Using Ant Colony Optimization Metaheuristic in Forest Transportation Planning*

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Abstract
Timber transportation is one of the most expensive activities in forest operations. Traditionally, the goal of forest transportation planning has been to find the combination of road development and harvest equipment placement that minimizes total harvesting and transportation costs. However, modern transportation problems are not driven only by the economics of timber management, but also by multiple uses of roads and their social and ecological impacts. These social and environmental considerations and requirements introduce side constraints into the forest transportation planning, making the problems larger and more complex. We developed a new problem solving technique using the ant colony optimization (ACO) metaheuristic, which is able to solve large and complex transportation planning problems with side constraints. We considered the environmental impact of forest road networks represented by sediment yields as side constraints. Results on a hypothetical transportation problem show that this algorithm (ACO-FTPP) is promising for solving real forest transportation planning problems with side constraints. A description of the development of the algorithm and its search process is presented.

Keywords: forest transportation planning, ant colony optimization metaheuristic, forest road networks, sediment minimization

1. INTRODUCTION

Problems related to forest transportation planning have long been an important concern due to the fact that timber transportation is one of the most expensive activities in forest operations (Greulich 2002). Traditionally, the goal of forest transportation planning problems (FTPP) has been to find the combination of road development and harvest equipment placement that minimizes total harvesting and transportation costs. However, modern FTPP are not driven only by the economics of timber management, but also by multiple uses of roads and their social and ecological impacts such as recreation, soil erosion, wildlife and fish habitats among others. These environmental and social considerations and requirements introduce side constraints to the FTPP, making the problems larger and more complex.

Two different approaches have been applied to solve FTPP: exact algorithms such as mixed-integer programming (MIP), and approximation algorithms generally called heuristics (Falcao 2001; Weintraub 1995). The most important advantage of exact algorithms is that they provide optimal solutions. However, they are limited to small scale problems. Contrarily,
heuristic techniques, although may not provide optimal solutions, have successfully been applied to solve large scale problems and are relatively easy to formulate compared with exact algorithms (Olsson 2003; Martell et al 1998; Weintraub 1995). Since real world transportation problems are usually large scale problems with thousands of variables, heuristic techniques have been the focus of a large number of researchers (Zeki 2001).

The case of FTPP with fixed and variable costs form complex optimization problems that to date have only been solved efficiently using heuristic approaches. NETWORK II (Sessions 1985) and NETWORK 2000 (Chung and Sessions 2003), which use a heuristic approach combined with the shortest path algorithm (Dijkstra 1959), have been widely used for the last twenty years. NETWORK 2000 can solve multi-period, multi-product, multi-origin and destination transportation planning problems, but it considers only either profit maximization or cost minimization without taking into account other attributes of road links. NETWORK 2001 (Chung and Sessions 2001) was developed to solve multiple objective transportation planning problems by combining the shortest path algorithm with a simulated annealing heuristic. NETWORK 2001 allows users to modify the objective function to evaluate solutions considering multiple objectives, but currently does not allow having side constraints.

Because heuristic approaches usually do not guarantee the optimality of solutions, testing different heuristic approaches has been a constant effort of numerous researchers. New heuristics and hybrids of existing heuristics are continually being developed, but only a few algorithms have been applied to FTPP having both fixed and variable costs. One of the promising algorithms not yet applied to FTPP is the Ant Colony Optimization (ACO) metaheuristic, an optimization technique introduced in 1991 by Dorigo and colleagues (Dorigo 1999a). To date there have been numerous applications of ACO metaheuristic developed to solve a number of different combinatorial optimization problems. Currently, some ACO algorithms have provided the best known results for solving many of the most important combinatorial optimization problems (such as the traveling salesman problem (TSP), quadratic assignment problem (QAP), job-shop scheduling problem (JSP), vehicle routing problem (VRP) among others), while others have matched the results of the best known algorithms (Dorigo 2002; Dorigo 1999a).

