



# Solving the integrated forest harvest scheduling model using metaheuristic algorithms

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## Abstract

In forestry, the highest operational costs arise from the construction of forest roads and the transportation of harvested wood. Hence, optimization models have been used at the tactical level of planning to reduce these costs by integrating decisions on: (1) the allocation of harvest-blocks, (2) the allocation of access roads to these blocks, and (3) the transportation costs that result from the latter two decisions. The integration of these three decisions, in one optimization model, has been referred to as the integrated model. The integrated model, when binary decision variables are used to represent the cut-blocks and roads, is NP-hard and has been solved using two approaches: exact and metaheuristic algorithms. Unlike exact methods, metaheuristic algorithms have thus far not solved the integrated model, but have solved models which either exclude transportation costs from the objective function, or solve the model sequentially. This is a significant gap in prior research because exact solution methods can only be used on smaller forests and metaheuristic algorithms have therefore been used to solve the tactical forest planning problem, without the integration of transportation costs, on large forests. This failure to integrate transportation costs, on a large scale, is the major economic consequence of this gap. The objective of this paper is to present and evaluate a new solution procedure in which all three elements of the integrated tactical planning model are included in the objective function and solved using metaheuristics. The solution procedure was applied to three forests and the attributes and qualities of the solutions were compared to near-optimal solution values generated using an exact solution approach. The results indicate that this metaheuristic procedure generated good quality solutions. We conclude that this research is a useful first step in representing transportation costs in the integrated tactical planning models to be solved using metaheuristics.

**Keywords** Forest management planning · Harvest-scheduling model · Fixed charge network design model · Simulated annealing · Integrated model

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## 1 Introduction

In forestry, the highest operational costs arise from the construction of forest roads and the transportation of harvested wood (Bjørndal et al. 2012). Hence, optimization models have been used at the tactical level of planning to reduce these costs by integrating decisions on: (1) the allocation of harvest-blocks, (2) the allocation of access roads to these blocks, and (3) transportation costs that result from the latter two decisions. The integration of these three decisions, in one optimization model, has been referred to as the integrated model (Jones et al. 1986).

The integrated model was first formulated in the 1970s (e.g., Weintraub and Navon 1976; Kirby et al. 1980, 1986) and the benefits of integrating allocation decisions simultaneously in one model *versus* solving them sequentially was demonstrated. For example, Jones et al. (1986) showed that solutions found using a model that integrates decisions on the location of roads and cut-blocks, simultaneously, yielded solutions that were 15–45% better than solutions where these decisions were generated separately. These earliest models were solved using exact solution approaches and used binary decision variables to represent the road network and continuous variables to represent the harvesting transportation decisions. It should be noted that the decision variables used to schedule the harvesting of cut-blocks were not, in these earlier models, binary; hence, the computational challenge of solving these models was less difficult than that of later models which required binary variables in order to satisfy adjacency constraints.

Beginning in the 1990s, the integrated model incorporated binary decision variables to represent harvesting decisions in order to meet spatial constraints on harvesting. Two approaches to solving the integrated model have since been used: (1) exact approaches (e.g., Nelson and Brodie 1990; Guignard et al. 1998; Andalaf et al. 2003; Silva et al. 2010; Veliz et al. 2015; Naderializadeh and Crowe 2020); and (2) metaheuristic approaches (e.g., Chung and Sessions 2003; Chung et al. 2012). The advantage of using metaheuristic solution methods instead of exact solution approaches is that much larger problem instances can be solved by practicing planners. The disadvantage is that the quality of the solutions generated has no guarantee of optimality nor is its proximity to the mathematical optimum known on large problem instances—which cannot be solved using exact solution procedures. For this reason, an estimate of the quality of solutions generated by new metaheuristics is typically evaluated by comparing the quality of its solutions to those solutions generated using exact approaches on smaller problem instances—evaluation method known as benchmarking (Reeves 1993). Hence, the solution quality of a new metaheuristic is initially evaluated by how close its solutions generated can get to the optimal benchmarks.

The sole metaheuristic solution procedure developed thus far for solving the integrated model, developed by Chung and Sessions (2003) and Chung et al. (2012), does so in a sequential, rather than an integrated manner; i.e., the decision variables are not interdependent within the search procedure. Other metaheuristic approaches to solving the integrated model have been developed but exclude

transportation costs from the objective function (e.g., Murray and Church 1995; Clark et al. 2000; Richards and Gunn 2000, 2003). Hence, there currently exists a gap in development of a metaheuristic solution procedure to the integrated model in which harvesting, construction, and transportation decisions are made inter-dependently. This gap is significant because exact solution methods can only be used on smaller forests and metaheuristic algorithms have therefore been used to solve the tactical forest planning problem, without the integration of transportation costs, on large forests. This failure to integrate transportation costs in a tactical planning model, on a large scale, is the major economic consequence of this gap.

The objective of this research is to design and evaluate a solution procedure in which all three elements of the tactical planning problem are integrated in the objective function and the search procedure. The solution procedure is to be applied to three forests. The quality of the solutions will be evaluated by their proximity to optimal benchmarks (Reeves 1993).

This paper is structured in the following manner. In the Methods, the mathematical formulation of the integrated model is first presented. This is followed by a detailed description of the new metaheuristic search procedure, illustrated with a worked example. Next, the Case Study, comprised of the three forests, is described. In the Results, the metaheuristic solutions are compared to solutions generated using CPLEX. In the Discussion, the benefits and limitations of this new search procedure are evaluated. We conclude that the solutions generated by this new method are quite good, but that one cannot guarantee, from these case studies, similar solution quality on much larger data sets.

## 2 Methods

The methods are presented in two parts. In the first part, the mathematical formulation of the integrated harvest-scheduling model is presented. In the second part, the new solution procedure used to solve the integrated model is described.

### 2.1 Mathematical formulation

The formulation of the integrated model used in this paper does not differ fundamentally from earlier formulations of the spatially constrained integrated model (e.g., Guignard et al. 1998; Andalaft et al. 2003; Naderializadeh and Crowe 2020). The formulation presented below is to be solved using both the branch and bound algorithm and the new metaheuristic procedure. This is because the quality of the solutions generated by the new metaheuristic procedure can be evaluated by comparison with solutions generated using an exact solution procedure.

#### Indices and Sets

$p, P$  = Index and set of polygons

$i, j, I$  = Indices and set of nodes (one inside each polygon)

$t, T$  = Index and set of time periods

$D$  = Set of the demand nodes

$A$  = Set of directed arcs

$O_i$  = Set of arcs where flow is directed out of node  $i$

$I_i$  = Set of arcs where flow is directed into node  $i$

$N_i$  = Set of polygons containing node  $i$  (this set has one member)

$P_t$  = Set of periods equal to or less than  $t$

$u, U$  = Index and set of maximum openings

$B_t$  = Set of polygons not eligible (by age) for harvest in period  $t$

### Parameters

$f_u$  = Number of polygons in the maximum opening  $u$

$APC_t$  = Allowable periodic cut in period  $t$  ( $\text{m}^3$ )

$v_{pt}$  = Volume harvestable from polygon,  $p$ , period  $t$  ( $\text{m}^3$ )

$c_{ijt}$  = Discounted cost of building a road between nodes  $i$  and  $j$  in period  $t$  (\$)

$r_{pt}$  = Discounted net revenue from harvesting polygon  $p$  in period  $t$  (\$)

$tc_{ijt}$  = Discounted transportation cost between nodes  $i$  and  $j$  in period  $t$  (\$ per  $\text{m}^3$ )

$M$  = A large number (in applications of this model, the maximum possible flow of wood through the system).

$W$  = Penalty weight used to reduce the spatial dispersion of cut-blocks selected.  $W$  penalize the total construction and transportation costs resulting from a high spatial dispersion of cut-blocks.

