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THE QUALITY OF OUTCOMES FROM TABU SEARCH WHEN ENHANCED TO ADDRESS CONTEMPORARY FOREST HARVEST SCHEDULING PROBLEMS

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Abstract. Tabu search is a metaheuristic search process that is useful for locating high-quality solutions to complex combinatorial forest harvest scheduling problems. In this work, we illustrate the quality of outcomes produced by a tabu search process when it is applied to four forest management problems, and we statistically compare the effectiveness of tabu search when it uses a range of parameters and enhancements. This illustration of the variability in results is novel to the use of tabu search to address complex agriculture and forest management problems. The addition of enhancements, which allow n-opt moves through the solution space, reversion back to high-quality positions in the solution space, and randomly designated tabu states (tenures), all seem to improve the ability of tabu search to locate near-optimal solutions with regularity. In addition, we assess whether the second-best selection from the tabu neighborhood has any value in improving the outcomes from the search process. We found that the use of 2-opt exchange moves seems essential for developing forest harvest schedules of higher quality, and the use of search reversion can often help improve the quality of solutions. The selection of the second-best solution from the tabu search neighborhood, while of little value when used exclusively, may be valuable when used sparingly and in conjunction with other search process enhancements.

Keywords: Heuristic; Local search; s-metaheuristic; Point-based search; Deterministic search.

1 Introduction

In the course of developing a forest harvest schedule, a computational process can be used to seek the best set of assignments to decision variables with respect to an objective function and subject to a set of constraints on those assignments (Martí et al. 2025). Contemporary forest harvest scheduling problems are combinatorial in nature, often due to policy constraints that require consideration of the spatial location of proposed management activities. These constraints can be related to wildlife habitat availability, the size and location of final harvests, and other issues that require discrete variables in the problem formulations. As forest harvest scheduling problems can be exceptionally large and complex, they may require efficient search processes to locate high-quality, if not optimal, solutions. If the problem contains nonlinear constraints, a complex objective function, or a wealth of discrete decision variables, the problem may become intractable for some search processes since locating the optimal solution may require a significant amount of computing time (Martí et al. 2025). Options for addressing these problems in the field of forestry have focused mainly on mathematical (exact) methods, simulation, and heuristic search procedures.

Heuristic search processes have gained popularity for addressing combinatorial optimization problems because they may be able to locate high-quality solutions with a relatively short amount of computing time, even though they cannot guarantee that the optimal solution to a problem will be located (Martí et al. 2025). Heuristic search processes can be predominantly stochastic or deterministic in nature, and they may rely on a population of diverse feasible solutions (i.e., a population-based or p-metaheuristic process), or they may concentrate on the modification of a single solution (i.e., a point-based or s-metaheuristic process) to a problem. From a technical standpoint, tabu search is a point-based s-metaheuristic search process that iteratively modifies a single solution, ideally improving its quality as the heuristic search converges toward the optimum solution. Tabu search employs memory to avoid recently visited locations in the solution space, with the goal of guiding the search process toward areas in the solution space where high-quality solutions might be found (Thomas and Salhi 1998). This sense of adaptation and learning is closely associated with artificial intelligence (Bettinger et al. 2024). When first described in a work related to efficient solutions for office space planning problems (Glover et al. 1985), the original name for tabu search was *adaptive memory programming* (Glover 2022). The notion that a move through a solution space might be considered taboo (off-limits) may have been first offered by Chung (1953) in their description of alternatives for avoiding certain solution states in a Markov chain simulation process. Tabu search is different, however, from Markov chain processes in that generally, there are no transition probabilities that influence the search, and there is a need to assess a considerable number (if not all) of potential changes to a current solution prior to selecting one.

In solving problems, tabu search is generally based on modifications to a deterministic hill-climbing search process (Nurmela 1993). However, unlike a deterministic hill-climbing search process, tabu search does not terminate when there are no more improving moves to make within a solution space. As it conducts its work, tabu search allows the selection of inferior solutions to the current solution so that it may avoid early termination of the search process (Glover 1986). The search moves in a stepwise (iterative) fashion toward the optimal solution of a problem using one or more memory mechanisms that act to prevent it from returning too soon to recently visited locations within the solution space (Hopper and Turton 2001), features that are designed to help the process avoid becoming trapped at local optima (Hertz and de Werra 1987). Once selected, potential assignments to decision variables are placed in a short-term (or tenure) *tabu list*, effectively designating them as off-limits for a while. These recently selected assignments are made fully available once again (without a potential penalty) after the tabu state (tenure) has expired. Given these characteristics of the search process, Glover (1986) suggested that under certain circumstances, tabu search might also be called *weak inhibition search* since the moves that are freely available (not tabu) at any one point in time during a search represent only a subset of the total moves available to the search. Although there are options for interjecting randomness into a tabu search process (Glover 1995), perhaps the deterministic nature of tabu search for solving problems is appealing because the search process makes logical modifications to a current solution in the search for the optimal solution to a particular problem. Given the need to assess many candidate moves through the solution space prior to selecting one, tabu search has been characterized as a slow, thoughtful, and rational method for navigating through a solution space (Bettinger 2025a). However, as with all heuristic search processes, locating the optimal solution to a problem in a vast solution space is not guaranteed.

The initial works fully describing tabu search were published approximately 35 years ago (Glover 1989, 1990), followed later by a seminal book (Glover and Laguna 1997). Some of the early works illustrating the application of tabu search for forest harvest scheduling purposes were developed by Murray and Church (1995), Bettinger et al. (1997), Brumelle et al. (1998), and Richards and Gunn (2000). Improvements in the manner and efficiency of which tabu search seeks the optimal solution to a very large problem include assessing a randomly selected subset of potential neighboring solutions from which a move is selected (Hertz and de Werra 1987; Huang et al. 2002; Shao et al. 2023), assessing only moves of high potential based on the application of a learning function (Niroumandrad et al. 2024), and assessing only a subset region-limited number of moves (Bettinger et al. 2007) during each iteration of the search process. Other adjustments have included forcing the selection of moves to be a certain distance (with respect to the objective function value) from the current solution to promote diversification (Glover and Lü 2021). Furthermore, in Goścień et al. (2015), the number of consecutive iterations of a tabu search process without leading to an improvement in the objective function value is used to prompt a diversification routine (restart mechanism) to direct the search to a different location in the feasible region of the solution space. Assuming that the quality of solutions generated via tabu search varies as the parameters and enhancements change, the objective of this work is to explore the behavior and success of the tabu search process when alternative parameters and enhancements are considered and use a statistical test to assess whether the sets of outcomes are significantly different. As with most works concerning the use of heuristic search processes when applied to forest harvest scheduling problems, the exact solution to each problem is also used to represent a point of comparison.

2 Methods

This work explores the behavior of tabu search when attempting to locate high-quality solutions to contemporary forest harvest scheduling problems and the variation in the quality of outcomes as parameters are modified and enhancements are added. An exact mathematical formulation is described below for the contemporary forest harvest scheduling problems that are assessed, along with a brief summary of the methods employed to locate the optimal solution to each problem. The heuristic search process is then described, along with several enhancements that are hypothesized to improve the quality of the outcomes. A description of the case study forests upon which these processes are applied then follows.

2.1 Problem formulation

To assess the quality of the solutions generated by tabu search, four forest management problems are addressed. As in the recent assessment of the behavior of the threshold accepting search process (Bettinger 2025b), the problems include the following:

1. Maximizing the discounted net revenue of forest harvest activities and constraining final harvests via the unit restriction harvest adjacency model (URM) (Murray 1999)
2. Maximizing the discounted net revenue of forest harvest activities and constraining final harvests via the area restriction harvest adjacency model (ARM)
3. Forcing an even-flow of scheduled harvest volume by minimizing squared deviations between scheduled and desired harvest volumes constraining final harvests via the URM
4. Forcing an even-flow of scheduled harvest volume by minimizing squared deviations between scheduled and desired harvest volumes constraining final harvests via the ARM

The notation used in the problem formulation described below involves the following:

a_n = the area of a stand of trees n;

$AVGV$ = the average scheduled harvest volume across all time periods in the time horizon;

β = the allowable deviation (decimal percentage, where 25% = 0.25) from the average scheduled harvest volume;

g = a green-up window for final harvest activities, expressed as the number of time periods t;

H_t = the scheduled harvest volume during time period t;

i = the interest rate for discounting revenues when they occur;

lw = the lower limit (time periods) of the period of time defining the green-up window of a final harvest activity;

m = a neighboring stand of stand n, defined as sharing a physical edge;

M = the total number of neighboring stands of stand n;

MA = the maximum assumed final harvest area size;

n = a single stand in a forest;

N = the total number of stands in a forest;

O_n = the set of neighboring stands of stand n;

$p = (1+i)^{(t-1)\cdot 5+(2.5)} = (1+i)^{5\cdot t-2.5}$;

r_{tn} = the potential revenue from stand n when a final harvest activity is scheduled during time period t;

S_n = the set of all stands adjacent to stands in set O_n and all stands adjacent to neighbors of neighbors, and so on (Murray 1999);

t = a single time period within the time horizon of the tactical plan;

T = the total number of time periods in the time horizon of the tactical plan;

TV = the desired (target) harvest volume to achieve during a time period;

uw = the upper limit (time periods) of the period of time defining the green-up window of a final harvest;

v_{tn} = the volume per unit area available within stand n during time period t;

x_{tn} = a binary decision variable that indicates whether (1) or not (0) stand n is scheduled; a final harvest activity is scheduled during time period t;

z = the time periods within the green-up window of a scheduled final harvest.