ACO algorithms are inspired by the observation of the foraging behavior of real ant colonies, and in particular, by how ants can find shortest paths between food sources and the nest. When walking, ants deposit a chemical substance on the ground called pheromone, ultimately forming a pheromone trail. While an isolated ant moves essentially at random, an ant that encounters a previously laid pheromone trail can detect it and decide with a high probability to follow it, therefore reinforcing the trail with its own pheromone. This indirect form of communication is called autocatalytic behavior, which is characterized by a positive feedback, where the more ants following a trail, the more attractive that trail becomes for being followed (Dorigo 1999b).

The ACO metaheuristic approach is promising for solving FTPP with fixed and variable costs for the following reasons: i) the inspiring concept of ACO metaheuristic is based on a transportation principle, and it was first intended to solve transportation problems that can be modeled through networks, ii) its effectiveness in finding good solutions to difficult optimization problems, as introduced in the literature, and iii) the nature of the FTPP, which allows the problem to be modeled as a network problem.

In this paper, we introduce ACO-FTPP, a specially designed ACO algorithm for solving FTPP with fixed and variable costs while considering total sediment yields from the road
network as a side constraint. A description of the ACO-FTPP algorithm and its search process are presented.

2. METHODOLOGY

2.1 Problem Formulation

The FTPP we address in this paper is finding the set of least cost routes from multiple timber sales to selected destination mills, while considering environmental impacts of forest road networks represented by sediment yields. As most of transportation problems, these FTPP can be modeled as network problems. The road system is represented by a graph $G$, where vertices represent destination points (i.e. mill locations), entry points (i.e. log landing locations), and intersections of road segments, while edges represent the road segments connecting these different points. The graph $G$ has three variables associated with every edge; fixed cost, variable cost, and the amount of sediment.

The transportation network may be composed of existing and/or proposed roads. Fixed cost for an existing road segment could either be zero or a fixed maintenance cost for the road segment. In the case of proposed roads, fixed cost represents the construction cost of the road segment plus fixed maintenance. Fixed cost is a one-time cost which occurs if the road segment is used. Variable cost refers to the hauling cost. Unlike the fixed cost, variable cost is proportional to traffic volumes. Although there are several ways to estimate the unit variable cost ($/vol$-edge), in most cases it is a function of the road length, driving speed, and operating costs (Byrne et al 1960, Moll and Copstead 1996). Since every road segment has different conditions, there will be a different unit variable cost associated with each edge. The sediment associated with each edge represents the amount of sediment eroding from the road segment in tons per year per edge. Like fixed cost, we assumed that sediment is produced when roads are open regardless of the traffic volume. The WEPP model can be used to estimate average annual sediment yields from each road segment (Elliot et al 1999). In addition to the three variables related to each edge, it is also required to have the total volume of wood per timber sale to be delivered to the selected mill location.

In this context the problem under consideration is to find the transportation routes that minimize the combination of fixed and variable costs (Eq. 1) subject to a sediment yield restriction (Eq. 2).

$$\text{Minimize} \quad \sum_{i=1}^{\varepsilon} \left[ (\text{var\_cost}_i \ast \text{vol}_i) + (\text{fixed\_cost}_i \ast B_i) \right]$$

[Eq. 1]

$$\text{Subject to} \quad \sum_{i=1}^{\varepsilon} (\text{sediment}_i \ast B_i) \leq \text{allowable \_sed}$$

[Eq. 2]

where,

- $\text{var\_cost}_i$ : variable cost for edge $i$ in $$/vol$.
- $\text{fixed\_cost}_i$ : fixed cost for edge $i$ in $\$.$
- $\text{sediment}_i$ : amount of sediment eroding from edge $i$ in tons.
- $\text{vol}_i$ : total volume transported over edge $i$
2.2 Ant Colony Optimization Metaheuristic

In ACO metaheuristic a colony of *artificial ants* is set to find good feasible solutions to combinatorial optimization problems. Computational resources are allocated to relatively simple agents – *artificial ants*. These *artificial ants* have a double nature. On one hand, they are the abstraction of those behavioral traits of real ants, which seem to control the shortest path finding ability. On the other hand, they are enriched with some capabilities not present in their natural counterparts (Dorigo 1999a).

