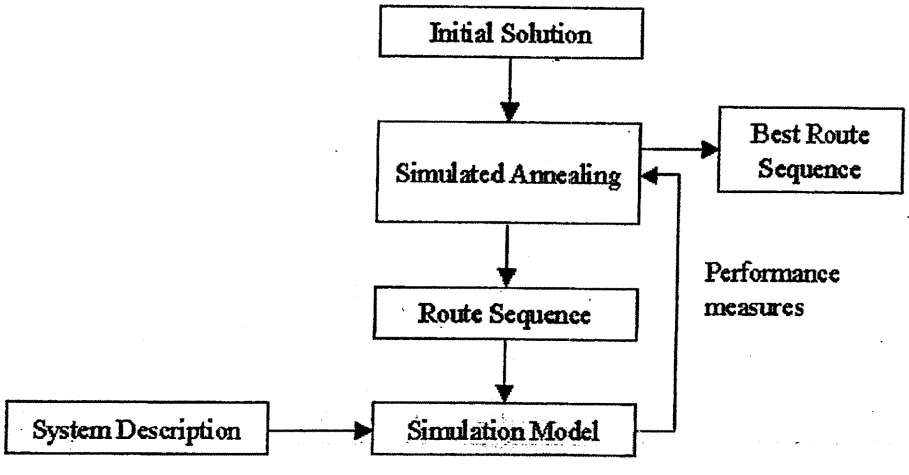


Figure 3. Optimization model.

Decide the initial temperature, number of repetitions at each temperature step, temperature reduction rule and total number of iterations to be performed.

Step Generate a new set of solution/s from the current solution.

Step 2: Evaluate the solution in terms of the objective function. Keep track of the best solution found so far.

Step 3: If the newly created solution is better, then update the current solution to the newly found better solution. If not, decide whether the new solution can still become the current solution, depending on Metropolis's criterion [13]. If it passes the criterion, then the newly found solution becomes the current solution; otherwise the current solution stays the same.

Step 4: Iterate through steps 1, 2 and 3 for a defined number of times as decided by the number of repetitions at each temperature step. After those many repetitions go to Step 5.

Step 5: Decrease the temperature using the decided reduction criterion. Iterate through steps 1, 2, 3 and 4 for the decided number of times. After those many number of iterations, stop. Use the best solution found so far.

EXPERIMENTAL RESULTS

Using data from a silviculture contractor located in South Alabama, we have created a test-bed problem to verify our approach. The problem consists of four projects that are performed at four different sites and one central site, namely worksite 0. Table 1 gives the distances between each of the worksites.

Table 1. Distance between worksites (in miles)

Worksites	0	1	2	3	4
0		107.5	220	330	82.5
1		-	112.5	437.5	142.5
2			-	550	245
3				-	322.5
4					-

The set of tasks performed at each of the worksites are given in Table 2. This table describes location (worksite), duration, precedence, and classes of moveable resource for each task.

We assume five classes of moveable resources are available. These resources are considered critical for the operation of the projects. Table 3 gives the number of identical units and their initial locations for each resource class. We assume that the resources move at a fixed average speed of 50 mph. Notice that this assumption is not a restriction since each moving object in the simulation can be modeled to move at its own speed.

Minimizing Project Durations (Makespan)

In order to test our model, we first set the objective of the optimization model as minimizing the makespan of all the projects. The makespan of a project is defined as the completion time of the last task. Minimizing project durations is equivalent to maximizing the utilization of the resources. After running the algorithm several times with different parameters, we decided to set up the initial and cooling temperature of the SA algorithm to be 150 and 10 F°, respectively. In addition, the temperature of the SA algorithm is decreased at each iteration by 2%. At each temperature step, the neighborhood of the current solution is searched two hundred times. To evaluate the sensitivity of the SA algorithm to the initial solution, we ran the algorithm ten times. For each run the initial solution was randomly generated. The results of the test problem – best, average, and worst – of ten replications were 225, 231 and 253 hours, respectively.