### Variables

$x_{pt}$  = 1 if polygon  $p$  is harvested in period  $t$ , 0 otherwise

$y_{ijt}$  = 1 if arc from node  $i$  to  $j$  is built in period  $t$ , 0 otherwise

$z_{ijt}$  = directed flow of harvested volume from node  $i$  to  $j$  in period  $t$  ( $\text{m}^3$ )

$H_t$  = total volume harvested in period  $t$  ( $\text{m}^3$ )

$$\text{Maximize} \quad \sum_{p \in P} \sum_{t \in T} r_{pt} x_{pt} - W \left( \sum_{(i,j) \in A} \sum_{t \in T} c_{ijt} y_{ijt} + \sum_{(i,j) \in A} \sum_{t \in T} tc_{ijt} z_{ijt} \right) \quad (1)$$

Subject to :

$$\sum_{t \in T} x_{pt} \leq 1 \quad \forall p \in P \quad (2)$$

$$x_{pt} = 0 \quad \forall t \in T, \quad p \in B_t \quad (3)$$

$$\sum_{p \in u} x_{pt} \leq f_u - 1 \quad \forall u \in U, \quad t \in T \quad (4)$$

$$H_t = \sum_{p \in P} x_{pt} v_{pt} \quad \forall t \in T \quad (5)$$

$$H_t \leq APC_t \quad \forall t \in T \quad (6)$$

$$\sum_{(i,j) \in O_i} z_{ijt} - \sum_{(j,i) \in I_i} z_{jit} = \sum_{p \in N_i} x_{pt} v_{pt} \quad \forall i \in I, \quad i \notin D, \quad t \in T \quad (7)$$

$$\sum_{(i,j) \in O_i} z_{ijt} - \sum_{(j,i) \in I_i} z_{jit} = -H_t \quad \forall i \in D, \quad \forall t \in T \quad (8)$$

$$\sum_{t \in T} y_{ijt} \leq 1 \quad \forall (i,j) \in A \quad (9)$$

$$z_{ijt} \leq M \sum_{t \in P_t} y_{ijt} \quad \forall (i,j) \in A, \quad t \in T \quad (10)$$

$$x_{pt} \in \{0, 1\} \quad \forall p \in P, \quad t \in T \quad (11)$$

$$y_{ijt} \in \{0, 1\} \quad \forall (i,j) \in A, \quad t \in T \quad (12)$$

$$z_{ijt} \geq 0 \quad \forall (i,j) \in A, \quad t \in T \quad (13)$$

$$H_t \geq 0 \quad \forall t \in T \quad (14)$$

The objective function of the model (1) is to maximize the net present value of revenue minus the discounted and weighted costs of road construction and transportation. The penalty weight,  $W$ , is used only in the metaheuristic procedure. It is used to reduce the spatial dispersion of cut-blocks selected. Construction and transportation costs tend to be high when the spatial dispersion of selected cut-blocks is high, and low when the spatial dispersion of cut-blocks is low. Hence, by penalizing construction and transportation costs,  $W$  is used to penalize spatial dispersion of cut blocks. The purpose of controlling spatial dispersion in this manner will become clear when the metaheuristic solution procedure is fully described (below).  $W$  is valued at 1 when the model is solved using the branch and bound algorithm, and its value varies when this model is solved using the metaheuristic search algorithm. The first constraint (2) ensures that a polygon may not be harvested more than once during the planning horizon. Equation (3) constrains the harvest of polygons that are ineligible, either by age or located in a reserve. The set of area-restricted adjacency constraints is defined in Eq. (4). This is a standard formulation of area-restricted adjacency model (ARM), known as the path formulation, used by McDill et al. (2002) and Crowe et al. (2003). To use this equation, a set of maximum openings has been defined. Each maximum opening contains the minimal set of adjacent polygons that, when harvested together will violate the maximum opening size limit. Maximum openings are defined for all possible openings that can violate the allowable opening size. The parameter  $f_u$  is the number of polygons in each maximum opening. As an example, if we assume that the opening size limit is 65 ha and one of the maximum openings is a set with two members—i.e., polygon A (64 ha) and

B (10 ha), then  $f_u$  would be 2 and the constraint defined for this opening would ensure that either A or B or neither of the polygons would be harvested. Note that the number of constraints required to model the ARM can be quite large, depending on the size of the forest. For the small forests used in this paper, this number did not present a computational problem. The problem of requiring a large number of linear constraints in order to model the ARM has been fully analyzed in Goycoolea et al. (2009).

Equation (5) defines an accounting variable,  $H_t$ , the volume harvested in each period. Equation (6) uses this accounting variable to impose an upper bound on the volume harvested in period  $t$ . The value of this upper bound is a parameter handed down from a strategic model, and is used to ensure the long-term sustainability of the forest's multiple values. Equation (7) provides the link between the harvest scheduling activity and the network-flow model; i.e., if a polygon is cut, then the harvest volume is triggered to flow out of the node within this harvested polygon. If the polygon is not cut, then (7) functions as a trans-shipment constraint. Equation (8) defines the demand-node, located at the entry-point of the forest. Equation (9) requires that a road may be built only once during the planning horizon.

Equation (10) ensures that, if a flow of harvested wood passes from node  $i$  to  $j$ , then a road must be built along this arc, either in periods prior to the period of the flow, or in the period during which flow occurs—but not later. The parameter to be chosen for Big-M, in this equation, must be as small as possible to facilitate an efficient search. Hence, for all applications of this model, the parameter selected for Big-M equals the maximum possible flow of wood through the road network in a given period.

Finally, Eqs. (11) and (12) constrain the harvest and road building decision variables to be binary; and Eqs. (13) and (14) define the model's continuous positive variables.

## 2.2 New solution procedure

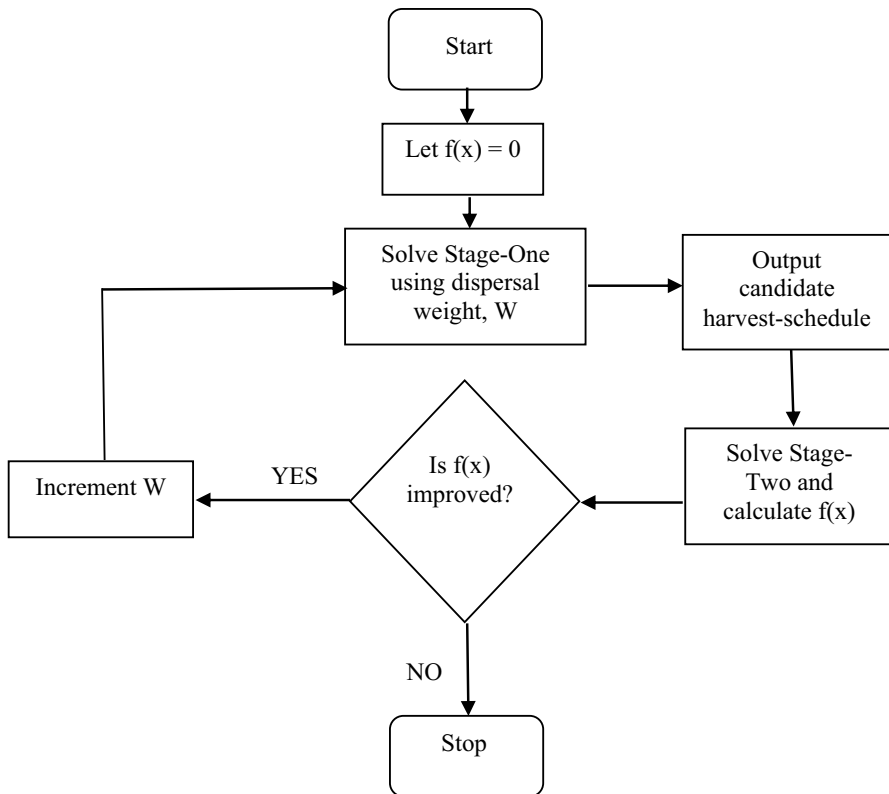
To solve the integrated tactical planning model using metaheuristic algorithms, the following two-stage procedure was used:

*Stage-one* select a set of cut-blocks to be scheduled for harvest.

*Stage-two* select an optimal road network that minimizes total construction and transportation costs.

These two stages are integrated, as illustrated in Fig. 1.

Figure 1 illustrates the overall strategy of the solution procedure; i.e., how stages one and two are integrated to form a greedy search that maximizes the objective function of the integrated model by iteratively incrementing the dispersal penalty function,  $W$ , used in stage one.  $W$  is incremented until no improvement in the objective function occurs. This method of integrating the two stages was used in order that a spatial dispersal of cut-blocks (selected in stage-one) be selected that lends itself to maximizing the objective function of the integrated



**Fig. 1** Algorithmic flowchart illustrating how stages one and two are integrated

model as a whole (calculated in stage-two). A detailed description of stages 1 and 2 is given below. Note that the iterative loop ensures that decisions on harvesting, construction, and transportation, are made interdependently.