The objective function for problems 1 and 2 is as follows:

$$Maximize \sum_{t=1}^{T}\sum_{n=1}^{N}\left(\frac{x_{tn}r_{tn}}{p}\right) \tag{1}$$

The objective function for problems 3 and 4 is as follows:

$$Minimize \sum_{t=1}^{T}(H_t - TV)^2 \tag{2}$$

Accounting rows (or functions) are employed to assess the scheduled harvest volume expected during each time period of the time horizon.

$$\sum_{n=1}^{N}(x_{tn}v_{tn}a_n) - H_t = 0 \;\; \forall\, t \tag{3}$$

Resource constraints are employed to ensure that only one final harvest (clearcut activity) is assigned to each stand within the time horizon.

$$\sum_{t=1}^{T} x_{tn} \leq 1 \; \forall n, \quad x_{tn} \in \{0,1\} \tag{4}$$

When the URM adjacency policy is employed, the following constraints apply when a stand (n) is scheduled for a final harvest during time period t:

$$x_{tn} + \sum_{z=lw}^{uw} \sum_{m \in O_n}^{M} x_{zm} \leq 1 \quad \forall n,\; t \tag{5}$$

$$lw \,=\, t \,-\, (g-1) \tag{6}$$

$$if\, lw \,<1,\, lw \,=\, 1 \tag{7}$$

$$uw \,=\, t \,+\, (g-1) \tag{8}$$

$$if\, uw \,>\, T,\, uw \,=\, T \tag{9}$$

The variable z in Equation 5 represents the green-up window, or the amount of time (based on a number of time periods) before and after a scheduled final harvest activity. In this case, each stand (n) and each neighboring stand (m) are assessed for scheduled final harvest activities, and at most, only one of the stands can be scheduled for a final harvest within the green-up window that ranges from *lw* to *uw*. When the ARM adjacency policy is employed, the following constraints apply when a stand (n) is scheduled for a final harvest during time period t and replace those suggested by Equation (5):

$$x_{tn}a_n \;+\; \sum_{z=lw}^{uw} \sum_{m \in O_n \cup S_n}^{M} x_{zm}a_m \leq MA \tag{10}$$

In Equation 10, each stand (m) that is adjacent to a focal stand (n) and other stands adjacent to m and their neighbors, etc., are assessed as a potential sprawling cluster of final harvest activity areas that are all scheduled within the time periods defined by the green-up window (*lw* to *uw*) of focal stand n.

For maximization problems (1) and (2), the following wood flow constraints are employed:

$$\frac{\sum\limits_{t=1}^{T} H_t}{T} - AVGV = 0 \tag{11}$$

$$H_t \geq (1-\beta)AVGV \quad \forall t \tag{12}$$

$$H_t \leq (1+\beta)AVGV \quad \forall t \tag{13}$$

Equation (11) is used to determine the average scheduled harvest volume across all time periods within the time horizon. Equations (12) and (13) limit the scheduled harvest volume in each time period to a bound (defined as $\pm\beta$) around the average harvest volume.

The maximization problems were subjected to the branch and bound search process within Lingo version 21 (LINDO Systems Inc. 2024). The minimization problems were subjected to a quadratic branch and bound search process within Lingo version 21. The maximization problems require less than one second to solve with Lingo. The minimization problems, owing to the desire to achieve exact even flow of harvest volume, were more difficult to solve and were allowed to run for 50-110 hours before the quadratic branch and bound search process was interrupted, and the highest-quality feasible solution was reported. Even though the termination point for these searches was unpredictable, we assume that the results from these searches are relatively close representations of the optimal solutions to the minimization problems. The tabu search process was developed via Visual Basic 2012. The heuristic search required approximately one second per instance (run) for the least diligent search and approximately 10 minutes for the most diligent search.

2.2 Mathematical programming (exact) search process

The mathematical programming, or exact search processes, employed to locate the optimal solutions to the problems addressed here were once considered *mixed case* or *partial linear programming* problems when they were first described by Dantzig (1958) and others. These types of problems have a set (c) of decision variables, where a subset of these (d) might be assigned a nonnegative continuous real numeric value in the final solution and where $c-d$ of these might be assigned a nonnegative integer value in the final solution. A mathematical procedure that uses a tree-like search pattern, the branch and bound process, can be used in an attempt to locate the optimal solution (Rensi and Claxton 1972). Branch-and-bound search is an intelligent search process that first solves a *relaxed linear programming model* (McDill and Braze 2001) and then uses an expanding *tree* of mixed-integer linear programming solutions that grows in many directions as it pursues the optimal solution to a problem (Sierksma 1996). The search process was described in early published works as a tree graph structure that is composed of nodes (solutions) and arcs (paths to other potential solutions) and has been characterized as a *branch and exclude algorithm* or *additive algorithm* (Balas 1965; Bare and Norman 1969), a form of *strong inhibition search* (Glover 1986), and a *conventional tech-*

nique that can be used to produce solutions to assignment problems (Thalman et al. 1991). With respect to decision processes, a branch and bound search might be viewed as a deterministic, intelligent strategy to search for the optimal solution to a problem (Michalewicz and Fogel 2002). However, the search process may terminate early when the difference between the relaxed upper bound and the best feasible lower bound (for a maximization problem of course) represents a value within a predefined range (optimality tolerance) often expressed as a percentage of the relaxed upper bound (McDill and Braze 2001).

Contemporary forest harvest scheduling problems, which include wood flow and harvest adjacency constraints, may require many policy constraints (Bettinger 2023) and therefore can be difficult to formulate and solve exactly via mathematical programming approaches. Like many contemporary forest management problems, those that utilize integer and mixed integer programming problem formulations reside in the nondeterministic polynomial (NP) class of problems (Karp 1972), and unfortunately, difficult or intractable problems may require computing time (or number of processing steps) that is an exponential function of the size of a problem. Although difficult to prove, when a problem is considered *NP-hard*, there are no known polynomial-time algorithms that can be employed to solve it. The effort expended to solve exactly (find the global optimum solution) *NP*-hard problems also increases exponentially with the size (number of decision variables, number of constraints) of the problem (Bodin et al. 1981), suggesting that it may be impractical to attempt to locate the optimum solution to certain problems via exact algorithms (Bianchi et al. 2008). As noted earlier, the maximization problems studied here were relatively easy to solve, whereas the minimization problems were more difficult.

2.3 Heuristic search process

This work investigates the quality of outcomes from tabu search, when enhanced, from efforts to locate the optimal solution to a forest harvest scheduling problem. After the development of an initial feasible solution or beginning with a null solution, a tabu search process constructs a neighborhood of potential moves or a set of alternative solutions, which can be reached from the current solution through a change to one or more assignments to decision variables. In theory, a tabu search neighborhood recognizes (a) each decision variable, (b) each potential change in the assignment to a decision variable, and (c) the potential objective function value that may result when the potential change is made. The best possible move is selected from the complete set of potential changes, and feasibility is subsequently assessed. Ideally, this potential change to the current solution leads to a feasible solution; however, if this is not the case, the next best move from the neighborhood is selected (and feasibility is again assessed). If the moves selected in this manner always lead to higher-quality solutions, the search behaves like a deterministic hill-climbing algorithm. However, unlike a deterministic hill-climbing search process, tabu search does not terminate when there are no other higher-quality solutions that can be reached from the current solution. For a problem where integer assignments are required for the decision variables, a general tabu search process, characterize as the *simple* form in Glover and Laguna (1997), involves the following steps:

1. Develop an initial feasible integer solution to the problem and call it the current solution.
2. Develop a set (neighborhood) of nearby local solutions. Select the best proposed move in the solution space from the neighborhood of options and call it a temporary proposed solution.
   - 2.1. If the temporary proposed solution is infeasible, ignore the move, and return to Step 2 to select a different move from the tabu search neighborhood.
   - 2.2. If the temporary proposed solution is feasible, assess the tabu tenure of the proposed move.
     - 2.2.1. If the proposed move is not considered tabu and has an objective function value that is higher in quality than the objective function value of the best solution held in memory, save the proposed move as the best solution and proceed to Step 3.
     - 2.2.2. If the proposed move is not considered tabu and does not have an objective function value that is higher in quality than the objective function value of the best solution held in memory, proceed to Step 3.
     - 2.2.3. If the proposed move is considered tabu yet has an objective function value that is higher in quality than the objective function value of the best solution held in memory, save the proposed move as the best solution and proceed to Step 3. This bypass results when the proposed move (and resulting solution) passes the aspiration criterion test.
     - 2.2.4. If the proposed move is considered tabu yet has an objective function value that is not higher in quality than the objective function value of the best solution held in

memory, label the move as unavailable for selection during this iteration and return to Step 2 to select a different move. In this case, the proposed move (and resulting solution) fails the aspiration criterion test.