To find whether the best solution was optimal, we computed the objective function assuming an infinite number of resource units available. In this relaxed problem, all projects can be independently completed at a minimum time, determined by the precedence relationships only, and not by the availability of the resources. The minimum makespan of this problem can be easily calculated by hand and it was equal to the minimum makespan of our best solution to the original problem. Therefore, we concluded that the best solution was optimal. However, if they had not been equal, then we could not conclude that the best solution was optimal. Nevertheless, the solution of the relaxed problem could be used as a lower bound.

The best solution, for this particular case, which was also solution, the total distance traveled by the resources was 3423 miles. As shown in table 4, the 2nd unit of resource class 1 had a route defined as "3®3 (1)®4 (6)", meaning the initial location of this unit was worksite 3 and it was scheduled to subsequently be used by the 1st task at the same worksite and by the 6th task at worksite 4. This particular route was 322.5 miles long.

Table 2. Task description.

Worksite	Task	Duration	Preceding Task	Resource Class (Quantity)
1	1	4	-	5(1)
1	2	7	-	2(1)
1	3	4	2	2(1)
1	4	8	1,3	5(1)
1	5	14	4	3(1)
1	6	4	5	2(1)
1	7	8	6	2(1)
2	1	4	-	5(1)
2	2	5	1	-
2	3	8	-	1(1)
2	4	6	3	4(1)
2	5	8	2,4	-
2	6	12	2,4	2(1)
2	7	8	6	2(1)
3	1	3	-	1(1)
3	2	8	1	4(1)
3	3	8	-	-
3	4	14	3	5(1)
3	5	10	2,4	-
3	6	4	5	2(1)
4	1	4	-	2(1)
4	2	9	-	2(1)
4	3	4	2	2(1)
4	4	3	1,3	-
4	5	8	4	2(1)
4	6	10	5	1(1)
4	7	8	4	4(1)
4	8	4	7	2(1)
4	9	3	6,8	-

Table 3. Resource units and their initial positions.

Resource Class	Resource Unit	Worksite
1	1	0
1	2	3
2	1	0
2	2	1
2	3	0
2	4	2
2	5	0
3	1	0
4	1	2
4	2	0
5	1	1
5	2	2

Table 4. Routes that minimized project durations.

Resource Class	Unit	Optimal Route Worksite (task)	Total Distan (Miles
	1	0→2 (3)	220.0
1	2	3→3 (1)→4 (6)	322.5
2	1	0	0.0
2	2	1→1(2)→4(2)→4(3)→1(3)	285.0
2	3	0→4(1)→2(7)→4(8)→1(6)	715.0
2	4	2→2(6)	0.0
2	5	0→1(3)→4 (5)→3(6)	572.5
3	1	0→1(5)	107.5
4	1	2→2 (4)	0.0
4	2	0→3 (2)→4(7)	652.5
5	1	1→1(1)→1(4)	0.0
5	2	2→2 (5)→3(4)	550.0

Minimizing Total Traveled Distance

Next, we changed the objective function to minim the total traveled distance. The results – best, avera and worst – of the computational experiment were 204 2387.5, and 2717.5 miles, respectively. The best solut is illustrated in Table 5. For this solution the duration the longest project is 366.55 hours.

Table 5. Best routes that minimize the total traveled d tance.

Resource class	Unit	Optimal Route Worksite (task)	Tota Distar (Mile
1	1	0→4(6)→2(3)	327.5
1	2	3→3(1)	0.0
2	1	0	0.0
2	2	1→1(2)→1(3)→1(5)→3(6)	437.5
2	3	0→4 (1)→4(2)→4(3)→4 (5)	82.5
2	4	2→2(6)→2(7)	0.0
2	5	0→1(4)→4(8)	250.0
3	1	0→1(5)	107.5
4		2→2(4)	0.0
4	2	0→4(7)→3(2)	405.0
5	1	1→1(1)→1(4)→3(4)	437.5
5	2	2→2(1)	0.0

It is clear that the real-world 'optimal' solution wou require making an explicit trade-off between the objecti of minimizing the makespan and minimizing the tot traveled miles. Figure 5 depicts this trade-off by displa ing a set of feasible solutions. Each point identifies t makespan and traveled miles of a particular solutio

