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A multilevel ACO approach for solving forest transportation planning problems with environmental constraints

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ABSTRACT

This paper presents a multilevel ant colony optimization (MLACO) approach to solve constrained forest transportation planning problems (CFTPPs). A graph coarsening technique is used to coarsen a network representing the problem into a set of increasingly coarser level problems. Then, a customized ant colony optimization (ACO) algorithm is designed to solve the CFTPP from coarser to finer level problems. The parameters of the ACO algorithm are automatically configured by evaluating a parameter combination domain through each level of the problem. The solution obtained by the ACO for the coarser level problems is projected into finer level problem components, which are used to help the ACO search for finer level solutions. The MLACO was tested on 20 CFTPPs and solutions were compared to those obtained from other approaches including a mixed integer programming (MIP) solver, a parameter iterative local search (ParamILS) method, and an exhaustive ACO parameter search method. Experimental results showed that the MLACO approach was able to match solution qualities and reduce computing time significantly compared to the tested approaches.

1. Introduction

Forest transportation planning problems (FTPPs) are a special case of the fixed-charge transportation problems (FCTPs), which have received significant attention from operations research and management science [20,27]. Traditionally, FTPPs are formulated as a MIP models and solved optimally using branch-bound methods [3]. However, the computational costs of these methods increase exponentially with the problem size as FCTPs are known to be NP-hard [28,13]. To efficiently solve large-scale CFTPP, metaheuristics such as simulated annealing [2], genetic algorithm [1,16] have also been applied. For example, Contreras et al. [5] applied for the first time an ACO algorithm [7,4] to solve medium-scale FTPPs. Lin et al. [23,24] developed an improved version of the ACO algorithm to address specific FTPPs: a CFTPP and a bi-objective FTPP, respectively. Although the improved results in terms of computing time and solution quality were obtained in the experiments, solving large scale CFTPPs remains difficult because they require significantly long computing times. Moreover, the performance of the ACO algorithm is highly dependent on their parameter settings [23,10].

As a general solution strategy, multilevel schemes have been used for many years and applied to several problem areas [11,18,21,26,17] where solution quality can benefit from having a relatively high-quality initial solution that can be computed inexpensively on a lower level scale. These schemes have proven to be efficient when solving discrete NP-hard problems with a finite but exponential number of problem component combinations [30,19,29]. One recent example of using a multilevel approach to solve related transportation problems is [25] where Lin et al. developed a multilevel parameter configuration scheme and an ACO was the target algorithm configured from the coarsest to the finest level problem. Based on this previous study, we present the design, implementation, and testing of a multilevel ACO approach (MLACO) to solve large-scale CFTPPs with reduced computing times. The essential idea is to solve the original problem, which might be computationally expensive, using a set of increasingly coarser level problems on which the computational cost is cheaper. The main objective of this study is to demonstrate that, for the problem instances tested, the MLACO approach can either accelerate solution convergence rate or improve solution quality. We also examined the underlying process driving performance improvements compared to the other methods, identify advantages and limitations of the approach, and suggest how it might be applied to other optimization

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problems. Ultimately, the MLACO approach presented in this study can serve as a framework for solving large-scale CFTPPs and provide managers with environment-friendly road network alternatives to help them make informed decisions.

2. Preliminary

2.1. Contained forest transportation planning problem (CFTPP)

The CFTPP considered in this study is the problem of finding the set of least-cost routes from timber sale locations to designated mill destinations while reducing the negative environmental impacts associated with timber transportation [5]. Sediments expected to erode from road surfaces due to the traffic of heavy log-trucks were considered as the problem constraints. Conceptually, the CFTPP can be modeled as a network comprised of a set of nodes V and edges E representing road intersections and segments, respectively. Three attributes associated to each edge in the network are: fixed cost (*Fixed_Cost*), variable cost (*Var_Cost*), and sediment amount (*Sed*). *Fixed_Cost* is a one-time road construction cost ($) and/or maintenance cost, *Var_Cost* represents hauling cost ($) per unit of timber volume, and *Sed* (tons/year) represents the amount of sediments that are detrimental to the forest ecosystem. To formulate the CFTPP objective function, let $S=\{s_1,\dots,s_m\}$ be the set of timber locations and $M=\{m_1,\dots,m_n\}$ the set of mill destinations, where $S,M\subset V$. Each timber sale $s_i\in S$ has a minimum volume of timber to be delivered at a given period to a designated mill $m_j\in M$. The main objective can be defined as a cost minimization function:

$$\text{Minimize}: \sum_E Var\_Cost_{i,j}\times Vol_{i,j}+Fixed\_Cost_{i,j} \quad (1)$$