3. Formally accept the proposed move and make the temporary proposed solution the current solution.
4. Update the tabu state of all decision variable/assignment combinations (potential moves).
5. If the termination criterion has been satisfied, stop and report the best solution stored in memory; otherwise, return to Step 2.

The neighborhood of proposed moves, in the basic implementation of tabu search, involves changing the assignment made to a decision variable, holding static all other assignments to all other decision variables in the current solution. Each potential change to the current solution is assessed in this manner, and these are considered 1-opt moves. Evaluating the potential exchange (or change (Bachmatiuk et al. 2015)) of assignments between two or more decision variables (n-opt moves) can require the assessment of a significantly larger neighborhood unless enhancements are employed (Bettinger et al. 2007; Niroumandrad et al. 2024; Shao et al. 2023). The proposed move temporarily selected from the neighborhood in Step 2 is assumed to be the best choice available from the set of proposed moves not already considered during the current iteration of the model. In this respect, the search process involves a deterministic hill-climbing search process. However, as Step 2.2.4 suggests, if the proposed move has been selected recently during the search, it is passed over for another proposed move from the neighborhood. In addition, Step 2.2.2 suggests that allowable moves within the search process may not improve the objective function value, and when followed, this course of action is contrary to the behavior of a deterministic hill-climbing search process.

From a forest planning perspective, the number (N) of 1-opt move assessments in a full neighborhood, assuming integer assignments are required for every decision variable, is as follows:

$$N_{\text{stands}} \times (N_{\text{potential assignments to stands}} - 1),$$

where the number of *potential assignments to stands - 1* reflects the fact that each stand has been assigned a choice in the current solution to the problem. This approach assumes that a single choice (harvest or more intricate management regime) is assigned to each stand. In this respect, the development of a full 2-opt exchange neighborhood within a tabu search can require:

$$N_{\text{stands}} \times (N_{\text{stands}} - 1) / 2,$$

potential moves to assess, which recognizes the fact that exchanging the assignments to stands j and k produces the same potential solution as exchanging the assignments to stands k and j. If multiple assignments can be assigned to a single stand throughout the time horizon, the size of the full neighborhood would obviously be larger. Since many potential moves need to be assessed prior to selecting one (much like deterministic hill-climbing), tabu search is a relatively slow search process unless only a portion of the tabu neighborhood is assessed (Bettinger et al. 2007; Hertz and de Werra 1987; Huang et al. 2002; Niroumandrad et al. 2024; Shao et al. 2023).

The short-term memory (tabu tenure) function in tabu search tracks the amount of time, in iterations of the search process, since a certain assignment was made to a decision variable. With one exception (Step 2.2.3), after a proposed move from the neighborhood has been formally accepted (Step 3), it cannot be considered again until a certain number of search process iterations have passed. The specific tenure assigned to a potential move is actively updated as the search progresses (Thalman et al. 1991). Although a static number of iterations are assumed in a basic tabu search process, *tabu list management* activities of various kinds have been proposed (Dammeyer and Voβ 1993). For practical purposes, tabu tenure can be random, static, or adaptive (Barnes and McKinzie 2006; Battiti and Tecchiolli 1994; Glover 1995; Hertz and de Werra 1990). *Cycling*, or the process of returning repeatedly to the same set of solutions (Figure 1) with oscillating objective function values and no apparent convergence (Mitchell and Kaplan 1968), can occur during a search unless the short-term memory function prevents this from happening (Hertz and de Werra 1987). By inhibiting certain moves in this manner, the use of a tabu state (or tenure) has been characterized as a *short-term strategic forgetting* aspect of a search process (Glover and Greenberg 1989). While the tabu tenure of a potential assignment might normally suppress the assignment of an activity to a decision variable, the aspiration criterion of tabu search (described in 2.2.3) overrides the constraint and allows a tabu move to be selected from the neighborhood (Nurmela 1993). Interestingly, some tabu search processes lack this criterion (Goścień et al. 2015). Since the search process learns and adapts to situations using a memory function, one could argue that there is a close association between tabu search and artificial intelligence in general (Bettinger et al. 2024). However, the tabu state needs to be carefully considered since, if it is short relative to the number of potential moves within the tabu neighborhood, it may not prevent cycling.

Another enhancement to s-metaheuristics such as tabu search involves the use of search reversion, a con-

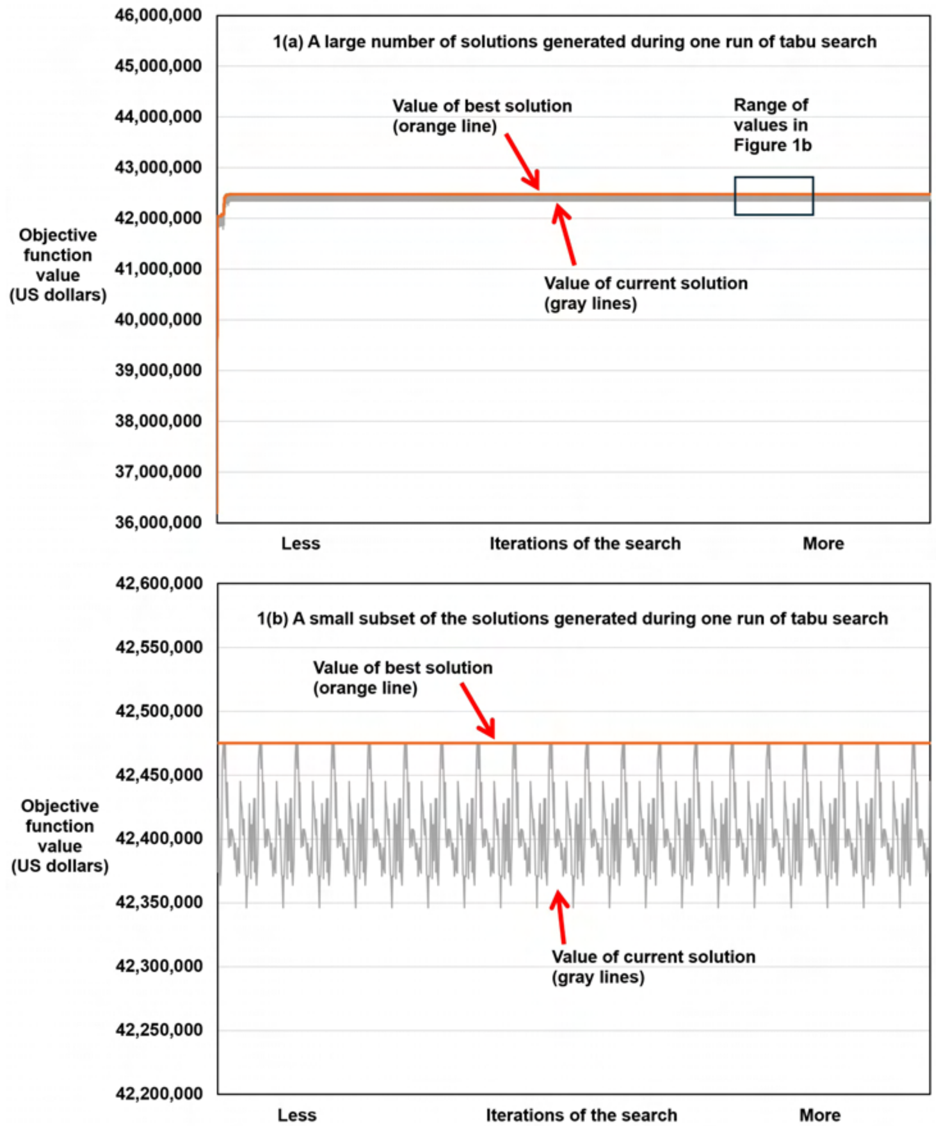

Figure 1: The behavior of tabu search when the tabu state (short-term memory, tenure) is too short. Figure 1a illustrates a long series of search iterations. Figure 1b focuses on a smaller subset, illustrating the cycling of solutions during the search process.

cept that promotes intensified search within high-quality areas of the solution space (Glover and Laguna 1997). Search reversion replaces the current solution with the best solution stored in memory after a predefined number of search iterations, although an adaptive process can be hypothesized. A short rate of reversion (few iterations that pass before reverting) can limit the diversification of a search process; a long rate of reversion may limit the intensification of a search process. From prior experiments, it appears that the appropriate rate of reversion differs from problem to problem (Bettinger et al. 2015; Bettinger and Zhu 2006).