Notice that the three points joined by the line dominate all other solutions. All solutions lying on this line are called Pareto optimal solutions [2]. Pareto optimality is a measure of efficiency. A solution is Pareto optimal if there is no other solution that makes every objective better off. A final decision that explicitly considers the trade-off between the makespan and the traveled miles should lie on or near this Pareto curve. Notice also that the range of the solutions is quite large. For example, there are many solutions that have the minimal makespan of 225 hours, but have different total traveled miles ranging from 2410 to 3400 miles. Here, there is a potential for an improvement of 990 fewer miles. Furthermore, without an optimization procedure, the company could be operating at any point to the right of the line in the figure, for example the point marked 'A' where traveled total distance is 2750 miles and makespan is 325 hours. By using one of the solutions lying on the curve, say traveled total distance equal to 2300 miles and makespan equal to 260 (point marked 'B' in the figure), the company could reduce the completion time by 65 hours (20%), and the total traveled distance by 450 miles (16%).

Minimizing Project Durations and Total Traveled Miles

The trade-off of makespan and total traveled miles was modeled using a linear cost function. We added a penalty cost of K_1 dollars per each hour that a project was overdue and a cost of K_2 dollars per each hour spent traveling between sites. We assumed equal overdue penalty costs for all the projects for simplicity only. Introducing different penalty costs for each of the projects can been done in a straightforward manner. The number of overdue hours for each project was calculated in hours as:

$$\text{Overdue hours} = \text{MAX}(0, \text{project completion hours} - \text{due date hours}) \quad (2)$$

In equation 2, the term "due date" refers to the number of hours from the current hour in which the project is required to be completed. The total overdue hours for all worksites was computed by adding up the individual overdue hours. Thus, the total cost of a particular schedule-solution was the sum of the total overdue penalty costs and total travel time costs:

$$\text{Total Cost} = K_1 \times \text{Total Overdue Hours} + K^2 \times \text{Total Travel Time Hours} \quad (3)$$

In our example, we assumed that K_1 and K_2 are 50$/hour and 80$/hour, respectively. Moreover, we assumed for this example that the due dates of each project were 225, 196, 180, and 187 hours. After running the solution algorithm, the best scheduling solution was found to have a total cost of $4,381. This schedule completed all the projects on time (before due date) and had a total traveled distance of 2,738 miles.

In Table 6, we have summarized the total costs by minimizing each cost component separately and both costs simultaneously. If we set the objective to minimize the total overdue hours of the projects only, the overdue cost is zero, but the travel cost is $4,249. On the other