### Stage-One: Solve the Integrated Model

The objective of stage one is to select a set of cut-blocks to be scheduled for harvest such that the selected cut-blocks, and their spatial dispersal, maximize the objective function of the integrated model when is calculated in stage-two. The road network generated in stage one, is a temporary network, to be improved in stage-two. The function of the road network generated in stage-one is to influence the spatial dispersal of the blocks scheduled for harvest in stage-one.

To solve the integrated harvest-scheduling model in stage-one, the simulated annealing algorithm (Kirkpatrick 1984) was used. This search algorithm has a long record of use in solving the tactical harvest-scheduling model (e.g., Lockwood and Moore 1993; Dahlin and Sallnäs 1993; Murray and Church 1995; Tarp and Helles 1997; Öhman and Eriksson 1998; Boston and Bettinger 1999; Van

Deusen 1999, 2001; Borges et al. 2014). Since the model solved in stage-one is an integration of harvest-scheduling decisions and road building and transportation decisions, a heuristic road-building algorithm (described below) was nested within the harvest-scheduling model in order that each scheduled block may be accessed by a road and that the total construction and transportation cost of the harvest-schedule may be calculated. The simulated annealing algorithm, used in stage-one, is described as follows.

1. Generate an initial feasible solution of the harvest-schedule,  $S$ , comprised of a random selection of cut-blocks to be harvested over the planning horizon. This initial solution must meet all constraints in the model, except those that concern roads.
2. Use a heuristic algorithm (described below) to generate a road network for  $S$  such that the road construction and transportation costs can be calculated in the objective function of  $S$ , i.e.,  $f(S)$ .
3. Define an initial temperature,  $T$ , and a reduction factor,  $r$ , where  $0 < r < 1$ .
4. While  $T$  is not below a minimum temperature:
  - (i) perform the following loop for  $nrep$  times:
    - (a) Randomly select a neighboring solution,  $S'$  of  $S$ .
    - (b) If  $S'$  is feasible, generate a road network using a heuristic (see below) for  $S'$  and calculate  $f(S')$ ; i.e., the total revenue minus the construction and transportation costs of solution,  $S'$ .
    - (c) Let  $\Delta = f(S') - f(S)$
    - (d) If  $\Delta > 0$ , let  $S = S'$
    - (e) if  $\Delta < 0$ , let  $S = S'$  with probability  $e^{\Delta/T}$
  - (ii) set  $T = rT$ .
5. Return  $S$  with the highest objective function value.

The heuristic road-building algorithm used in step 2 (above) for selecting a road network, must execute quickly in order that the solution space for an optimal harvest-schedule may be effectively explored using the simulated annealing algorithm. Hence, the heuristic used was highly simplified and executed as follows:

- (i) For each polygon harvested, in each period, a lowest cost path, from the location of the harvested polygon's landing to the forest's point of entry, is pre-calculated. This cost equals both the cost of construction and the cost of transporting the polygon's harvested flow of wood through this path. Note: Each lowest cost path, for each polygon, in each period, was pre-calculated using Dijkstra's shortest path algorithm (1959).
- (ii) For each polygon harvested in  $S'$ , the lowest cost path is added to the road network of  $S'$ , and the total cost of the resulting construction and transporta-

tion, without double-counting any road-construction costs, is used to calculate  $f(S')$ .

The road network designed using this heuristic procedure is far from optimal; but direct optimization of the road network is not the primary objective in stage-one. The objective in stage-one is to select the locations and timing of polygons such that: (i) revenue is maximized; and (ii) the selected polygons are spatially dispersed for the generation of a low-cost road network in stage-two.

The method of selecting a set of polygons that are not excessively dispersed is now described. In stage-one, a penalty weight,  $W$ , is used to influence the dispersal of the locations of the cut-blocks selected for harvest. A penalty weight is used because the total cost of construction and transportation is treated as an indicator of dispersal. This is because a schedule of cut-blocks with a high total cost is likely to be more dispersed than a solution with low total cost. Hence, by adding a penalty weight to the total cost of construction and transportation, one is penalizing solutions with a harvest-schedule that is excessively dispersed spatially, and thereby influencing the search to favor solutions where the harvest-schedule is less dispersed spatially.

This method of influencing the spatial dispersal of the harvest has a direct effect on the solution quality of the integrated model as a whole: for it influences the costs of construction and transportation that result from stage-two. This influence can be inferred from Fig. 1.

In step 4 of the above algorithm, a neighboring solution,  $S'$ , is generated as follows:

- (i) Randomly select a harvesting scheduling decision variable,  $x_{pt}$ , from the current solution,  $S$ .
- (ii) If  $x_{pt}=0$ , let  $x_{pt}=1$ ; and
- (iii) If  $x_{pt}=1$ , let  $x_{pt}=0$ .
- (iv) If the permuted solution is feasible, proceed to generate a road network otherwise, return to step i.

This permutation operation is known as a one-opt permutation operation (see Bettinger et al. 1999).

#### Stage-Two: Optimize a Road Network for the Harvest-Schedule Generated in Stage-One

The objectives in stage-two are: (i) to design a road network that facilitates access to the cut-blocks scheduled for harvest which were selected in stage-one, such that the total construction and transportation costs are minimized; and (ii) to calculate the objective function of the resulting solution to the integrated model as whole (i.e., the revenue – construction cost – transportation cost).

The road network designed in stage-two is accomplished using the classic fixed charge network design model (Magnanti and Wong 1984). The objective of this model is to connect, on graph  $G$ , where  $G=(N, E)$ , a set of supply nodes to a set of demand

nodes, such that total fixed cost of all edges selected and the variable cost of all transportation from supply nodes to demand nodes, is minimized.

The network design model used in this section can also be found integrated within earlier formulations of the integrated harvest-scheduling model (e.g., Weintraub and Navon 1976; Guignard et al. 1998; Naderializadeh and Crowe 2020). The mathematical formulation of this model is presented below:

### Indices and Sets

$i, j, I$  = Indices and set of nodes

$t, T$  = Index and set of time periods

$S$  = Set of supply nodes

$N$  = Set of intermediate (trans-shipment) nodes

$D$  = Set of the demand nodes

$A$  = Set of directed arcs

$O_i$  = Set of arcs directed out of node  $i$

$I_i$  = Set of arcs directed into node  $i$

$P_t$  = Set of periods equal to or less than  $t$

### Parameters

$v_{it}$  = Harvested volume originated from node  $i$  in period  $t$  ( $\text{m}^3$ )

$c_{ijt}$  = Discounted cost of building a road between nodes  $i$  and  $j$  in period  $t$  (\$)

$tc_{ijt}$  = Discounted transportation cost between nodes  $i$  and  $j$  in period  $t$  (\$ per  $\text{m}^3$ )

$M$  = An arbitrarily large number

$H_t$  = Total volume originated from supply nodes in period  $t$  ( $\text{m}^3$ )

### Variables

$y_{ijt}$  = 1 if arc from node  $i$  to  $j$  is built in period  $t$ , 0 otherwise

$z_{ijt}$  = Directed flow of harvested volume from node  $i$  to  $j$  in period  $t$  ( $\text{m}^3$ )

$$\text{Minimize} \quad \sum_{(i,j) \in A} \sum_{t \in T} c_{ijt} y_{ijt} + \sum_{(i,j) \in A} \sum_{t \in T} tc_{ijt} z_{ijt} \quad (15)$$

Subject to :

$$\sum_{(i,j) \in O_i} z_{ijt} - \sum_{(j,i) \in I_i} z_{jit} = v_{it} \quad \forall i \in S, \quad t \in T \quad (16)$$

$$\sum_{(i,j) \in O_i} z_{ijt} - \sum_{(j,i) \in I_i} z_{jit} = 0 \quad \forall i \in N, \quad t \in T \quad (17)$$

$$\sum_{(i,j) \in O_i} z_{ijt} - \sum_{(j,i) \in I_i} z_{jit} = -H_t \quad \forall i \in D, \quad t \in T \quad (18)$$

$$\sum_{t \in T} y_{ijt} \leq 1 \quad \forall (i,j) \in A \quad (19)$$

$$z_{ijt} \leq M \sum_{i \in P_t} y_{ijt} \quad \forall (i, j) \in A, \quad t \in T \quad (20)$$

$$y_{ijt} \in \{0, 1\} \quad \forall (i, j) \in A, \quad t \in T \quad (21)$$

$$z_{ijt} \geq 0 \quad \forall (i, j) \in A, \quad t \in T \quad (22)$$

The objective function of the model (15) is to minimize the discounted costs of road construction and transportation. Equations (16) to (18) are flow-balance equations. Equation (16) defines a supply node; i.e., it ensures that the volume which originates from a supply node must flow out of it and into an adjacent node within the network. Equation (17) is a trans-shipment constraint. Equation (18) defines the demand-node and the value of the demand. Equation (19) requires that a road may be built only once during the planning horizon. Equation (20) ensures that, if a flow of harvested wood passes from node  $i$  to  $j$ , then a road must be built along this arc, either in periods prior to the period of the flow, or in the period during which flow occurs—but not later. Finally, Eq. (21) constrains the road building decision variables to be binary; and Eq. (22) defines the model's continuous positive variables.