Although not the subject of this paper, a frequency-based memory strategy might be employed to prompt penalties or inducements that promote or discourage the selection of moves from a tabu search neighborhood (Glover and Laguna 1997). This memory strategy might track the frequency of selection of assignments to decision variables during a tabu search process. A structure such as that used for short-term memory might be designed to hold a running sum of the number of occasions that each decision variable/assignment move has been selected from the neighborhood. At some point, the search process will pause briefly and attempt to insert into the current solution those moves that have been selected least frequently. The intent of this memory strategy is to interject some diversification into the search and explore unknown (perhaps) areas of the solution space.

With this background in mind, the following four enhancements and associated assumptions are employed and assessed in this work:

- Random-length short-term memory. The short-term tabu state (tenure) of 1-opt moves (measured in model iterations) has a value as long as 20% or 25% of the potential decision variables associated with the problem. However, it is randomly selected from a set ranging from one iteration to the maximum amount each time a tabu state is applied to a stand/harvest assignment. In the work described here, tabu states are applied to the stand/harvest assignments associated with 1-opt moves. Tabu states are not applied to the stand assignment/stand assignment exchanges associated with 2-opt moves.

- Reversion to a high-quality solution. Search reversion is either employed or not employed. When it is employed, it occurs every 10 or 20 iterations of the search process. Noted as a search intensification strategy in Glover and Laguna (1997) and a search diversification strategy in Thomas and Salhi (1998), search reversion has previously been suggested to be valuable for heuristic search processes associated with forest harvest scheduling problems (Bettinger et al. 2015; Bettinger and Zhu 2007; Sun et al. 2019).

- 2-opt exchange moves. At each iteration of the search process, 2-opt exchange moves are either employed or not employed. When employed, they are conducted for ten consecutive iterations after (a) every fifty or (b) every one hundred consecutive 1-opt moves of the search process. Glover (1996) described the value of n-opt moves to a search process. Bettinger et al. (1999) first illustrated their value in addressing forest harvest scheduling problems. In a forest management context, Bachmatiuk et al. (2015) illustrated the value of exchange and change forms of n-opt moves within a search process.

- Semi rational selection of a move from the tabu search neighborhood. The semi rational selection of a move from the tabu search neighborhood is either employed or not employed. When employed, the second-best choice from the neighborhood of moves is selected (instead of the best choice) after (a) every five or (b) every 10 iterations of the search process. Alternatively, the basic search process of selecting the best choice from the neighborhood is followed during each iteration of the search process.

In the latter case, selecting the second-best choice from the tabu search neighborhood is not as rational as selecting the best choice and is inconsistent with a deterministic hill-climbing search process. However, in doing so, this course of action may provide some level of search diversification that is unavailable to the basic form of tabu search. Notably, given steps 2.1 and 2.2.4 of the process, the second (or third, or fourth, etc.) choice from the neighborhood can often be considered. The only difference from the enhancement noted above is that the best choice from the neighborhood is deliberately ignored for at least one iteration of the search process. This deliberate manner of ignoring the best move from the neighborhood in favor of the second best is different than the probability function approach Huang et al. (2002) used to decide whether to choose the best move from the neighborhood or the second best move. We hypothesize that each of these four enhancements (Table 1) can lead to higher-quality solutions to contemporary forest harvest scheduling problems than cases where no enhancements are employed and that in combination, they may lead to even greater quality results.

Table 1: Conditions of parameters and enhancements related to a tabu search process when it was applied to a forest harvest scheduling problem.

Sub-process within tabu search	Sub-process Options		
	Opt. 1	Opt. 2	Opt. 3
Short-term memory[a]	20%	25%	—
Search reversion[b]	none	10	20
2-opt exchange moves[c]	none	10/50	10/100
Second-best selection[d]	none	5	10

[a]The tabu tenure is a random number of iterations between one and x% of the total potential moves.
[b]Every x iterations the search pauses and replaces the current solution with the best one held in memory.
[c]The number of 2-opt moves (10) consecutively conducted for every consecutive 1-opt moves (50 or 100).
[d]The number of iterations that pass before a second-best solution is selected from the neighborhood.

Additional scenarios included: (1) Short-term memory 20%, no 2-opt moves, no search reversion, second-best selection during every iteration; and (2) Short-term memory 20%, 10/50 2-opt moves, search reversion every twenty iterations, second-best selection during every iteration. These scenarios assess the use of the second-based selection from the tabu search neighborhoods during each iteration of the search process with no other enhancements (1), and with enhancements that seemed to lead to the higher quality solutions (2). The total scenarios assessed was $2 \times 3 \times 3 \times 3 + 2 = 56$.

2.4 Case study forest areas

Two hypothetical case study forests are scheduled management activities (final harvests, or clearcuts of trees) over a time horizon to illustrate the differences in outcomes when search parameters and enhancements are adjusted. Both forests are subject to the problems described above, where there is a maximization (net discounted revenue) and a minimization (deviations from a target wood flow value) objective.

The Lincoln Tract (Bettinger et al. 2017) is a hypothetical forest situated in the western United States and is composed of 87 stands that encompass 1,842 hectares. Three of these stands are unavailable for harvest, as they represent predominantly riparian (wetland) areas. The remaining 84 stands encompass 1,788 ha of even-aged stands of Douglas-fir (*Pseudotsuga menziesii*) and western hemlock (*Tsuga heterophylla*) trees of various ages. The time horizon for the tactical problem is 30 years, and each of the six time periods is five years in length. The final harvests are assumed to occur, for modeling purposes, in the middle of each time period. The volumes are represented in thousand board feet[1] (MBF), a traditional unit of sawtimber employed in the United States. A harvest target of 13,950 MBF (32,918 m^3) per time period is assumed in the minimization problem, an amount that was estimated as a sustainable harvest level on the basis of the Hanzlik formula (Hanzlik 1922), where there are substantial amounts of forests older than the desired final harvest age (as is the case here). One management action (final harvest) is modeled, and the minimum final harvest age is assumed to be 35 years. The maximum size of a final harvest area is assumed to be 48.6 ha (the legal maximum in Oregon). The green-up period after a final harvest has been scheduled is assumed to be 5 years (one time period), which implies that final harvest activities should not be scheduled during the same time period as those already scheduled if the stands under consideration are physically adjacent (share an edge).

The Jones Tract is a hypothetical forest situated in the southern United States and is composed of 81 stands that encompass 1,053 hectares, although 16 stands are unavailable for harvest, as they represent wetland areas. Thus, 65 stands of trees are available for harvest activities (867 ha), and these are composed of even-aged stands of loblolly pine (*Pinus taeda*) of various ages. The time horizon is 20 years, and the time periods are each 5 years long. The final harvests are assumed to occur, for modeling purposes, in the middle of each time period. The volumes are represented in tons (907.2 kg), a traditional unit of weight in the United States. A harvest target of 19,000 tons (17,236,800 kg) per time period is assumed in the minimization problem, an amount estimated as a sustainable harvest level on the basis of the Meyer amortization method (Meyer 1952). One management action (final harvest) was modeled, and the minimum final harvest age was assumed to be 22 years. The maximum size of the final harvest area is assumed to be 48.6 ha, and the green-up period after a final harvest has been scheduled is again assumed to be one time period.

For both case study areas, the interest rate for discounting purposes (i) is assumed to be 5% in the maximization problem, and timber volumes per time period are allowed to vary (β) by 25% from the average scheduled volume per time period when scheduled.