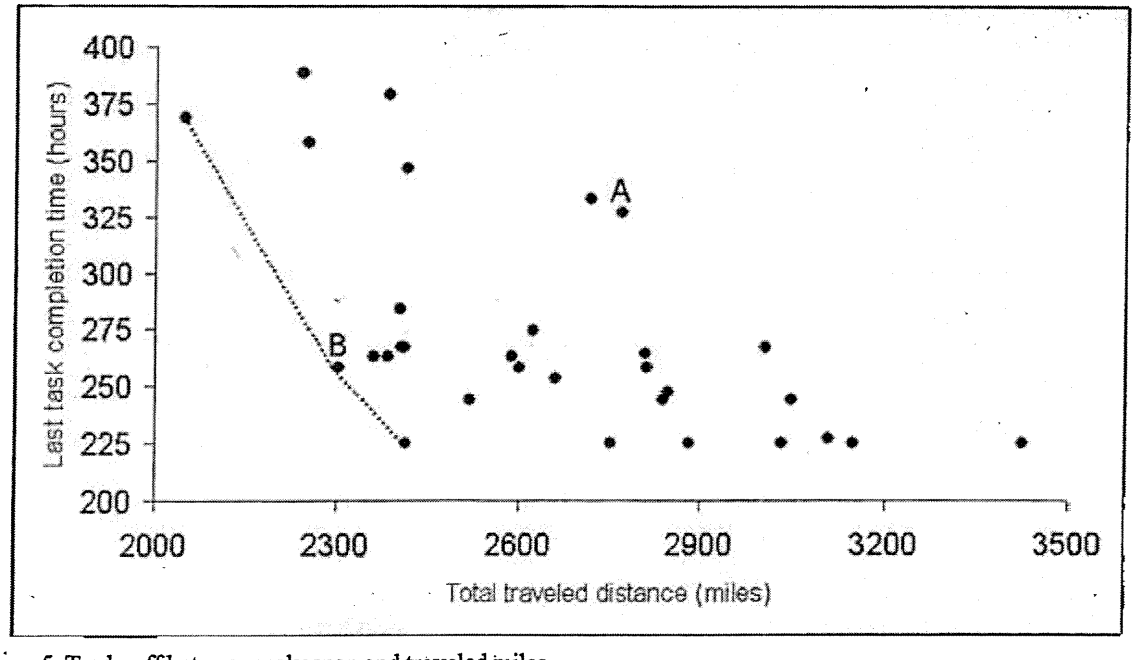


Figure 5. Trade-off between makespan and traveled miles.

hand, if we set the objective to minimize just the total travel hours, the travel cost is $3,246 and the overdue cost is $46,092. However, if we set the objective to minimize both total overdue hours and the total travel hours, the proposed algorithm gives a solution in which the travel costs is $4,381 and zero overdue cost. All projects are completed on time.

Table 6. Cost components with different objectives.

Objective	Travel cost ($)	Overdue cost ($)	Total cost ($)
Minimizing total overdue hours	4,249	0	4,249
Minimizing travel time	3,246	46,092	49,338
Min. both total overdue and travel time	4,381	0	4,381

Sensitivity Analysis

The previous results depended on the values of K_1 and K_2. To observe the effect of these two cost coefficients, we changed K_1 within the range $10/hour to $70/hour and K_2 within the range $40/hour to $100/hour. Table 7 gives the cost components, travel miles and overdue hours for different values of K_1 and K_2.

To study the effect of the problem size on the CPU time, we ran the algorithm with four larger problems. These new problems had 8, 10, 15, and 20 worksites. We set the size of the local search proportional (40 times) to the number of worksites. Figure 5 shows the CPU time versus the number of worksites of each of these problems for the cases in which the local search was kept constant over the problem size, and when the local search was proportional to the problem size.

RESOURCE CAPACITY PLANNING

Resource capacity planning is the process of determining how much equipment is required to accomplish tasks. The goal of capacity planning is to achieve a balance between resource capacity and work demand. Resource capacity planning is critical in the current forest business environment as companies strive to achieve the highest return on investment for their project portfolios while minimizing expenses. Project-related work often requires significant adjustment during its lifecycle to align capacity and demand. Such changes inevitably affect other work. Our proposed model can also be used to assess the impact of changes on the amount of equipment. The al ity of the model to manage capacity is achieved by m ing modifications to the number of resources and serving the performance of the projects. The perfor ance of the projects is evaluated by the total cost. Fig 6 shows the percent reduction in total cost when a n resource is added and the added resource starts at works 0. For example, adding one unit of resource 1 the to cost of completing all the projects can be reduced 13%. This is from $4,381 to $3,812. Similarly, if one unit resource 2, instead of resource 1, is added the total c of completing all the projects can be reduced by 4%. T capacity analysis shows that for this example addition resources 1 and 5 provide the highest cost reductions

We next decrease each resource class in one unit. Fi ure 7 shows the percent of increase in total cost wh one unit of each resource is removed. For example, moving one unit of resource 1 the total cost of compl ing all the projects can be increased by 13%. This is fro $4,381 to $4,942. Similarly, if one unit of resource 2, i stead of resource 1, is removed then the total cost completing all the projects can increase 20%, i.e. to $5,27 Notice that resources 4 and 5 have the highest cost i creases, 43% and 61%, respectively. Reduction in resour class 3 is not shown in Figure 7, because resource class has only one unit that the reduction leads to an infeasib solution.