To solve the fixed charge network design model, in stage-two, a metaheuristic search algorithm was used. In this paper, we used a permutation operation of a metaheuristic algorithm based on the work of Ghamlouche et al. (2003). This permutation operation was selected because of the speed with which it can be executed and the high quality of the solutions generated by it. The metaheuristic algorithm of Ghamlouche et al. (2003) was designed to solve the network design model for one period, and we had to innovate upon this work such that the road network construction could occur in multiple periods, since the harvest-scheduling problem is comprised of multiple periods.

At the core of the Ghamlouche et al. (2003) metaheuristic algorithm is the cycle-based permutation operation. The cycle-based permutation operation is a method by which a candidate solution to the fixed charge network design problem,  $S'$ , is generated from a current solution,  $S$ , in the search for an optimal solution. The general approach of generating  $S'$  from  $S$ , in using the cycle-based operation, entails:

- (i) randomly selecting an existing road-link in the network, and then
- (ii) redirecting the flow of harvested wood around this link; and,
- (iii) reconnecting the redirected flow with the currently existing road network.

The opening and closing of road-links, to facilitate this redirected flow efficiently, is also a necessary part of this operation—in order that the objective function  $f(S')$  (i.e., total construction cost + total transportation cost) may be minimized.

The cycle-based permutation operation is quite complex. Hence, a worked example, in four steps, is now given.

Step 1: Select an arc,  $a'$ , from the current solution,  $S$

In the first step, arc  $a'$  is randomly selected from a subset of all arcs,  $A'$ , such that:

- (i)  $A'$  is the set of arcs where split flow occurs. A split flow occurs when, from the same node, the flow of wood moving in the same destination, is split, i.e., it proceeds along two separate arcs from that same node.

If the set  $A'$  is empty, then arc  $a'$  is randomly selected from set  $B'$ , such that:

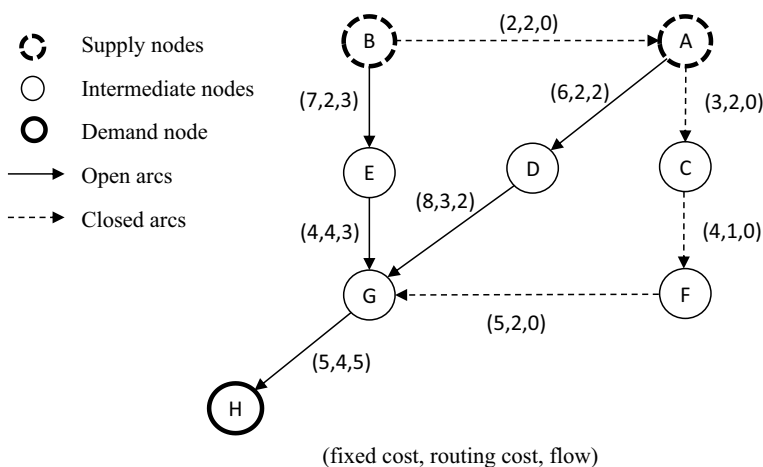
- (ii)  $B'$  contains all unbuilt arcs in the solution,  $S$ , and each arc in  $B'$  also shares a node which functions as the tail-node of flow that is directed along another arc, which is built.

In other words, the first step involves randomly selecting a candidate road,  $a'$ , that is attached to the current road network in order to redirect flow through this road. For example, in Fig. 2, a current solution,  $S$ , is illustrated. Here, a feasible random selection of  $a'$  would be arc B–A. Hence, in this permutation operation, the flow currently passing along arc B–E would be redirected through arc B–A.

## Step 2: Generate auxiliary graph

A preliminary step to be taken, before the selection of arcs to open and close can be made in order to define the diversion of flow, is the creation of an ‘auxiliary graph’ of the network. In this auxiliary graph, construction and transportation costs are temporarily changed to reflect the potential change in costs of redirecting flow through them. The procedure for generating this auxiliary graph is as follows:

- (i) Replace each arc  $(i,j)$  in the current road network by two arcs  $(i,j)^+$  and  $(j,i)^-$ .
- (ii) Arc  $(j,i)^-$  is not included in the auxiliary graph when the current flow on arc  $(i,j)$  is less than  $\alpha$  (where  $\alpha$  = the value of the diverted flow)



**Fig. 2** An example of a current solution,  $S$ , to a network design problem

(iii) The cost of  $(i,j)^+$  is calculated as:

$$c_{ij}^+ = tc_{ij} \cdot \alpha + c_{ij} \cdot (1 - \min(1, z_{ij})) \quad (23)$$

where  $tc_{ij}$ =cost of transportation, per unit, on arc  $(i,j)$ ,  $c_{ij}$ =construction cost of arc  $(i,j)$ ,  $z_{ij}$ =flow on arc  $(i,j)$  in solution,  $S$ .

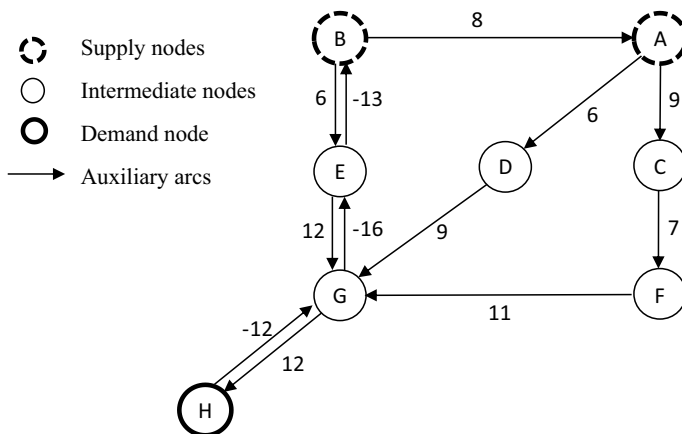
iv. The cost of each  $(j,i)^-$  is calculated as follows:

$$\text{if } z_{ij} > \alpha \text{ then } c_{ji}^- = -tc_{ij} \cdot \alpha \quad (24)$$

$$\text{if } z_{ij} = \alpha \text{ then } c_{ji}^- = -tc_{ij} \cdot \alpha - c_{ij} \quad (25)$$

Equation (23) calculates the increase in road network costs when an additional flow of  $\alpha$  appears on the arc  $i$  to  $j$ . This cost equals the additional transportation cost for  $\alpha$  units, plus the construction cost if there were no prior existing flow on that arc. Equations (24) and (25), on the other hand, calculate the decrease in the flow on arc  $i$  to  $j$ . The value of this decrease depends on whether the flow on the arc is more than  $\alpha$  or not. If it is more than  $\alpha$ , then (24) is used. This is because, if the flow is greater than  $\alpha$ , this implies that the arc had not been built, and there should be no reduction in cost for removing a road that had not been built. If, on the other hand, the flow on the arc equals  $\alpha$ , then this implies that an arc had been built, and (25) is used to ensure that the reduction in cost includes removing the cost of this constructed road.

To illustrate the generation of an auxiliary graph, an example is presented in Fig. 3. Figure 3 shows the auxiliary network produced when 3 units of flow are diverted from arc B–E to arc B–A. For example, arc B–A is not built in the solution  $S$  and the cost of adding 3 units of flow to this arc is the construction cost of this arc (cost=2) plus the transportation cost of routing 3 units of flow (cost=6)



**Fig. 3** Example of auxiliary network when flow is diverted from arc B–E to B–A

which equals 8. As another example, arc B–E is already built in the solution  $S$  and has 3 units of flow. According to Eq. (25), since the flow equals  $\alpha$  (i.e., 3), the cost of deducting 3 units of flow is the construction cost of this arc with minus sign (cost =  $-7$ ) plus the transportation cost of routing 3 units of flow with minus sign (cost =  $-6$ ) which equals  $-13$ . This value is then assigned to arc E–B in the auxiliary graph. Figure 3 shows the total cost of each directed arc, given the redirected flow.