2.5 Statistical tests

For each of the combinations of assumptions (scenarios), independent runs of tabu search are conducted to generate 200 solutions. Given two case study forests (described below), four management problems, and 56 enhancement scenarios, 89,600 solutions (forest plans) are created, each representing the best solution from independent runs of the tabu search process. Each run of the tabu search process was initiated with a randomly generated, feasible harvest schedule. Here, the random number list of the personal computer (12th generation Intel®Core™i9-2900, 2.4 GHz processor and 64 GB RAM) was first accessed at a point that was based on the clock of the computer when each independent run was initiated. Others have asserted that solutions generated by independent runs that begin in different areas of the solution space can be considered independent samples from a broader sampling distribution (Golden and Alt 1979; Los and Lardinois 1982), even though it has been suggested that a poor starting solution may hinder the ability of a search process to converge upon the optimal solution to a problem (Mitchell and Kaplan 1968). As each scenario contains 200 samples (the independent runs), we assume that the distribution of the 200 objective function values is relatively normal. Two-tailed $t-$tests were conducted to determine whether the quality of solutions when comparing two scenarios is significant when different parameters and enhancements are employed. In this effort, 12,320 two-tailed t-tests were conducted.

3 Results

For each of the four management problems described above, and for both case study forests, 11,200 inde-

[1] A board foot is theoretically a piece of wood that is 1 inch (2.54 cm) thick, 12 inches (30.5 cm) wide and 12 inches tall, or some other reasonable combination of thickness and size equal to 144 cubic inches (2,362.8 cubic cm) of solid wood.

pendently developed forest plans (56 scenarios ×200 heuristic solutions each) were generated via the heuristic search process (89,600 plans in total given the two forests and four management problems).

3.1 General trends in Problem 1: Maximization of net discounted revenue, URM model of adjacent final harvests

With respect to the application of the heuristic search process to the Lincoln Tract, the following trends were observed (see the corresponding letter in Figure 2).

(a) Employing 2-opt exchange moves with no search reversion; however, the selection of second-best moves every five iterations seems to result in the highest-quality solutions with the smallest range and variability.

(b) Selecting the second-best moves during every iteration without any other enhancements generally leads to the poorest set of solutions on average with the largest interquartile range.

(c) Employing 2-opt exchange moves with search reversion every ten iterations yields solutions not quite as good as employing 2-opt exchange moves with search reversion every twenty iterations.

(d) Not employing 2-opt exchange moves generally leads to solutions with greater variability.

(e) Utilizing a tabu state that represents 20% of the available choices in the tabu search neighborhood leads to solutions with approximately the same quality and variability as when using a tabu state that represents 25% of the available choices.

(f) Occasionally, one or more outliers are produced.

Some of these trends (b, d, e) were also observed when the heuristic search process was applied to the Jones Tract (Figure 2).

The optimal solution (using mixed integer programming) for this problem when applied to the Lincoln Tract was $43,581,416.80. The optimal solution was not located from 11,200 runs of the model. Considering all 56 scenarios, heuristic search solutions were within 1% of the optimal solution 4.8% of the time. Considering only the top five scenarios (sorted by the average solution value), heuristic search solutions were within 1% of the optimal solution 29.8% of the time. The optimal solution for the Jones Tract was $2,020,050.97. The optimal solution was located two times from 11,200 runs of the model. Considering all 56 scenarios, heuristic search solutions were within 1% of the optimal solution 5.9% of the time. Considering only the top five scenarios (sorted by the average solution value), heuristic search solutions were within 1% of the optimal solution 11.3% of the time.

3.2 General trends in Problem 2: Maximization of net discounted revenue, ARM model of adjacent final harvests

With respect to the application of the heuristic search process to the Lincoln Tract, the same trends were observed with respect to the results for this problem, as was observed for the previous maximization problem (Figure 3). Similarly, some of these trends (b, d, e) were also observed when the heuristic search process was applied to the Jones Tract (Figure 3).

The optimal solution for this problem when applied to the Lincoln Tract was $43,882,583.90. As with the URM model of final harvest adjacency, the optimal solution was not located from 11,200 runs of the model. Considering all 56 scenarios, heuristic search solutions were within 1% of the optimal solution 2.6% of the time. Considering only the top five scenarios (sorted by the average solution value), heuristic search solutions were within 1% of the optimal solution 11.6% of the time. The optimal solution for the Jones Tract was $2,045,594.00. The optimal solution was located one time from 11,200 runs of the model. Considering all 56 scenarios, heuristic search solutions were within 1% of the optimal solution 16.1% of the time. Considering only the top five scenarios (sorted by the average solution value), heuristic search solutions were within 1% of the optimal solution 32.9% of the time.

3.3 General trends in Problem 3: Minimization of deviations from a harvest volume target, URM model of adjacent final harvests

With respect to the application of the heuristic search process to the Lincoln Tract, the following trends were observed (see the corresponding letter in Figure 4).

(x) Employing 2-opt exchange moves and perhaps second-best selections from the neighborhood without employing search reversion generally leads to less variation in the solutions generated.

(y) Employing 2-opt exchange moves and perhaps second-best selections from the neighborhood, yet with 20-iteration search reversion, leads to higher-quality solutions being generated.

(z) Selecting the second-best moves during every iteration without any other enhancements generally leads to the poorest set of solutions on average.

These trends were also evident in the quality of the forest plans generated for the Jones Tract (Figure 4). However, the results from the Lincoln Tract to this minimization problem contained much wider ranges of variation, with multiple solutions among the poorer sets that might be found in Q4 of the box-and-whisker illustrations.

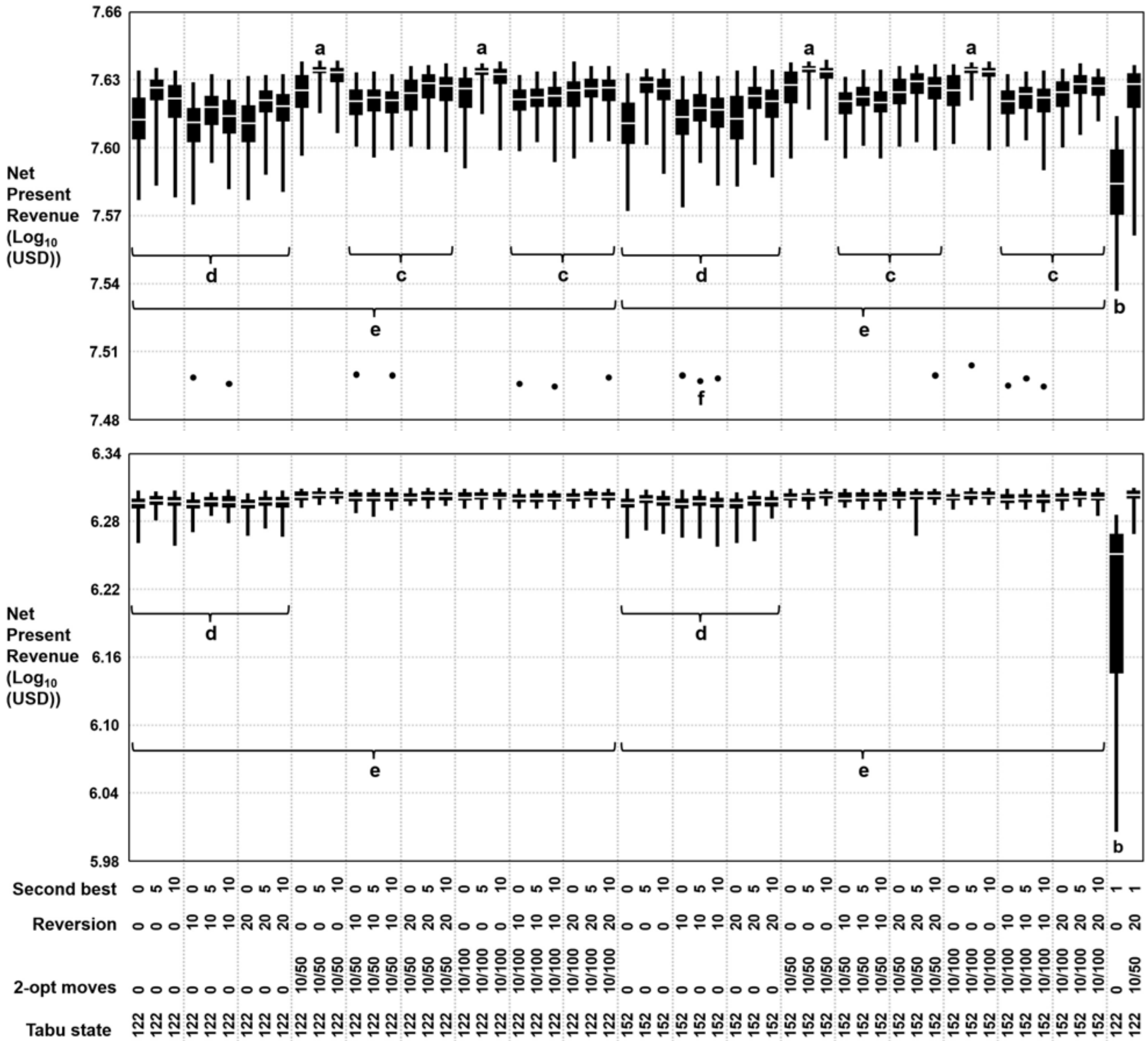

Figure 2: Box-and-whisker plots illustrating the variation in solution quality from sets of tabu search runs when applied the Lincoln Tract (Top) and the Jones Tract (Bottom) under the maximization objective and URM model of final harvest adjacency.