DISCUSSION

A heuristic procedure for scheduling transport r sources to tasks at remote locations has been describe The use of a simulation model makes the proposed a proach very attractive because detailed features of a con pany's operation can be easily included. The results ob tained solving one instance of a small size problem showe that the best solution could be found in less than fou minutes using a personal computer with a processo Pentium III (1 GHz). Notice that the problem may be sma compared with a real world problem, but the search spac of the problem is still quite large. For example, the numb of all possible paths, through which a particular resourc unit can visit worksites is a function of the number permutations of all these locations. Considering that th small size problem has 12 resources and that each r source unit visits on the average 4 locations, the size the solution space is roughly $(4!)^{12}$, which is close to 10^{1}

The results from problems of larger sizes show that th relation between CPU time and number of worksites de pends strongly on the size of the local search. If th number of local searches is set independently of the prob lem size (number of worksites), the relation between CPU

Table 7. Total cost of best solution when travel and due-date costs are minimized

K_1 ($/hour)	K_2 ($/hour)	Total Cost ($)	Overdue Cost (% of total cost)	Travel Cost (% of total cost)	Traveled mile
10	40	2374	8%	92%	54.43
10	60	3635	16%	84%	50.89
10	80	4667	11%	89%	51.98
10	100	5491	12%	88%	48.53
30	40	2326	0%	100%	58.16
30	60	3752	0%	100%	62.54
30	80	4419	0%	100%	55.24
30	100	6203	0%	100%	62.03
40	40	2326	0%	100%	58.16
40	60	3490	0%	100%	58.16
40	80	5003	0%	100%	62.54
40	100	5524	0%	100%	55.24
50	40	2326	0%	100%	58.16
50	60	3490	0%	100%	58.16
50	80	4381	0%	100%	54.76
50	100	6254	0%	100%	62.54
60	40	2104	0%	100%	52.59
60	60	3490	0%	100%	58.16
60	80	4653	0%	100%	58.16
60	100	5476	0%	100%	54.76
70	40	2187	0%	100%	54.67
70	60	3490	0%	100%	58.16
70	80	4653	0%	100%	58.16
70	100	5816	0%	100%	58.16

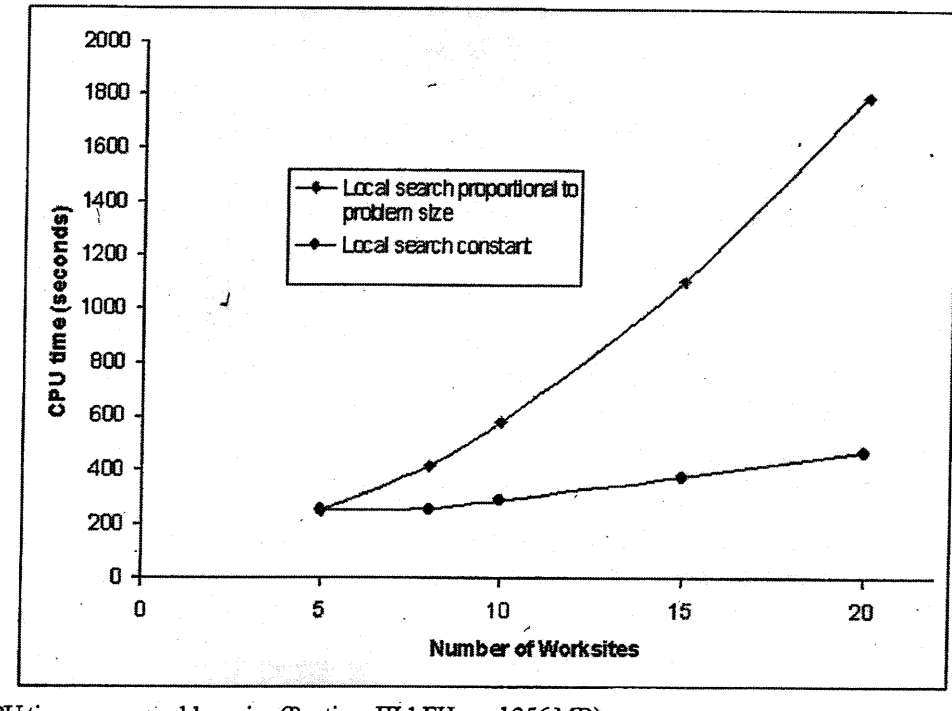


Figure 5. CPU time versus problem size (Pentium III 1 FHz and 256 MB)