Step 3: Generate a lowest cost cycle, from arc  $a'$ , using the auxiliary graph

In step three, a lowest cost cycle is generated for the flow redirected through arc  $a'$ . This lowest cost cycle is used as a preparatory step to deciding how to divert flow beyond  $a'$ . This cycle connects the head of arc  $a'$  (node A) back to its tail (node B), and the costs on the auxiliary graph are used to calculate the cost of this cycle. To find the lowest cost cycle, a modified label-correcting shortest path algorithm, described in Ghamlouche et al. (2003), is used. This is a standard label correcting shortest path algorithm modified such that the label of node  $j$  does not change if it is already on the path from the source node to  $i$ . This modification avoids getting trapped in a cycle where the cost would be negative.

In the current simplified example, the lowest cost cycle, from the head of B–A to its tail, found using the shortest path algorithm, is: B–A–D–G–E–B, and its cost is  $-6$ . This cost is the summation of the costs for different arcs over the lowest cost cycle (i.e.,  $8 + 6 + 9 - 16 - 13 = -6$ ). This cycle is illustrated in Fig. 4.

Step 4: Use the lowest cost cycle to divert flow and generate  $S'$

Given the lowest cost cycle, the following algorithmic procedure is used to divert flow on the solution,  $S$ :

For each road-link,  $c'$ , in the lowest cost cycle:

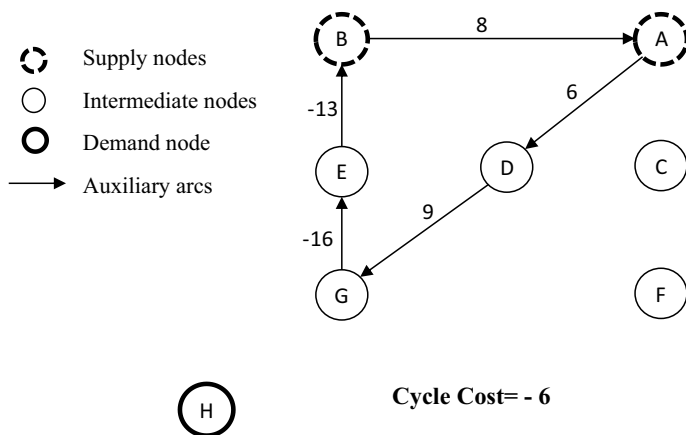


Fig. 4 Lowest cost cycle for arc B–A on the auxiliary graph

- If the direction of  $c'$  in the lowest cost cycle is the same direction as  $c'$  in  $S$ , or if  $c'$  does not exist in  $S$ , then add  $\alpha$  units to the flow on  $c'$  in  $S$ .
- If the direction of  $c'$  in the lowest cost cycle is the opposite direction of  $c'$  in  $S$ , then deduct  $\alpha$  units from the flow on  $c'$  in  $S$ .

For example, the road-link connecting nodes A and D, in the lowest cost cycle, has the same direction in  $S$ . Therefore, three units of flow are added to arc A–D in  $S$ . Similarly, the road-link connecting nodes G and E, in the lowest cost cycle, has the opposite direction in  $S$ . Therefore, three units of flow are deducted from arc E–G in  $S$ . In this way, the described procedure is used on each road-link in the cycle to generate  $S'$ . The resulting solution,  $S'$  is illustrated in Fig. 5.

Step 5: Calculate  $f(S')$

To calculate  $f(S')$ , sum the costs of the cycle on the auxiliary graph. For example, adding the costs of all arcs in the cycle (B–A–D–G–E–B) equals a value of  $-6$ . The minus sign of this value indicates that  $f(S')$  is 6 units lower in cost than  $f(S)$ . In the context of the simulated annealing algorithm which is used to solve the network design model,  $S'$  is accepted or rejected by the following procedure:

- Let  $\text{delta} = f(S') - f(S)$ .
- If  $\text{delta} < 0$ , let  $S = S'$ .
- If  $\text{delta} > 0$ , let  $S = S'$  with probability  $e^{-\text{delta}/T}$  (where  $T$  refers to the current temperature in the simulated annealing algorithm).

Adjust the final solution to satisfy the multi-period planning horizon

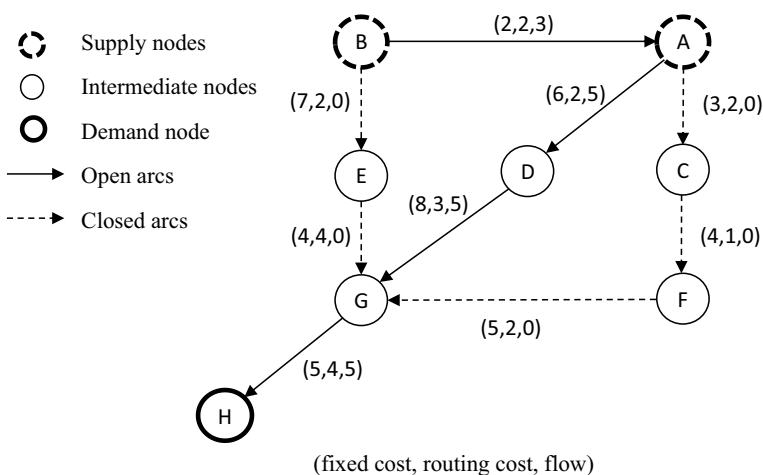


Fig. 5 Permuted solution,  $S'$ , given a diversion of flow from arc B–E to arc B–A

The cycle-based permutation operation treats the network design model as a single-period problem. Hence, after the simulated annealing search algorithm has finished executing, the best solution's road construction must be adjusted to satisfy the harvest-scheduling problem over multiple periods. This adjustment entails the following two steps.

First, the periodic schedule of constructing the road network must be derived from the schedule of harvests. To do this, begin in period 1 and, for each polygon harvested, find the shortest path on the selected road-network, from each polygon harvested in period 1 its demand node; and label all arcs on each path as "constructed in period 1". Next, in period 2, find all such shortest paths for all polygons harvested in period 2; but label only the unlabelled arcs comprising this set of paths as "constructed in period 2". Execute the same procedure in period 3 as was used in period 2. In this way, the precedence of the construction of each arc is derived from the harvest-schedule.

The second step requires a calculation of the objective function's discounted construction and transportation costs. Discounted construction costs are calculated based on the period in which each arc was constructed, as labelled in step 1 (above). Double-counting of paths which share common arcs is avoided. Discounted transportation costs are calculated using the period in which a polygon is scheduled for harvest, the volume harvested, and the distance between the harvested polygon and its demand node. This distance is equal to the shortest path on the selected road network calculated in step 1.

This adjustment of the final solution occurs after the simulated annealing algorithm has concluded. This is because the calculation of these adjustments, while the search is running, would slow the search and restrict an adequate exploration of the search space. There is an implicit cost in optimality by doing this because the search is directed by an objective function in which the cost parameters have not been discounted. Hence, the overall cost in optimality of using this metaheuristic in this manner will be evaluated by comparison with branch and bound solutions in the results.

### 3 Case study

The solution procedure was tested on three problem instances, derived from three forested areas found in the Kenogami Management Unit, located in the boreal forest of Ontario, Canada. All polygons, in each data-set, contain one of six yield curves, and the mean area of each polygon was 19.5 ha. The three problem instances were of different sizes: 400, 707 and 900 forested polygons.