There are four main ideas taken from real ants (Dorigo 1999a, 1999b); the use of: i) *colony of cooperating ants* – high quality solutions emerge as a result of the interaction of the entire ant colony, ii) *pheromone trail and indirect communication* – artificial ants change some numerical information stored in the problem’ stage they visit, iii) *shortest path searching and local moves* – artificial ants have the purpose of finding the shortest path moving step by step, and iv) *stochastic and myopic state transition policy* – artificial ants move through adjacent states applying a probabilistic decision policy.

To increase the efficiency and efficacy of the colony, some enriching characteristics have been given to artificial ants. Some of these characteristics are that artificial ants i) live in an environment where time is discrete, ii) have an internal state, which contains the memory of the ants’ previous actions, iii) deposit an amount of pheromone proportional to the quality of the solution found, and iv) are not completely blind and can incorporate look-ahead information, local optimization and backtracking to improve overall system efficiency.

In ACO algorithms, ants moves through adjacent states of the problem applying a stochastic transition policy that considers two parameters called *trail intensity* and *visibility*. Trail intensity refers to the amount of pheromone in the path and visibility is usually computed as some heuristic value such as cost or distance (Maniezzo 2004). Therefore, moving through adjacent steps, ants incrementally build a feasible solution to the optimization problem. Once an ant finds a solution, it evaluates the solution and deposits pheromone on the connections it used, proportionally to the goodness of the solution. Ants can deposit pheromone on a connection either directly after the move is made without waiting for the end of the solution or after a solution is built by retracing the same path backwards (Dorigo 2002).

2.3 ACO-FTPP algorithm

ACO-FTPP is the specialized ACO algorithm we developed to solve the FTPP described. ACO-FTPP has a finite number of ants (*m*) that search for *r* least cost paths, one from each timber sale-destination pair. After a certain number of transitions from vertex to vertex, an ant arrives at its destination thus completing a *route*.

When an ant is located on a given vertex, it has to choose where to go based on a transition probability for each adjacent edge, which is calculated by the following equation (Eq. 3).
where, \( \rho_j(c) \) indicates the transition probability with which an ant, chooses the edge \( j \) in iteration \( c \); \( l \) is the number of edges in the set \( N_i \) sharing the same origin vertex; \( \alpha \) and \( \beta \) are the parameters that control the relative importance of the pheromone trail intensity \( (\tau_i) \) and the visibility \( (\eta_j) \) values on edge \( j \). The visibility value is calculated according to the following equation (Eq. 4).

\[
\eta_j = \left(\text{var}_j \cdot \text{vol}_j\right)^{-1} \cdot \left(\text{fixed}_j \cdot \text{sediment}_j\right)^{-1} \quad \text{[Eq. 4]}
\]

Consequently, by combining equations 3 and 4, the resulting transition probability formula for a given edge is determined as follows:

\[
\rho_j(c) = \frac{(\tau_j)^{\alpha} \cdot (\eta_j)^{\beta}}{\sum_{i=1}^{l} (\tau_i)^{\alpha} \cdot (\eta_i)^{\beta}} \quad \text{if } j \in N_i \quad \text{[Eq. 5]}
\]

Based on the transition probability values of all edges in \( N_i \), accumulated transition probabilities for each of these edges are computed. Then, a random number between zero and one is selected using a random number generator. If this random number is smaller than the accumulated transition probability of edge \( i \) and larger than the accumulated transition probability of edge \( i-1 \), then edge \( i \) is selected.