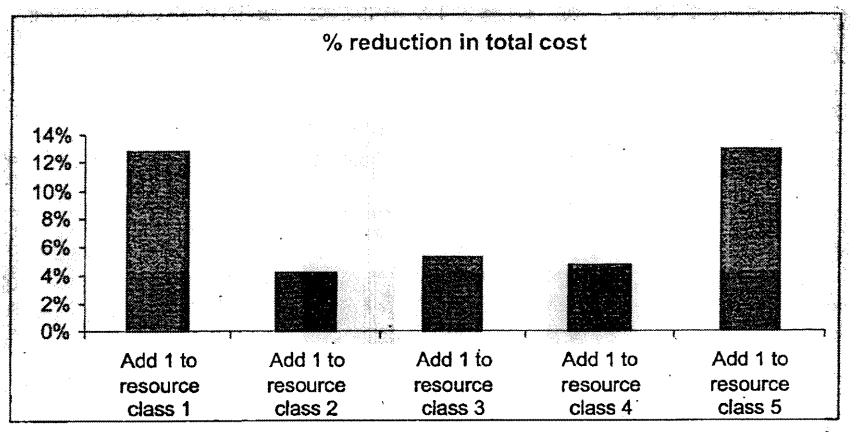


Figure 6. Capacity analysis by increasing the number of resources.

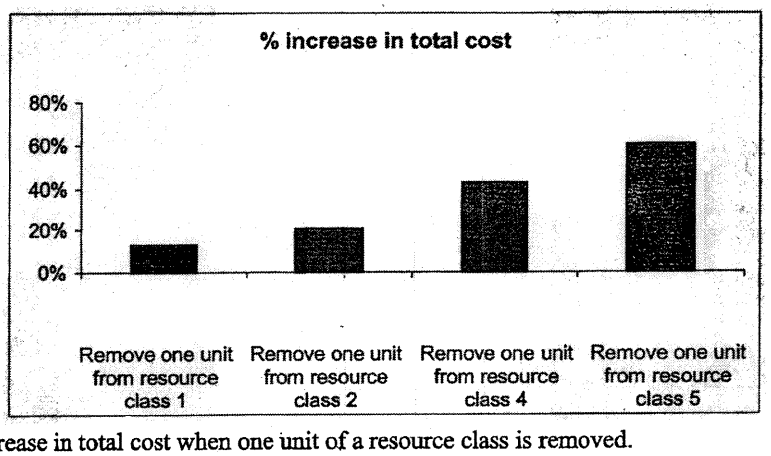


Figure 7. Percent increase in total cost when one unit of a resource class is removed.

time and problem size is almost linear; however, when the number of local searches is set proportional to the number of worksites, the relation between CPU time and problem size becomes close to a quadratic function. The CPU time depends more on the size of the local search than on the execution time of the simulator. Nevertheless, if a real world problem is too big to be solved directly with our approach, the problem can be partitioned into smaller manageable sub-problems by identifying resources and geographic areas for each of them and using the proposed algorithm solve each sub-problem separately.

A silvicultural services company could achieve significant savings by using this approach to schedule its operations. It is well known that transportation costs represent a significant portion of the total operating cost of a forest products company. Additionally, transportation cost reduction has positive environmental effects as fuel use is minimized. Future research plans are to incorporate into the simulation model random components such as breakdowns of machines or trucks and weather uncertainties.

ACKNOWLEDGEMENT

This research was supported by the USDA Forest Ser ice Forest Operations Research Unit.

AUTHOR CONTACT

Professor Valenzuela can be reached by email at -- jvalenz@eng.auburn.edu

REFERENCES

[1] Baskent, E.Z., and G.A. Jordan. 2002. Forest lan scape management modeling using simulated a nealing. Forest Ecology and Management. 165(1-3 29-45.