For each forest, the existing age-class distribution found in the case study was used. The minimum rotation age for each stand was set at 70 years. Revenue values of the standing timber were estimated using Armstrong's (2014) conversion return approach. Harvesting cost i.e., the cost of felling, processing and extraction to the roadside, stumpage charges, reforestation and other management fees were deducted from the mill gate value of logs to calculate the revenue values. These values varied as a function of log diameter: \$54 *per m*<sup>3</sup> (ages 70–90 years), \$62 *per m*<sup>3</sup> (ages

91–20 years), and \$70 *per* m<sup>3</sup> (ages greater than 120). Average road construction cost was assumed to be \$30,000 *per* km which has since been confirmed by T. Harris (private communication, 2017). Transportation costs were estimated using the formulation in Martin (1971): assuming a truck load of 44 m<sup>3</sup> and an average cost of \$96 *per* hour for truck operation (private communication, 2017), the mean transportation cost used inside the forest was \$0.30 *per* m<sup>3</sup> *per* km. Both costs and revenues were discounted at 4% *per* annum, from the middle of each period. Adjacent polygons were defined as polygons sharing a common vertex, and the maximum allowable opening size was limited to 65 ha.

The three forested areas were without a set of candidate roads. The existing road network begins at each forest's access point. Therefore, a network of candidate roads was generated for each forest by using the optimal road location model of Anderson and Nelson (2004). This road location model allows one to generate an operationally feasible road, subject to vertical and horizontal design standards, that will connect two points on a forested landscape at minimal cost. The optimal road location model of Anderson and Nelson (2004) was used with a 50 m×50 m grid layer and a digital elevation model, to define the resolution of the road design. All other parameters used in this work were default parameters of Anderson and Nelson (2004). The density of the entire set of candidate roads emerged from using the following rule: all pairs of adjacent forested polygons must be connected by one candidate road (where a polygon is adjacent to another when a common edge is shared). This method entails the production of a dense set of candidate roads which allows for more options in designing a lowest cost road network and has shown promising results when compared to solutions generated using a sparse set of candidate roads (Naderializadeh and Crowe 2018).

The number of decision variables required to solve the integrated harvest scheduling problem, for these three forests, over three periods, is presented in Table 1.

Table 1 shows that the number of roads is quite high, relative to the number of polygons. Hence, the two-stage procedure is applied to a rather dense set of operational roads, which can be useful for two reasons: (i) given a heterogeneous landscape, a denser set of roads allows for more opportunities to optimally locate the network as a whole than a sparse set; and (ii) the use of operational roads allows for the transition from the tactical to the operational scale to be more feasible than if operational constraints were not used in the design of candidate roads.

The maximum run-time for stage-one of the procedure was 60 min, and for stage-two it was 30 min. The two-stage search procedure was written in the JAVA

**Table 1** Dimensions of modeled problem instances, for three periods

Number of polygons	Directed roads (#binary variables)	Polygons (#binary variables)	Flow (#continuous variables)
400 polygons	5868	1200	5868
707 polygons	10,668	2121	10,668
900 polygons	13,470	2700	13,470

programming language and executed on an Intel® Xeon X5650 hex-core processor, using 96 gigabytes of RAM, and a CentOS 5.5 operating system. In addition, each problem instance was also solved using the default search parameters in CPLEX® 12.5, with a maximum run-time of 24 h. The solutions generated using CPLEX are used to evaluate the quality of solutions generated by the two-stage procedure.

## 4 Results

The two-stage solution procedure was executed on the three forests, and the resulting objective function values, and their components, are presented in Table 2. Table 2 also presents a comparison of these results with those found using CPLEX 12.5.

The results in Table 2 yield several observations. First, after executing the CPLEX program for 24 h, the gaps were not closed. The remaining gaps, for each forest, were 3.78%, 10.58%, and 7.16%, respectively. These gaps are large, given the size of the problem instance and the 24 h of run time. No progress was made after 3 h of computing. This indicates that the integrated model is not integer friendly and that future work on improving its formulation is needed if run-time gaps are to be improved. These gaps are not ideal for precisely evaluating the solution quality of the two-stage procedure; but they are, nonetheless, useful for the purpose of approximate evaluation, so long as one bears in mind that the comparison made is not against mathematical optima. Second, the percent difference in objective function values, between the solutions yielded by CPLEX *versus* the two-stage procedure, is quite tight for all three forests: the two-stage procedure fell short of CPLEX's objective function value by only 4.6%, 1.5%, and 2.7% for each of the problem instances, moving from smallest to largest. Hence, good quality solutions were found in this benchmarking exercise. In addition, the problem instance did not adversely affect the solution quality of the metaheuristic procedure, at this scale.

Third, in Table 2 a trend can be observed among the three components of the objective function value (*viz.*, revenue, construction cost and transportation cost): results from the two-stage procedure consistently fell short of those generated by CPLEX with regard to maximizing revenue, but also regularly improved upon those of CPLEX with regard to minimizing total costs. The revenue generated by two-stage procedure fell short of the revenue generated using CPLEX by an average of 5.2% (for the three problem instances); and the total costs of the solutions generated using the two-stage procedure were, on average, 12.9% lower than those generated by CPLEX.

Finally, Table 2 also reveals the improvements that were made to the road network, in stage-two, by solving the road-network design problem as fixed charge network design model, given the simplistic road network generated in stage-one. Here, a trend can be observed with regard to changes in transportation *versus* construction costs: in stage-two, for all three problem instances, transportation costs were increased while construction costs were decreased. This trend makes sense, when one recalls that the road networks generated in stage-one were a set of shortest paths, which tend to minimize transportation costs while sacrificing opportunities for minimizing construction costs. Stage-two corrects this imbalance in the trade-off

**Table 2** Objective function values and components resulting from solving the integrated model using the two-stage procedure versus CPLEX 12.5

Number of polygons and the solving method used	Revenue (\$)	Construction cost (\$)	Transportation cost (\$)	Total cost (\$)	Objective function (\$)	CPLEX gap <sup>a</sup>
<i>400 polygons</i>						
Stage 1 (A)	10,497,549	1,303,063	220,676	1,523,739	8,973,810	–
Stage 2 (B)	10,497,549	1,191,298	243,122	1,434,420	9,063,129	–
CPLEX (C)	10,916,900	1,158,227	254,825	1,413,052	9,503,848	3.78%
% difference <sup>b</sup> (B vs. A)	0.00%	– 8.58%	10.17%	– 5.86%	1.00%	–
% difference (A vs. C)	– 3.84%	12.50%	– 13.40%	7.83%	– 5.58%	–
% difference (B vs. C)	– 3.84%	2.86%	– 4.59%	1.51%	– 4.64%	–
<i>707 polygons</i>						
Stage 1 (A)	20,814,178	3,059,423	790,340	3,849,763	16,964,415	–
Stage 2 (B)	20,814,178	2,749,497	822,404	3,571,901	17,242,277	–
CPLEX (C)	22,456,684	4,033,804	921,263	4,955,067	17,501,617	10.58%
% difference (B vs. A)	0.00%	– 10.13%	4.06%	– 7.22%	1.64%	–
% difference (A vs. C)	– 7.31%	– 24.16%	– 14.21%	– 22.31%	– 3.07%	–
% difference (B vs. C)	– 7.31%	– 31.84%	– 10.73%	– 27.91%	– 1.48%	–
<i>900 polygons</i>						
Stage 1 (A)	23,548,758	3,267,249	946,135	4,213,384	19,335,373	–
Stage 2 (B)	23,548,758	2,912,261	1,005,872	3,918,132	19,630,625	–
CPLEX (C)	24,635,100	3,365,807	1,103,608	4,469,415	20,165,685	7.16%
% difference (B vs. A)	0.00%	– 10.87%	6.31%	– 7.01%	1.53%	–
% difference (A vs. C)	– 4.41%	– 2.93%	– 14.27%	– 5.73%	– 4.12%	–
% difference (B vs. C)	– 4.41%	– 13.48%	– 8.86%	– 12.33%	– 2.65%	–

<sup>a</sup>CPLEX gap (%) = [(value of the current upper bound/value of the best known feasible solution) – 1] × 100<sup>b</sup>% difference (B vs. A) = [(B/A) – 1] × 100

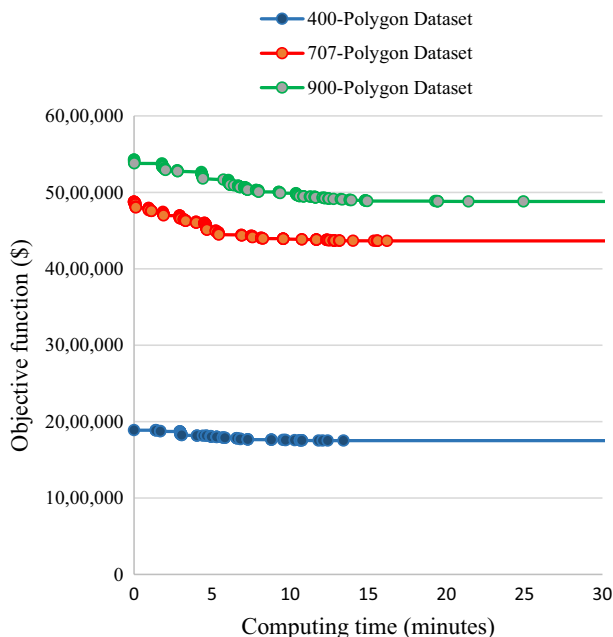
of construction *versus* transportation with an average reduction in construction costs of 9.9% and an average increase in transportation costs of 6.9%. The average total reduction in costs, achieved in stage-two, was 6.7%.

