SPATIAL FOREST PLAN DEVELOPMENT USING HEURISTIC PROCESSES THAT ARE INITIATED WITH A RELAXED LINEAR PROGRAMMING SOLUTION

by

RAMAZAN AKBULUT

(Under the Direction of PETE BETTINGER)

ABSTRACT

Linear programming is often used in forest planning models; however, these models usually lack spatial (e.g., harvest adjacency) constraints. To accommodate adjacency constraints, a linear problem often becomes a mixed-integer linear programming model because binary variables are needed to represent harvest decisions. Hence, heuristic methods have been suggested to use for forest planning problems that involve complex spatial relationships. In this study, heuristic methods (threshold accepting and tabu search) were used with a high-quality initial solution acquired from a relaxed linear programming solution rather than randomly initiated traditional heuristics. A western and a southern U.S. forest were used as study areas. A mixed-integer programming solution and randomly initiated heuristic solutions were used to compare the results. The findings of the study suggested seeding heuristics with a high-quality relaxed initial starting point provided better solutions than randomly initiated heuristics.

INDEX WORDS: Spatial Forest Planning, Harvest Scheduling, Heuristics, Tabu Search, Threshold Accepting, Linear Programming

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DEDICATION

To my parents, Mrs. Emine and Mr. Idris Akbulut, whose unconditional love and support have been so significant in bringing my work to accomplishment. I could never repay your love and effort on me.

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To all my family and friends who supported and believed in me all the time.

And finally, to my beautiful country, Türkiye…

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CHAPTER 1

INTRODUCTION

Modelling is an important part of decision making in environmental management today (Jørgensen, 2000). Modelling allows forest managers to consider and evaluate numerous alternatives without having to implement those specific actions and examine the physical outcomes. Today, spatial and temporal constraints are used in forest management planning to assist in the selection of management activities that facilitate managing forest land within organizational and regulatory frameworks (Bettinger et al., 2003). As a result of increased societal interest in natural resources, multi-functional use of forest resources makes forest management planning a complicated task (Kazana et al., 2003; Fotakis 2015). Thus the significance of spatial harvest scheduling and planning has increased in recent years, due to a number of factors, one of which is the realization of potential cost savings through simultaneously scheduling harvesting operations and transportation-related activities (Baskent and Keles, 2005; Boston and Bettinger, 1999).

Spatial forest planning problems can involve determining the location and timing of specific units of harvest, and can be difficult to solve because often they require integer decision variables (Bettinger and Zhu 2006). When the nature of the forest planning effort is considered, one of two general harvest scheduling approaches is pursued. One is based on mathematical programming techniques and the other is based on heuristics (Bettinger et al., 2007). With regard to mathematical programming, linear programming, integer programming and mixed-integer programming are often used (Bevers and Hof 1999; Hof et al., 1994; Weintraub et al., 1994).

Linear programming, which transforms a matrix describing a problem until an optimal solution is located, is one of the most widely used methods for addressing forest management problems (Öhman & Eriksson, 2002). A linear programming problem is comprised of an objective function, constraints (at least one) and accounting rows (Bettinger et al., 2009). Linear programming harvest scheduling models can contain spatial constraints (Kurttila, 2001) but often these require integer variables, making them a mixed integer linear programming problem. Baskent and Keles (2005) noted some applications of linear programming in forestry as following: (1) scheduling of timber harvests, (2) product optimization, and (3) multifunctional use of forest management planning. The major advantage of using conventional exact methods (i.e., linear programming) is that the generated solution is proven to be the optimum for the defined problem (Bettinger et al., 2009). Linear programming forest planning models can usually be solved very quickly; however, these models often lack spatial (i.e., adjacency) constraints that prevent harvest openings from exceeding a certain size. As noted earlier, to adopt adjacency constraints, the linear problem often becomes a mixed-integer linear programming model because binary or integer variables are needed. In the last twenty years many research publications have focused on incorporating spatial constraints into mixed integer models (Lockwood and Moore, 1993; Boston and Bettinger, 1999; McDill and Braze 2000; Falcão and Borges 2002). However, the main disadvantage of doing this is related to the computer processing time required when the integer variables are needed (Fischer et al., 2014). Depending on the size of the planning problem and the type of constraints developed, the process to solve a problem may require a few minutes or a few days for the branch and bound or cutting plane algorithms employed.