[2] Caballero, R., T. Gomez, M. Luque, F. Miguel, and Ruiz. 2002. Hierarchical generation of pareto optim solutions in large-scale multiobjective systems. J. Computers & Operations Research. 29: 1537-1558.

[3] Demeulemeester, E., and W. Herroelen. 1997. A branch-and-bound procedure for the generalized resource-constrained project scheduling problem. Operations Research. 45: 201-212.

[4] Demeulemeester, E., and W. Herroelen. 1996. Modeling setup times, process batches and transfer batches using activity network logic. European J. of Operational Research. 89: 355-365.

[5] Desrosiers, J., Y. Dumas, M.M. Solomon, and F. Soumis. 1995. Time constrained routing and scheduling. In M.O. Ball, T.L. Magnanti, C.L. Monma, and G.L. Nemhauser, editors, Network Routing, Handbooks in Operations Research and Management Science, 8: 35-139.

[6] Gordon, J. and R. Tulip. 1997. Resource scheduling. Int. J. of Project Management. 15(6): 359-370.

[7] Helms, J. 1998. The Dictionary of Forestry. Society of American Foresters, Bethesda, MD, USA.

[8] Jansen, B., P.C.J. Swinkels, G.J.A. Teeuwen, B.A. Fluiter, and H.A. Fleuren. 2004. Operational planning of a large-scale multi-modal transportation system. European J. of Operational Research. 156: 41-53.

[9] Kirkpatrick, S., C.D. Jr. Gelatt, M.P. Vecchi. 1983. Optimization by simulated annealing. Science. 220: 671-680.

[10] Klein, R. 1999. Scheduling of resource-constrained projects. Kluwer Academic Publishers, Boston, 392 p.

[11] Kolish, R. 1995. Project scheduling under resource constraints: Efficient heuristics for several problem classes (production and logistics). Springer-Verlag, Heidelberg, 212 p.

[12] Liu, S.T., and C. Kao. 2004. Solving fuzzy transportation problems based on extension principle. European J. of Operational Research. 153: 661-674.

[13] Metropolis, N., A. Rosenbluth, M. Rosenbluth, A. Teller, and E. Teller. 1953. Equation of state calculations by fast computing machines. J. of Chemical Physics. 21: 1087-1092.

[14] Öhman, K., T. Lämås. 2003. Clustering of harvest activities in multi-objective long-term forest planning. Forest Ecology and Management. 176(1-3): 161-171.

[15] Pritsker, A., L. Watters, and P. Wolfe. 1969. Multiproject scheduling with limited resources: A zero-one programming approach. Management Science. 16: 93-108.

[16] Vidal, R.V.V. 1993. Applied Simulated Annealing. Springer-Verlag, Berlin, 396 p.

[17] Winston, W. 2004. Operations research: Applications and algorithms. Duxbury Press, Toronto, 1418 p.

INTERNATIONAL
JOURNAL OF
FOREST ENGINEERING VOL. 16, NO. 1 JANUARY 2005

CONTENTS

Tell Us About Your Organization

Editor's Note

TECHNICAL PAPERS

P. Hakkila
Fuel From Early Thinnings 11

K. Kärhä, A. Jouhiaho, A. Mutikainen, and S. Mattila
Mechanized Energy Wood Harvesting from Early Thinnings 15

E.L. Lindholm and S. Berg
Energy Use in Swedish Forestry in 1972 and 1997 27

D. Puttock, R. Spinelli, and B.R. Hartsough
Operational Trials of Cut-To-Length Harvesting of Poplar in a Mixed Wood Stand .....