Figure 6 shows the progress of the search over time for stage-two of the two-stage procedure. Here, one can observe that the cycle-based permutation operation facilitated most of the improvements to the solutions of the fixed charge network design problems within the first 15 min of the search, and that little progress was made thereafter. Hence, the size of these three problem instances was not an obstacle to the computational progress of this search algorithm.

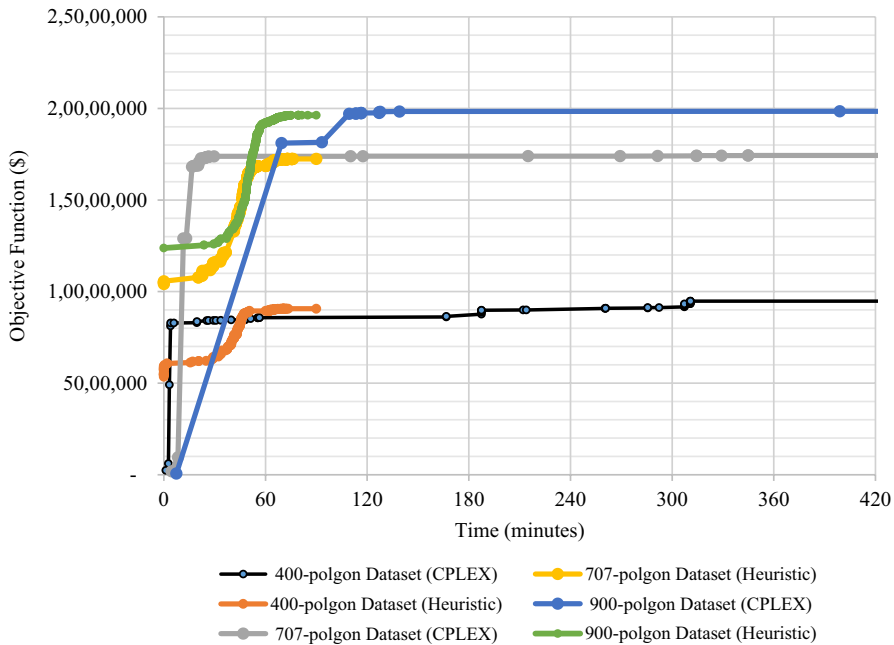
Figure 7 shows the progress of two-stage heuristic compared to CPLEX in solving the three problem instances.

Figure 7 shows that the two-stage procedure (which started at a randomly generated feasible solution) made most of its progress in stage-one (the first 60 min). Improvements that occurred in stage two increased in relative magnitude as the problem size increased. Figure 7 also shows that the CPLEX algorithm made rapid progress early in the search; but that this progress was slower as the problem size increased. The size of the problem instances clearly influenced the progress of these two search procedures differently.

The effect of changing the dispersal penalty over three iterations of the overall solution procedure, through the use of different penalty weights, is shown in Fig. 8. Figure 8 reveals a consistent trend; viz., for each of the three forests, the quality of the final solutions of the two-stage procedure was improved as the weight was



**Fig. 6** Progress over time of stage-two's search algorithm in solving the fixed charge network design problems

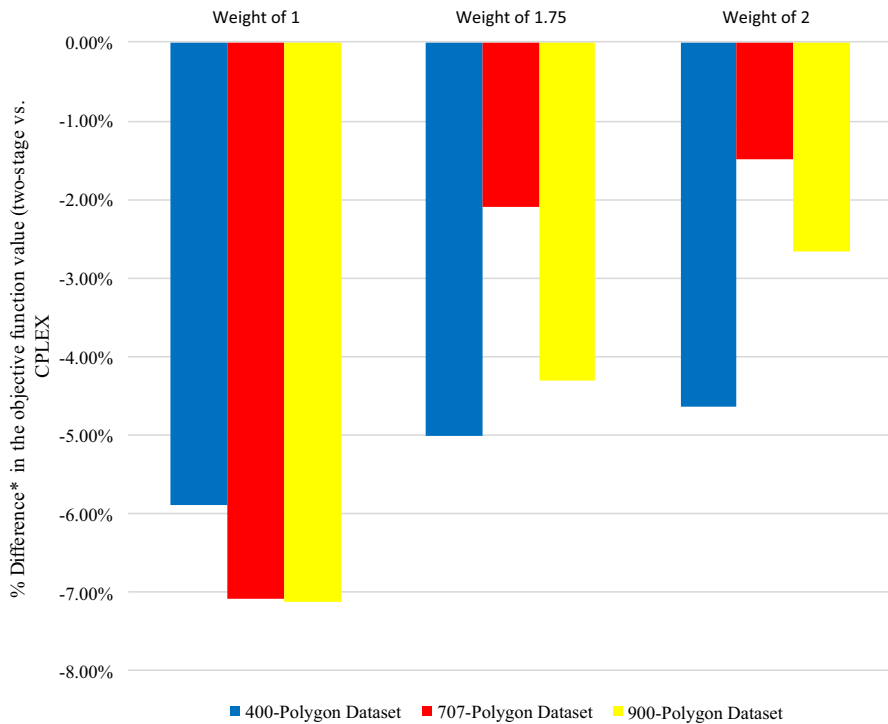


**Fig. 7** A comparison of search progress between CPLEX and the two-stage heuristic

increased from 1 to 2. From this, we infer that, as the spatial dispersal of selected harvest units was increasingly penalized in stage-one, the solution quality, yielded after stage-two, was improved and that integration of all three decisions (harvest, construction, and transportation) was successful.

Figure 9 presents three mapped solutions for the forest comprised of 707 polygons. These maps represent solutions found after executing: (a) stage-one; (b) stage-two; and (c) the CPLEX model. Several observations can be made from these maps. First, the different attributes of the road-network can be observed from the mapped solutions of stage-one *versus* stage-two. In stage-two, the construction costs incurred in stage-one have been reduced by 10.1% while transportation costs have increased by 4.1%, with a total reduction in costs of 7.2%. The road network in stage-two shows a more strategic use of branching, which leads to a reduction in construction costs. In addition, the increased transportation cost resulting from a more parsimoniously constructed network is also evident, especially in the southern half, where less direct routes from the harvested stands to the point of entry exist than in the solution generated in stage-one.

Second, Fig. 9 shows that, when comparing the solution generated in stage-two *versus* that generated using CPLEX, the solutions are very different spatially. The solution generated by CPLEX is more dispersed spatially than the solution generated by stage-two. In other words, the higher revenue achieved by the CPLEX solution comes at a cost; namely higher transportation cost and higher construction cost. Figure 9b, c provide an example of how two solutions with nearly equal objective function values can be so different spatially; and this in turn raises the interesting