where $Var\_Cost_{i,j}$ is the variable cost, $Fixed\_Cost_{i,j}$ the fixed cost, and $Vol_{i,j}$ the total timber volume transported from node i to j ($Vol_{i,j}=0$ if the road segment ij is not used). Also, the total timber volumes arriving at mills must agree with the total timber volumes shipped out from the timber sales:

$$\sum_{i=1}^{m} Vol_{s_i}=\sum_{j=1}^{n} Vol_{m_j} \quad (2)$$

and the amount of sediment eroding from the entire transportation network must not exceed a maximum allowable value:

$$Constraint: \sum_E Sed_{i,j}\le Sed_{max}. \quad (3)$$

where Sed_{max} is the maximum sediment threshold. The equality (2) and the inequality (3) are the constrains in addition to minimizing the objective function (1) to determine the optimal solution for the CFTPP. A detailed description of CFTPPs can be found in [5,23,24].

2.2. Ant colony optimization

ACO was developed in the mid 1990s to solve the traveling salesman problem [9,8]. The algorithm was inspired by ant foraging behavior. When searching for food, ants walking to and from a food source deposit a substance called pheromone on the ground. Other ants can perceive the presence of the pheromone and tend to follow paths where pheromone concentrations are higher.

In the ACO algorithm to find minimum routes, a set of artificial ants are placed at origin locations and move through adjacent locations one at a time towards the destinations. Guided by the pheromone values, artificial ants construct routes simultaneously. Let C be a set of all possible locations, an ant placed at location x chooses what location y to visit next according to a transition probability:

$$P^t_{x,y}=\begin{cases}\dfrac{\tau^\alpha_{x,y}\times\eta^\beta_{x,y}}{\sum_{k\in Nbr}\tau^\alpha_{x,k}\times\eta^\beta_{x,k}} & \text{if } y\in cities\\ 0 & \text{Otherwise}\end{cases}$$

where $x,y\in C$, $P^t_{x,y}$ is the probability of ant t moving from x to y, $k\in Nbr$ represents one of unvisited locations adjacent to x, τ is the pheromone intensity on the path connecting two locations, η is the visibility (typically calculated as the inverse to the distance between the two locations) α and β are positive parameters that control the relative importance of pheromone intensity versus visibility. The pheromone intensity τ is updated iteratively using the following formula:

$$\tau_{x,y}\leftarrow\rho\times\tau_{x,y}+\Delta\tau_{x,y},$$

where ρ is the pheromone persistence rate and $\Delta\tau_{x,y}$ is the amount of pheromone to be added to path (x,y). For a more detailed description of ACO algorithm, see [7].

2.3. Multilevel scheme

Typically, a multilevel scheme solves a large problem using a set of increasingly smaller problems through a sequence of solution refinements [25]. These smaller problems are obtained by successively applying a coarsening process to the original problem. As a result, a hierarchy of coarser problems are generated where a given coarser level problem is always smaller than its finer level problem. The solution obtained for a given coarser level problem in the solution refinement process is projected into the finer level problem components which are then used to help search for the finer level solution. The process is illustrated in Fig. 1 where a finer problem is coarsened into a coarser problem. After the ACO algorithm is applied to a given coarser problem, the solution is interpolated into a set of finer level components that can help the ACO algorithm find good solutions for the finer level problem.

For clarity, we define the following terms:

Coarser/finer level problems: a set of increasingly coarser level problems $\Pi=\{\Pi_0,\Pi_1,\dots,\Pi_N\}$ where Π_0 is the original

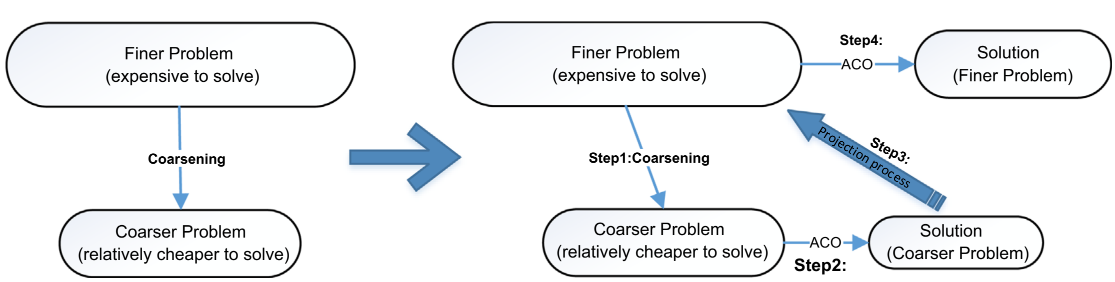

Fig. 1. Diagram illustrating a multilevel scheme at its simplest form (only two levels), where the finer level problem is coarsened into a coarser level problem (left-hand side). The ACO algorithm solves the coarser level problem first and the obtained solution is used to help find high-quality solutions for the finer level problem (right-hand side).