Starting from a given timber sale and ending on the selected mill destination, an ant incrementally builds a route, moving through adjacent edges according to the transition probability equation (Eq. 5). When all ants have found a route, the best route among the \( m \) generated by the \( m \) ants is selected as the least cost path. Then, ants move to the next randomly selected timber sale to find the least cost path. When all timber sales have been routed to their destination mills an iteration is complete, all the edges forming all least cost paths (one for every sale-destination pair) are identified, the objective function value is computed and the solution feasibility is evaluated. If the current solution is not better than the best found so far or is infeasible, the solution is ignored, the pheromone trail intensities remain the same and another iteration starts. However, if the current solution is better than the best solution found so far, the current solution becomes the new best solution and the pheromone trail intensity of the edges forming all least cost paths is updated. At the same time, pheromone intensity on all edges decreases (evaporates) in order to avoid unlimited accumulation of pheromone. Also pheromone evaporation avoids a too-rapid convergence of the algorithm towards a sub-optimal solution, allowing the exploration of other solution spaces. Pheromone trail intensity is updated using the following equation (Eq. 6):

\[
\tau_i(c+1) = \lambda \cdot \tau_i(c) + \Delta \tau_i \quad \text{[Eq. 6]}
\]
where two components are considered; the current pheromone trail intensity on edge $i$ at iteration $c$, indicated by $\tau_i(c)$, multiplied by $0 < \lambda < 1$ which is a coefficient such that $(1 - \lambda)$ represents the pheromone evaporation rate between iteration $c$ and $c + 1$; and $\Delta \tau_i$ which represents the newly added pheromone amount to edge $i$, calculated as follows:

$$\Delta \tau_i = \sum_{k=1}^{s} \Delta \tau_i^k$$  \hspace{1cm} \text{[Eq. 7]}$$

where, $s$ is total number of timber sales, and $\Delta \tau_i^k$ is the quantity of pheromone laid on edge $i$ by the ants in iteration $c$; which is given by:

$$\Delta \tau_i^k = \begin{cases} 
Q / L_k & \text{if the ants used edge } i \text{ in the shortest path} \\
0 & \text{otherwise}
\end{cases} \hspace{1cm} \text{[Eq. 8]}$$

where $Q$ is a constant and $L_k$ is the total transportation cost over the selected route. The value of $Q$ has to be chosen so the amount of pheromone added to edge $i$ by a given ant slightly increases the probability of that edge during the following iterations.

Given the definitions above, ACO-FTPP can be stated as follows (see Figure 1). At iteration 1 an initialization phase takes place in which ants start at a random timber sale location. An initial equal small amount of pheromone $q$ is set for each edge, and transition probabilities for each edge are computed considering the volume of the chosen timber sale. Thereafter each ant can find a route by moving through adjacent edges until the mill destination is reached.

When an ant moves through an edge, the edge is recorded with its from- and to- vertex in the ant’s internal memory. This memory is used to avoid ants returning to a previously visited vertex. When an ant is located at a vertex whose all adjacent vertices have been previously visited, it stops without reaching its destination and a high cost is assigned to the ant’s route as a penalty. Likewise, if an ant has not found its destination after a maximum number of moves $Max\_moves$, the ant stops and a high cost is assigned. For applications currently being tested, the $Max\_moves$ is set to be the number of vertices in the network plus one ($v + 1$).
2.4 Setting Parameters

ACO-FTPP requires values for the parameters $\alpha, \beta, \lambda, q, Q, m,$ and $I_{max}$. Our initial test runs of ACO-FTPP confirmed the findings of previous studies that different parameter combinations affect the performance of the ACO (Dorigo et al 1996). Thus, we conducted a search for the best parameter combination. Because more than one parameter combination can reach the same quality solution, to select the best parameter combination we consider the number of iterations taken to find the best solution as well as solution quality.

Three of the seven parameters required by ACO-FTPP ($q, m,$ and $I_{max}$) do not affect the calculation of the transition probability (Eq. 3 - 8). Therefore these parameter values were fixed in our trials. For our applications, $q$ was set to 0.001, $m$ was set equal the number of edges ($e$), and $I_{max}$ was set to 100 to give the algorithm enough time to find the best solution.