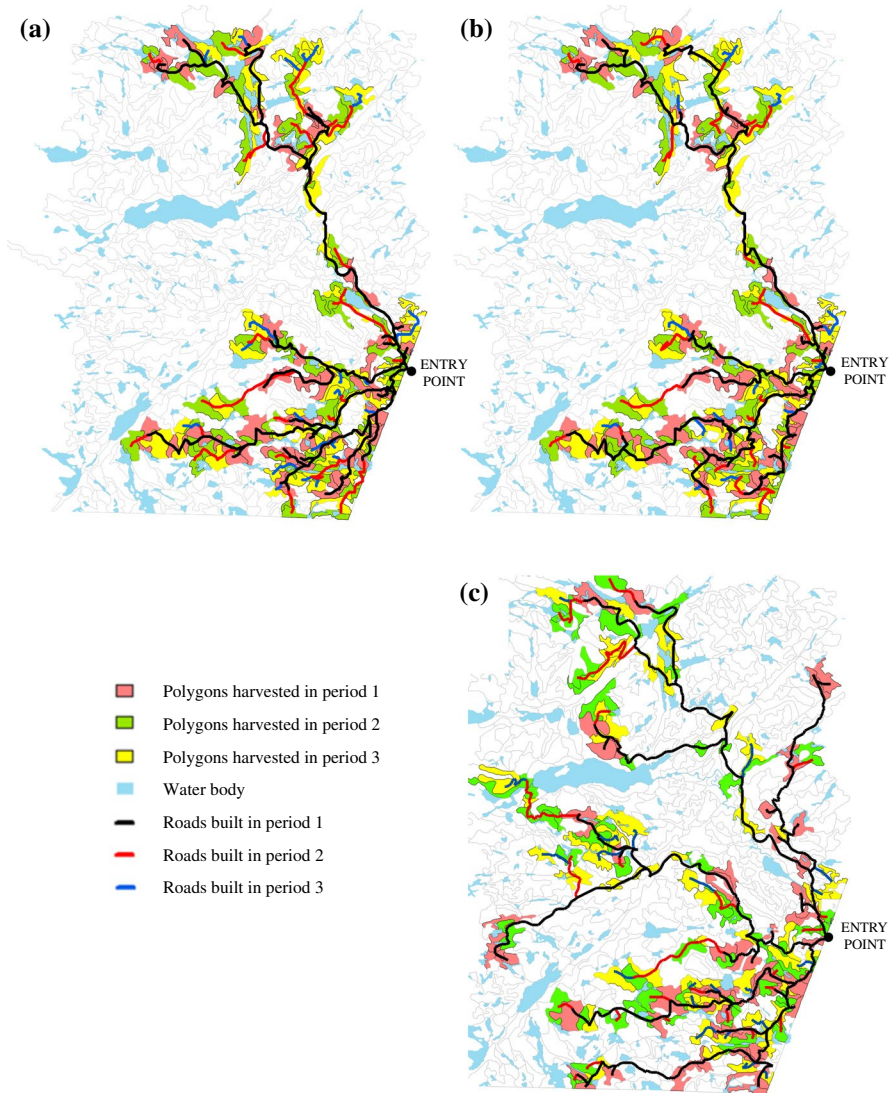
\*\*% Difference = [(two-stage objective function value/CPLEX objective function value)-1]× 100

**Fig. 8** The effect of three iterations of the solutions procedure, using different weights, upon the objective function

question of what radical spatial diversity might exist among a population of near-optimal solutions to the tactical harvest-scheduling problem.

## 5 Discussion

The three major results of this work may be summarized as follows. First, the quality of solutions generated for the three problem instances, using the two-stage procedure, was quite good, based on comparison with the solutions generated using CPLEX (see Table 2). Second, the adaptation of the cycle-based permutation operation proved quite effective; for, in stage-two it was used to decrease the total construction and transportation costs by an average of 6.7%, within a reasonable period of computing time. Third, the integration of stages one and two, through the iterative use of a dispersal penalty in stage-one, also proved quite effective. Adjustments to the dispersal penalty showed improvements to the objective function for the integrated model, as a whole.



**Fig. 9** Map of (a) stage-one, (b) stage-two and (c) CPLEX solutions for the 707-polygon dataset

These three major results are to be interpreted as illustrating the potential of the two-stage procedure, rather than any statistical properties of its efficacy. Each of the three major results will now be discussed in greater detail.

First, the quality of the solutions generated using the two-stage procedure should be evaluated within the context of the difficulty of the model solved. The model used to test this two-stage procedure is quite difficult to solve, from the perspective of computational complexity; for the integrated harvest scheduling model is itself comprised of two models that are each difficult to solve computationally; viz. (i) the

spatial harvest scheduling model, which is NP-hard (Murray 1999); and (ii) the fixed charge network design model, which is also NP-hard (Magnanti and Wong 1984). In addition, the problem instances ranged in size such that the number of binary decision variables was pushed near the limit at which useful solutions could be obtained using CPLEX. Comparing the metaheuristic solutions with the optimal benchmarks has been identified by Bettinger et al. (2009) as the highest level of validation (level 6) for heuristic techniques in forest planning, compared to the lowest level (level 1) in which no validation occurs. As addressed in Bettinger et al. (2009), one disadvantage of this validation type is an optimality gap over 0.1% usually happens for the exact solutions. Our exact results, after 24 h of computing on CPLEX ® 12.5 retained gaps (i.e., 3.78%, 10.58%, and 7.16%) that were not closed.

Given these gaps, how do we interpret the quality of the results generated using this new solution procedure? We may infer that the solution procedure yielded solutions of good and promising quality. We regard the results as good because: within 90 min of computing time, the new procedure yielded solutions that, on average, were within 2.92% of CPLEX's solutions (which ran for 24 h of computing time); and that the quality of CPLEX's solutions were, on average, within 7.17% of the optima. Hence, for a first attempt (within the literature on this problem) at solving the integrated tactical planning model using an integrated metaheuristic approach, these results are quite good. Second, these results are promising because they should encourage future research on this important problem— which has received little attention, perhaps because of its computational challenge. We regard the modeling procedure presented here as a prototype, or a framework, upon which improvements can be undertaken by future researchers.

A second topic of discussion concerns evaluating the cycle-based permutation operation. Figure 6 shows that only a small fraction of the solutions was sampled, and that the solutions found were of good quality. In the cycle-based permutation operation, the most time-consuming procedure is execution of the shortest path algorithm. Hence, one can expect that, as the size of the problem instance increases, the time required to execute the cycle-based permutation operation will increase because the complexity of the shortest path algorithm is  $O((v + e) \log v)$ . Hence, in order to adapt this permutation operation to much larger problem instances, a subset of vertices and edges within a reasonable proximity of the road-link selected for permutation must be used—instead of all vertices and edges in the problem instance.

A third topic of discussion concerns evaluating the integration of the search procedure by controlling the dispersal penalty in stage-one of the procedure. The results in Fig. 8 illustrate that this integration can be useful in improving the objective function of the problem as a whole using only three iterations of the loop illustrated in Fig. 1. We regard the integration presented here as a prototype, on which future improvements can be made through increasing the number of iterations executed by the search procedure within a reasonable period of time. Nonetheless, given the good quality of the results, this prototype of integration has been shown to be a useful method for solving the integrated harvest-scheduling model.

Finally, the managerial implications of this work are discussed. Given the scale of the cost of transporting harvested wood in forest operations, it is clearly important that transportation costs be integrated with harvest and road allocation decisions in a

metaheuristic procedure. In this work, we have shown that such an integration is possible using a metaheuristic procedure. With regard to practical implementation, we must be cautious in our evaluation. This is because a practical implementation would involve problem instances many times larger than those tested in this paper. We cannot therefore, from this paper, infer that the quality of the solutions generated using this new procedure would produce solutions of comparable quality on much large problem instances.

## 6 Conclusion

In this paper we presented the design and evaluation of a new metaheuristic solution procedure by which the integrated tactical forest planning model could be solved. The procedure was tested on three forests and we conclude that the quality of solutions generated using this procedure were quite good. This conclusion is important for three reasons. First, in prior work, metaheuristics have been used to solve the integrated model imperfectly: either transportation costs were not accounted for in the objective function, or the model was broken into two parts and solved sequentially. This paper presents a procedure in which metaheuristics are used to solve the model as an integrated whole. Solving the integrated model as a whole, rather than sequentially, has been shown to produce superior solutions, using exact solution approaches. In addition, solving the model without accounting for transportation costs can lead to unnecessarily high transportation costs, resulting from the model's road construction decisions. Hence, there is a clear economic benefit in solving the integrated model as a whole. Second, the development of a metaheuristic procedure allows the integrated model to be used on problem instances that are too large for exact solution approaches (e.g., CPLEX) but are not uncommon in the real world of forest management planning. Hence, this research, since it is on metaheuristics, may be regarded as a first step toward solving the integrated model on real-world problems.

We limit ourselves from concluding, in this work, that this method would be equally effective on much larger datasets. This is because, in order to evaluate the quality of solutions generated *versus* those of an exact solution approach, the data sets used in this study were relatively small. Hence, future research stemming from this work would therefore be: (i) to test this procedure on larger datasets; (ii) to speed up the execution of the cycle-based permutation; and (iii) to explore the effectiveness of other permutation operations to the road-network.

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