The optimal solution for this problem when applied to the Lincoln Tract was 0.90 squared units (thousand board feet, or MBF). The tabu search process was able to locate solutions of higher quality 64 times (out of 11,200 runs), with most (68.8%) of these being located when assuming a tabu state (or tenure) of up to 25% of the potential neighborhood moves, ten 2-opt exchange moves after every 50 1-opt moves, and a reversion rate of 20 iterations. In these cases, the frequency of second-best moves did not matter, as nearly equal numbers of these solutions were located when it was assumed that the second-based selection from the neighborhood would be selected every 0, 5, or 10 iterations of the model. The optimal solution for this problem when applied to the Jones Tract was 0.05 squared units (tons of wood). The tabu search process was able to locate solutions of higher quality 301 times (out of 11,200 runs), with most (70.4%) of these being located when assuming a tabu state (or tenure) of either 20% or 25% of the potential neighborhood moves, ten 2-opt exchange moves after every 50 1-opt moves, and a reversion rate of 20 iterations. As with the Lincoln Tract, in these cases, the frequency of second-best moves did not matter, as nearly equal numbers of these solutions were located when it was as-

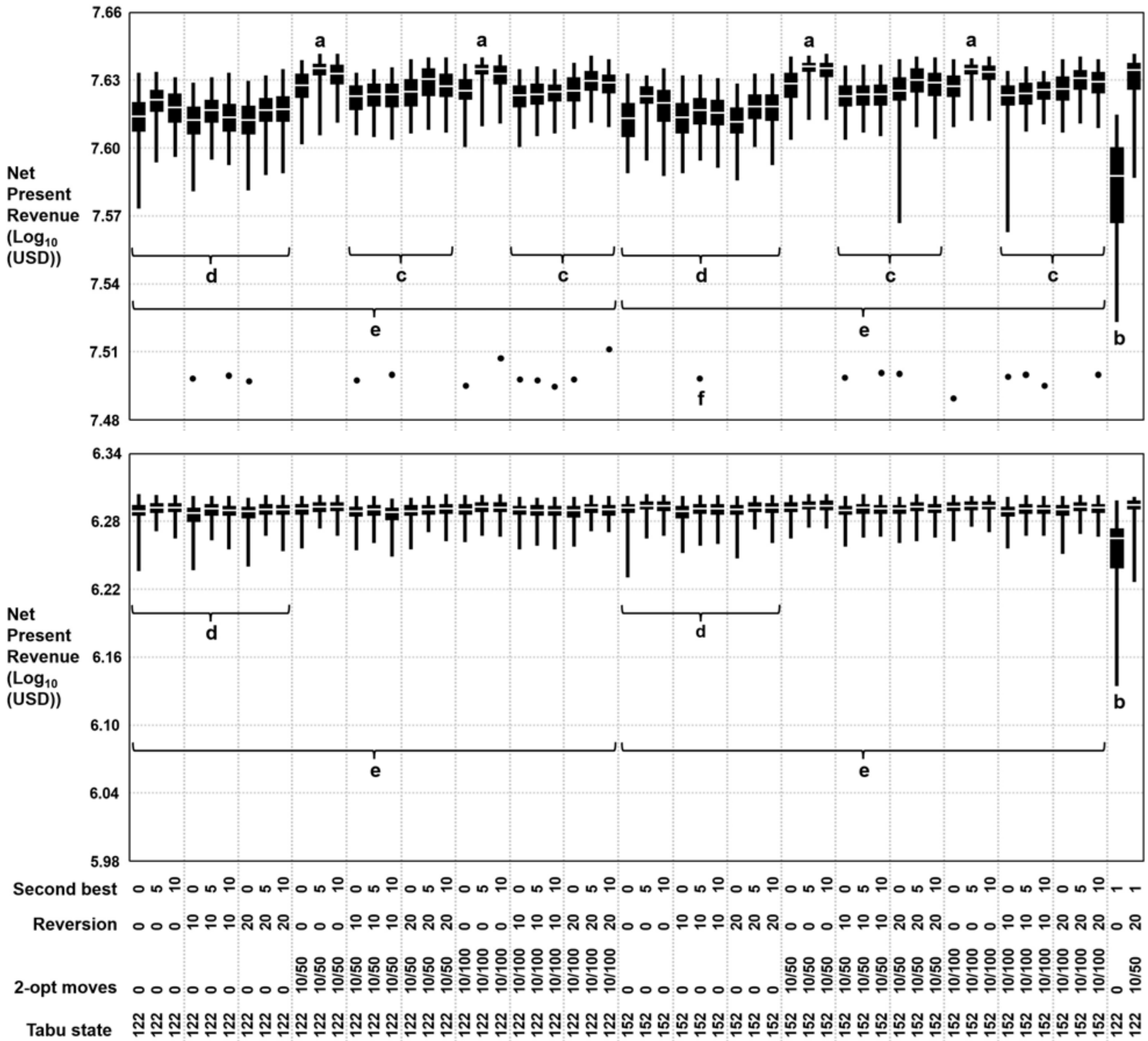

Figure 3: Box-and-whisker plots illustrating the variation in solution quality from sets of tabu search runs when applied to the Lincoln Tract (Top) and the Jones Tract (Bottom) under the maximization objective and ARM model of final harvest adjacency.

sumed that the second-based selection from the neighborhood would be selected every 0, 5, or 10 iterations of the model.

3.4 General trends in Problem 4: Minimization of deviations from a harvest volume target, ARM model of adjacent final harvests

With respect to the application of the heuristic search process to both the Lincoln Tract and the Jones Tract, the same trends were observed as in the previous minimization problem (Figure 5). The optimal solution for this problem when applied to the Lincoln Tract was 0.45 squared units (thousand board feet, or MBF). The tabu search process was able to locate solutions of higher quality 87 times (out of 11,200 runs), with most (74.7%) of these being located when assuming a tabu state (or tenure) of 20% or 25% of the potential neighborhood moves, ten 2-opt exchange moves after every 50 1-opt moves, and a reversion rate of 20 iterations. As with the previous cases noted above, in these cases, the frequency of second-best moves did not matter, as nearly equal numbers of these solutions were located when it was assumed that the second-based selection from the neighborhood would be selected every 0, 5, or 10 iterations of the model.

The optimal solution for this problem when applied to the Jones Tract was 0.02 squared units (tons of wood).