The parameters $Q, \alpha, \beta,$ and $\lambda$, directly affect the calculation of the transition probability (Eq. 3 - 8), therefore they may significantly affect the performance of the algorithm. The constant $Q$, related to the quantity of pheromone deposited by ants, has to be chosen so the transition probability of an edge from one iteration to the next is slightly increased. Because initial test runs showed that $Q$ do not have a significant effect on the solution quality, we set $Q$ to
0.001. The remaining parameters (α, β, and λ) were identified to directly affect the performance of the algorithm, and therefore subject to the search for the best parameter combination.

To test different values of the parameters α, β, and λ, a range for each parameter was defined and partitioned into ten, fifteen, and ten discrete values respectively. The tested values for α were from 0.5 to 9.5 in increments of 1.0. For β we tested values from 0.5 to 14.5 in increments of 1.0. Lastly, for λ the values tested were from 0.05 to 0.95 in increments of 0.1. This yielded 1,500 different parameter combinations. After applying ACO-FTPP in initial test runs the best parameter combination found by this search was α = 1.5, β = 0.5 and λ = 0.65.

2.5 Hypothetical Transportation Problem

To examine the behavior and performance of the algorithm, ACO-FTPP was applied to a 25-edge hypothetical FTPP (see Figure 2). This problem includes three timber sale locations, represented by nodes 1, 2 and 3 respectively, and one destination mill, indicated by node 12. Timber sales 1, 2 and 3 have a total volume of timber to be delivered of 983, 1278, and 901 units of volume. In Figure 2, there are three variables associated with each edge: variable cost, fixed cost, and amount of sediment are indicated by the top, middle, and bottom numbers respectively.

Figure 2. Hypothetical forest transportation problem with 25 edges, three timber sales and one destination mill.

3. RESULTS
Two different cases with a different level of sediment restriction were analyzed to test the ACO-FTPP algorithm. *Case I*: a cost minimization problem considering a sediment restriction of 180 tons, and *Case II*: a cost minimization problem considering a sediment restriction of 150 tons. The sediment restriction values were chosen based on the sediment amount associated with the solution of the cost minimization problem without sediment restriction.

The best solution found by ACO-FTPP for *Case I* has an objective function value of $109,195 ($34.54/vol) with an associated sediment amount of 179.69 tons. For *Case II*, the best solution found by ACO-FTPP reached a minimum total cost of $117,954 ($37.30/vol) with an associated total sediment amount of 146.77 tons. Therefore, when the sediment restriction value was reduced from 180 to 150 tons, (approximately 17%) the minimum total cost increased by $8,759 (around 8%).

![Figure 3. Results from ACO-FTPP for Case I (a) considering a sediment restriction of 180 tons, and Case II (b) considering a sediment restriction of 150 tons.](image)

### 4. CONCLUSIONS

A specialized algorithm, ACO-FTPP, was developed for solving forest transportation planning problems with fixed and variable costs considering side constraints. The ability to consider these constraints allows us to address various environmental issues in road system management decision making.

ACO-FTPP was able to find a solution for both cases considered. We believe our approach is promising for solving large real forest transportation problems with multiple goals. ACO-FTPP can be easily modified to solve more complex transportation problems that consider multiple periods, products, origins and destinations. ACO-FTPP can also solve the problem of mills having a maximum volume capacity by including these mill capacities into the ACO-FTPP formulation as additional constraints.

Because ACO-FTPP is a heuristic algorithm, the solutions may not be optimal. Therefore, to test the performance of ACO-FTPP comparisons with exact techniques such a
mixed-integer programming will need to be done. Additionally, since the algorithm parameters are heavily dependent on the nature and size of the problem, further evaluation of the robustness of the parameters should be done by applying ACO-FITPP to different problem types and sizes.

5. LITERATURE CITED