K. Väätäinen, A. Asikainen, and J. Eronen
Improving the Logistics of Biofuel Reception at the Power Plant of Kuopio City 51

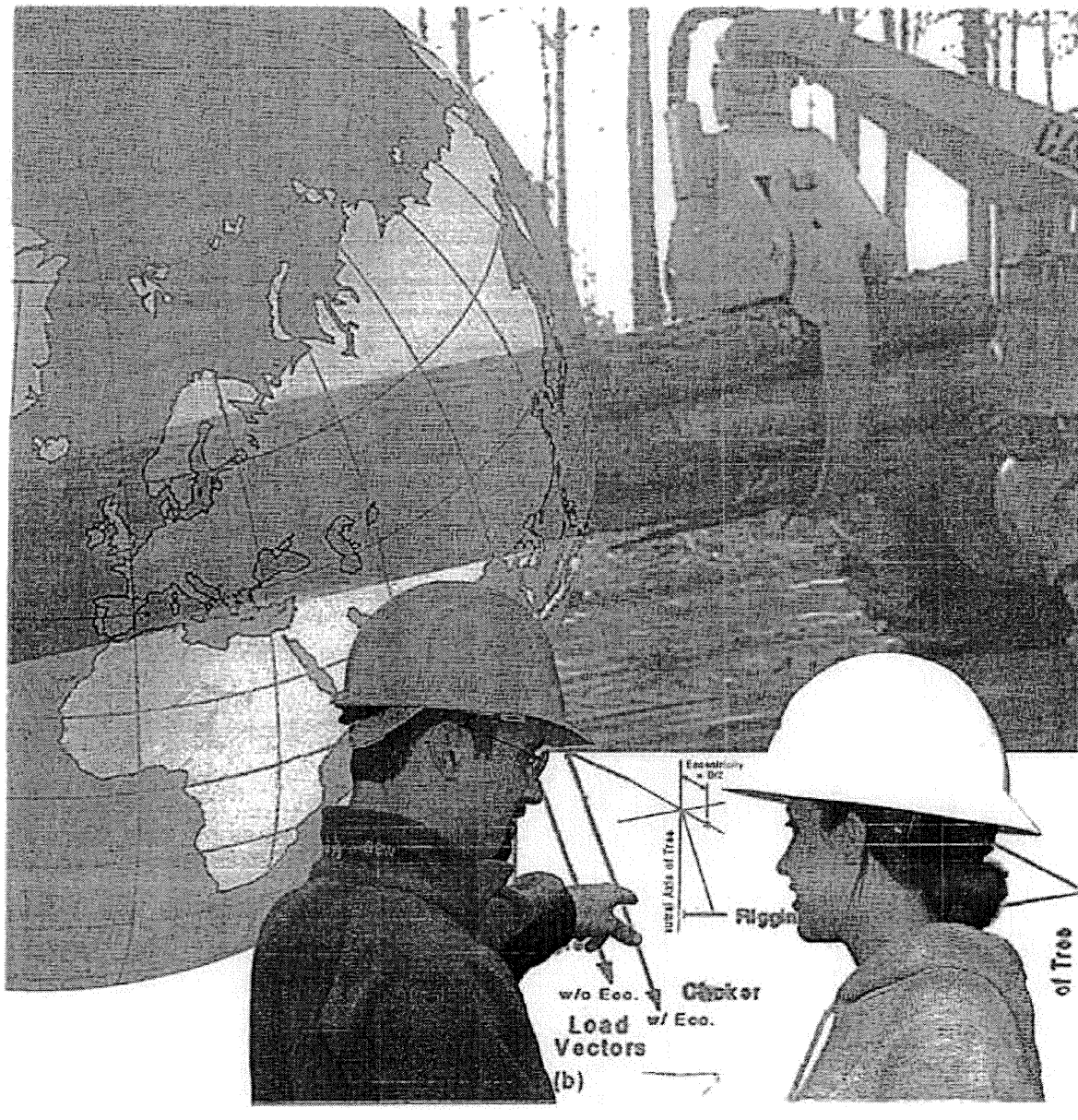
J.F. Valenzuela, H.H. Balci, and T. McDonald
A Transportation-Scheduling System for Managing Silvicultural Projects 65

J. Wang, C.B. LeDoux, and L. Wang
Modeling and Validating the Grabbing Forces of Hydraulic Log Grapples Used in Forest Operations 77

INTERNATIONAL

JOURNAL OF FOREST ENGINEERING

VOL. 16 NO. 1 JANUARY 2005



UNB *A publication of the University of New Brunswick*

ISSN 0843-5243