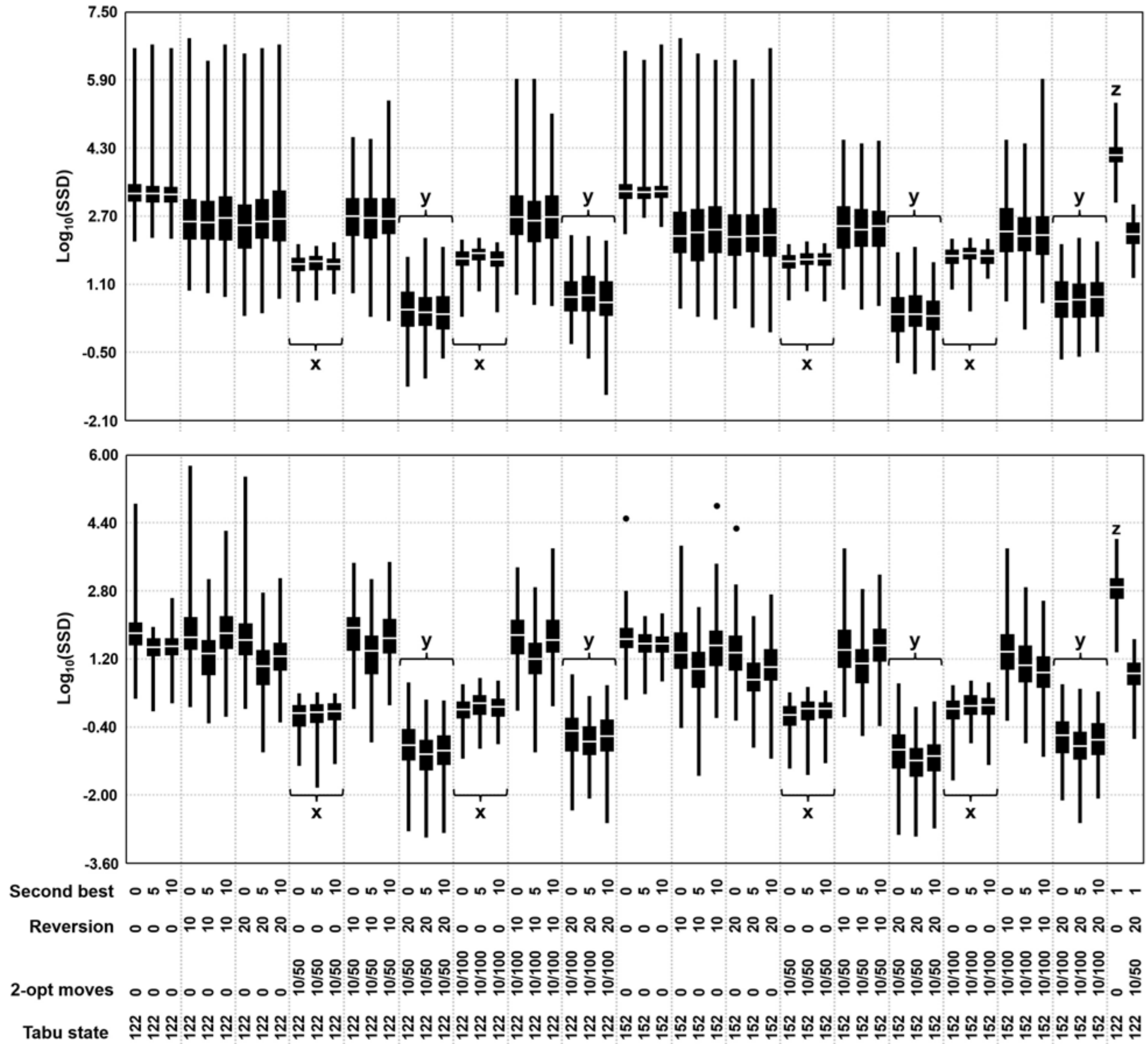

Figure 4: Box-and-whisker plots illustrating the variation in solution quality from sets of tabu search runs when applied to the Lincoln Tract (Top) and the Jones Tract (Bottom) under the minimization objective and URM model of final harvest adjacency.

The tabu search process was able to locate solutions of higher quality 396 times (out of 11,200 runs), with most (75.3%) of these being located when assuming a tabu state (or tenure) of either 20% or 25% of the potential neighborhood moves, ten 2-opt exchange moves after every 50 1-opt moves, and a reversion rate of 20 iterations. As with the other cases noted above, here, the frequency of second-best moves did not matter, as nearly equal numbers of these solutions were located when it was assumed that the second-based selection from the neighborhood would be selected every 0, 5, or 10 iterations of the model.

3.5 Outcomes of statistical tests

To assess the statistical significance of the differences in sets of solutions, 12,320 two-tailed t-tests were conducted for pairwise comparisons of scenarios involving the eight problems (two case study forests, four management problems) and 56 parameter/enhancement arrangements. When comparing solely the use or nonuse of 2-opt exchange moves, often (66.9% (Jones Tract) to 89.1% (Lincoln Tract) of the time), the results were statistically significant ($p = 0.05$), and better results were obtained when 2-opt exchange moves were used in the

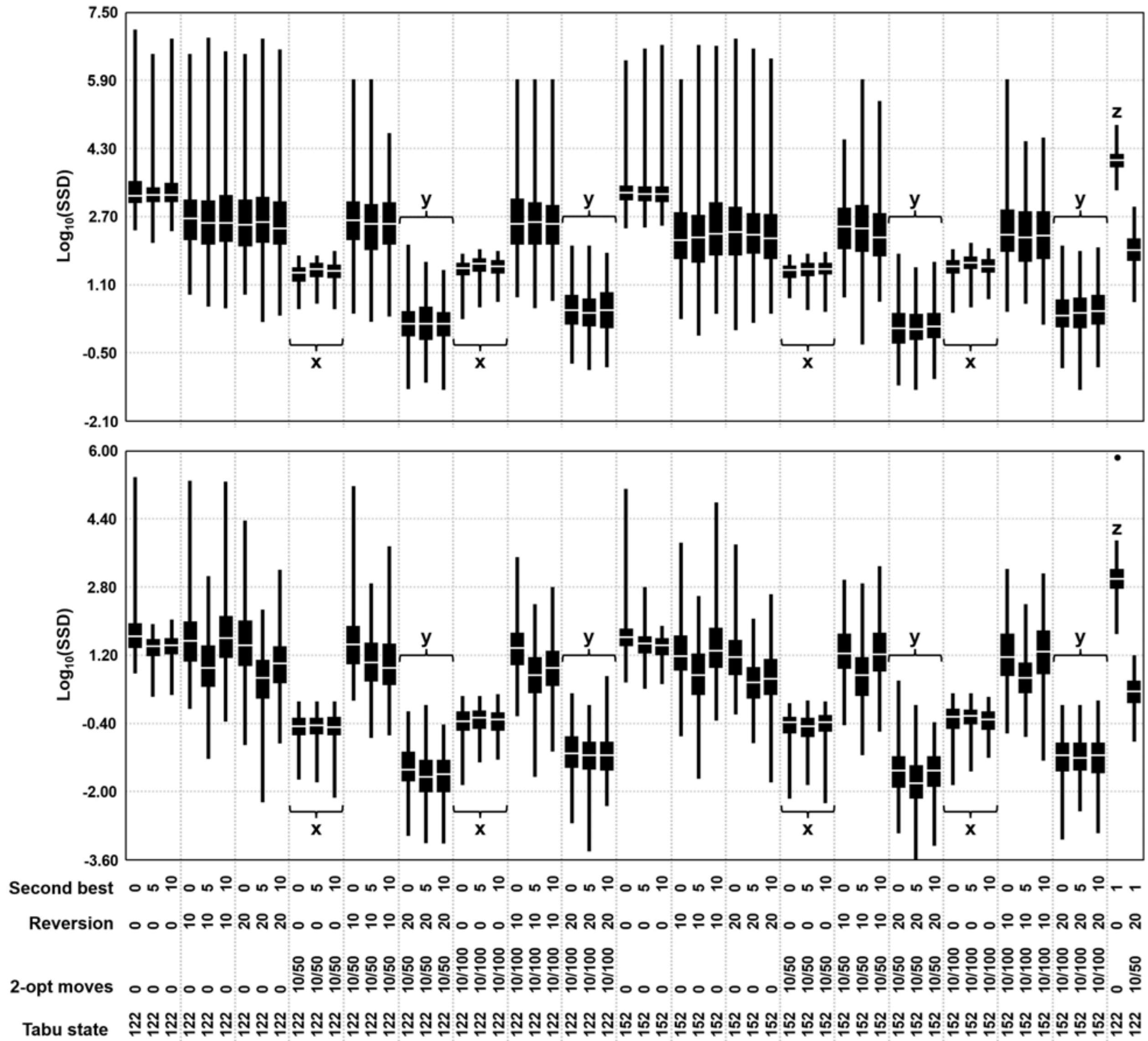

Figure 5: Box-and-whisker plots illustrating the variation in solution quality from sets of tabu search runs when applied to: the Lincoln Tract (Top) and the Jones Tract (Bottom) under the minimization objective and ARM model of final harvest adjacency.

maximization problems that included the URM model of final harvest adjacency. However, when the 2-opt exchange moves were used in the maximization problems that included the ARM model of final harvest adjacency, statistically significant ($p = 0.05$) and better results were obtained 97.5% (Lincoln Tract) to 100% (Jones Tract) of the time.

When comparing the outcomes generated for the minimization problems, the differences between employing the ARM and URM constraints were not as clear. For the cases where the URM model of final harvest adjacency was employed (86.8% (Lincoln Tract) to 91.2% (Jones Tract) of the time), the results were statistically significant ($p = 0.05$), and better results were obtained when 2-opt exchange moves were used. Similarly, in cases where the ARM model of final harvest adjacency was employed, often (89.5% (Lincoln Tract) to 94.7% (Jones Tract) of the time), statistically significant ($p = 0.05$) and better results were obtained when 2-opt exchange moves were used.

When the second-based choice from the tabu search neighborhood was selected at every iteration of the search process, with no other enhancements to the search, the set of 200 solutions was statistically significant ($p = 0.05$) and worse in quality than every other scenario tested (440) under the eight problems (two case study forests, four management problems) and 55 other parameter/enhancement scenarios. With respect to the maximization problems, exclusively selecting the second-best solution from the tabu search neighborhood during every iteration of the search, in conjunction with enhancements (ten 2-opt exchange moves for every fifty 1-opt moves, and reversion every twenty iterations), produced a set of solutions that was not statistically significant ($p = 0.05$) and different than only 10.9% to 29.1% of the other 55 other parameter/enhancement scenarios. However, the outcomes from this scenario were statistically significantly different than (a) sets of outcomes that represented solutions of higher quality and (b) sets of outcomes that represented solutions of lower quality. With respect to the minimization problems, the results were worse. Exclusively selecting the second-best solution from the tabu search neighborhood during every iteration of the search, in conjunction with the same enhancements, produced a set of solutions that was not statistically significant ($p = 0.05$) and different than only 0% to 9.1% of the other 55 other parameter/enhancement scenarios. Again, the outcomes from this scenario were statistically significantly different than both (a) sets of outcomes that represented solutions of higher quality and (b) sets of outcomes that represented solutions of lower quality. As a result of these limited and exploratory tests, bypassing the best solution from the tabu search neighborhood during each iteration of the search process (a semi rational approach to decision-making) seems to be of little value.

With respect to employing search reversion as an enhancement by itself, most of the time, statistically significant ($p = 0.05$) and better sets of results for the maximization problems could be found when using reversion with another enhancement. When the URM model of final harvest adjacency was considered, 79.9% (Jones Tract) and 93.0% (Lincoln Tract) of the sets of solutions were significantly different and lower in quality when search reversion was used alone. When the ARM model of final harvest adjacency was considered, 81.3% (Jones Tract) and 92.5% (Lincoln Tract) of the sets of solutions were significantly different and lower in quality when search reversion was used alone. Similar observations were noted for the minimization problems. When the URM model of final harvest adjacency was considered, 86.9% (Jones Tract) and 80.4% (Lincoln Tract) of the sets of solutions were significantly different and lower in quality when search reversion was used alone. When the ARM model of final harvest adjacency was considered, 90.2% (Jones Tract) and 77.6% (Lincoln Tract) of the sets of solutions were significantly different and lower in quality when search reversion was used alone.

Interestingly, the combination of 2-opt exchange moves and second-best selection from the tabu search neighborhood every five iterations of the tabu search model often produced statistically significant ($p = 0.05$) and better sets of results than the other combinations of enhancements tested here. With respect to the maximization problems that employed the URM model of final harvest adjacency, 84.6% (Jones Tract) and 97.7% (Lincoln Tract) of the sets of solutions were significantly different and higher quality when only 2-opt exchange moves and second-best selection from the tabu search neighborhood were employed. When the ARM model of final harvest adjacency was employed, 83.6% (Jones Tract) and 97.2% (Lincoln Tract) of the sets of solutions were significantly different and higher in quality. Even more striking results were observed for the minimization problems. For the minimization problems that employed the URM model of final harvest adjacency, 97.2% (Jones Tract) and 96.3% (Lincoln Tract) of the sets of solutions were significantly different and higher quality when only 2-opt exchange moves and second-best selection from the tabu search neighborhood were employed. When the ARM model of final harvest adjacency was employed, 94.9% (Jones Tract) and 94.4% (Lincoln Tract) of the sets of solutions were significantly different and higher in quality. However, even though this combination of enhancements (2-opt exchange moves and second-best selection every five iterations) seemed superior to other scenarios, when comparing these directly to scenarios that employed 2-opt exchange moves and second-best selection every ten iterations, 68.8% of the time, there was no statistically significant difference ($p = 0.05$) in the quality of the sets of solutions.

4 Discussion

Tabu search represents an endeavor to enhance a deterministic hill-climbing search process by remembering recent moves selected within the solution space while searching for the optimal solution. Tabu search might be considered one of the more rational decision processes for developing high-quality solutions to complex problems, as initially, a tabu search process heads directly for a local optimum solution to a problem (Glover 1986). Once there, other moves are selected in an attempt to break free of the local optima by avoiding those moves that have been recently made, in some cases to prevent recent moves from being reversed. This short-term memory of recent moves helps the search process avoid becoming trapped at local optima, a common problem with deterministic hill-climbing methods, by allowing the search process to move to lower-quality solutions with the hope of eventually locating other nearby higher-quality solutions. This short-term memory also helps prevent the cycling of solutions. These aspects of tabu search, remembering recent moves and preventing cycling, act as a filter to direct the search process to alternative promising regions of the solution space (Romanycia and Pelletier 1985). These characteristics of the search process can be of value in solving complex combinatorial problems in agriculture and forestry, where assignments of management activities to areas of land are necessary.

The objective of this work was to illustrate how the results generated by a heuristic search process may vary under different assumptions of parameters and enhancements. The detailed results provided from tabu search runs have arguably never before been presented in a research article. The variation amongst solutions generated from a random starting point, and the comparisons of these when different parameters and enhancements are employed, should be informative to those interested in addressing complex combinatorial problems in agriculture and forestry. As was demonstrated, metaheuristics such as tabu search may require careful parameter tuning to enable efficient and effective high-quality near-optimal (if not optimal) solutions to combinatorial optimization problems (Martí et al. 2025). The selection of search parameters is often based on the experience and expertise of the person or group conducting the work (Martí et al. 2025), yet others have suggested secondary optimization methods to locate the set of parameters most appropriate to guide the search process (Pukkala and Heinonen 2006). Therefore, one limitation of this work is that the optimal parameters and combination of enhancements were not determined, although from prior experience (Bettinger et al. 2015; Bettinger and Zhu 2006), it seems that these will vary from problem to problem. As was noted, the initial solution for each of the 89,600 runs of the tabu search heuristic was randomly defined, which is suggested for research purposes (Golden and Alt 1979; Los and Lardinois 1982). However, in at least one prior published work (Akbulut et al. 2017), the initial solution for the tabu search process consisted of an optimal solution generated by discretizing the assignments from a relaxed solution generated via linear programming. In Akbulut et al. (2017), 18 different ways to convert continuous value harvest assignments to discrete value assignments were examined, and in some cases, higher quality outcomes were produced as compared to the random starting strategy. With respect to the present work, this additional enhancement to the search process was not employed; therefore, one might also view this omission as a limitation of the study.

The integration of heuristic search enhancements within the basic structure of certain s-metaheuristics is important to effectively and efficiently utilize their search behavior to locate higher quality solutions to complex problems. For example, the use of search reversion is important, yet seems to be more useful when accompanied by n-opt exchange moves within a heuristic search process (Bettinger et al. 2015), a suggestion that is confirmed in this work. Furthermore, a random tabu state has been suggested in other works (Bettinger et al. 2015) as a way to explore high-quality areas of the solution space more effectively when search reversion is employed, as the use of search reversion may frequently return the search process to the same place (solution) within the solution space. Aside from the programming code necessary to implement search process enhancements, the main issue challenging the integration of heuristic search enhancements is that the characteristics of employment may be different for each problem. For example, using too many consecutive n-opt exchange moves stifles diversification, as no new assignments are interjected into the solution (they are simply exchanged amongst the decision variables). The amount of n-opt exchange moves deemed necessary, and the timing of their entry into the search process are hypothesized to be important, yet perhaps problem (and hence domain) specific. This suggests that artificial intelligence might be useful in the future to sense the behavior of a search and to adjust the parameters and enhancements employed as a search process progresses to sufficiently balance intensification and diversification tactics. These advances in knowledge, albeit small, can be of value to many aspects of society where s-metaheuristic search processes are used to address increasingly complex optimization problems (Bettinger and Boston 2017).

5 Conclusions

When appropriate parameters and enhancements are employed, tabu search may be able to locate high-quality, if not optimal, solutions to complex, contemporary forest harvest scheduling problems. These findings are domain-specific and may not be transferable to other areas of work unless the problem formulations are similar. Nonetheless, a randomly defined short-term tabu state helps the process avoid cycling. The periodic use of 2-opt exchange moves and search reversion helps intensify the search within high-quality areas of the solution space. The ability to select the second-best alternative from the tabu neighborhood sometimes allows diversification from what may be considered the logical path through the solution space. While the tabu search process is computationally slow compared with other s-metaheuristics, owing to the need to assess many alternatives prior to making a move through the solution space, the rational, deterministic manner in which a problem is solved may be appealing.

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