As a result of this limitation with mixed integer programming, heuristic search algorithms have increasingly been used in forest management planning problems to accommodate spatial objectives to the planning models (Borges et al., 2002; Heinonen and Pukkala, 2004). Also, another reason that heuristic techniques are getting more popular is that forest management problems involve non-linear relationships or complex mathematical relationships (or logic) to link management activities and ecosystem outcomes. This compounds problem development and makes the problem more difficult to solve with the current formulation of exact methods (Pukkala and Heinonen, 2006). Some of the heuristic techniques used recently in forestry are: Monte Carlo simulation (Nelson and Brodie 1990; Boston and Bettinger 1999), simulated annealing (Baskent and Jordan 2002; Borges et al., 2014; Dong et al., 2015), threshold accepting (Bettinger et al., 2003; Pukkala and Heinonen 2006; Zhu and Bettinger 2008), tabu search (Bettinger et al., 1999; Boston and Bettinger 2002; Bettinger et al., 2015), raindrop method (Zhu et al., 2007) and genetic algorithm (Glover et al., 1995; Falcão and Borges 2001). One advantage of using a heuristic technique includes their problem development flexibility. When developed correctly, these models can be used to solve problems that exact methods are not able to solve due to additivity and proportionality requirements (Jin et al., 2016). Also, with heuristic methods it is possible to generate a good solution to a complex problem very quickly (Baskent and Keles 2005), if the heuristic parameters and the problem are developed properly (Bettinger et al., 2009). On the other hand, the main limitation of heuristic techniques is that they do not guarantee that they can find the optimum solution to a planning problem; only near-optimal solutions can be assured (Hoganson and Borges, 1998; Bettinger et al., 2009; Jin et al., 2016). Therefore, good heuristics usually find high quality solutions but never guarantee that they will find the global optimum solution.

Two heuristics are used in this research, threshold accepting and tabu search. Threshold accepting is a stochastic directed heuristic search algorithm, and was introduced by Dueck and Scheuer (1990). In iteratively searching a solution space, threshold accepting accepts every new solution to a problem that is within a threshold of currently (previously) accepted solution. Within forest management planning, threshold accepting has been applied to problems related to ecological and economic goals (Bettinger et al., 2003), forest road maintenance (Coulter et al., 2006), and harvest scheduling (Zhu and Bettinger 2008).

Tabu search, one of the most widely used heuristic methods in forestry, is a deterministic directed search algorithm that was initially described by Glover (1989, 1990). In tabu search, the search process is forced to explore a wider set of substitute solutions by temporarily prohibiting recent moves (Jin et al., 2016). The best change to a solution, which is generally non-tabu, is selected through the moves (Reeves, 1993). The early work in forestry was conducted by Murray and Church (1995) who applied tabu search to a harvest scheduling problem that included adjacency constraints. Bettinger et al. (1997) applied tabu search to a harvest scheduling problem involving wildlife constraints. Bettinger et al. (1998) also applied tabu search to a spatial harvest scheduling problem with aquatic constraints.

Both threshold accepting and tabu search algorithms are generally initiated with random starting points (randomly generated feasible forest plans). This guidance is based on the work of Los and Lardinois (1982) and Golden and Alt (1979) who explain that while heuristic search processes all have a common goal (find the optimal solution), initiating them with a random starting solution can allow researchers to consider the final solutions as independent samples from a larger population of feasible solutions. This assumption then facilitates the use of statistical inference to describe and characterize the outcomes.

In practice, a random starting position for a heuristic has been questioned. Some have suggested that a higher-quality starting position should be employed, since the quality of an initial solution can play a significant role in determining the quality of final optimal solution (Paul et al., 2014). Seeding is a technique that uses previous knowledge about a problem to initiate a heuristic (Rojas et al., 2016). If there is exiting information about a problem, then it can be used to create a high quality initial starting point instead of a randomly generated starting point. This may lead to an improvement of performance of the method. Langdon and Nordin (2000) used a seeding process with a genetic algorithm (GA) to create the initial population. Also, Westerberg and Levine (2001) presented five alternatives for seeding a GA, and they found that some of these strategies improved the quality of the initial population.

In this study, heuristic methods will be initiated (seeded) with a high-quality initial solution acquired from a relaxed linear programming solution. The outcomes will be evaluated to understand whether this provides better heuristic solutions. A randomly generated initial solution will be used to compare the results.

The contribution of this study is to test the applicability of a method that combines linear programming with a heuristic method for incorporating spatial objectives into long-term forest management planning. For this purpose, heuristic methods will be seeded with a high quality starting point informed by using linear programming. Outcomes from linear programming will be applied to 18 different scenarios that convert the fractional decisions (e.g., cut half of a stand) to integer decisions (e.g., cut the entire stand). This study will therefore provide a new approach to the use of heuristic methods in forestry.

In this study, we use two hypothetical forests; one is located in Oregon, and the other in South Carolina. Our management objectives are, respectively, to maximize an even-flow of timber harvest, and to maximize net present value of management regimes. Each is subject to final harvest adjacency, green-up, and minimum harvest age constraints. For this purpose, we formulate adjacency constraints using the area restriction model (Murray, 1999). As alluded to objective of the study is to determine whether the new approach (initiating a heuristic with a high-quality solution) provides better solutions than the traditional assumption (initiate a heuristic with a random solution). Three hypotheses that will be tested in the study include:

- Heuristic solutions initiated using relaxed linear programming initial solutions are no better than heuristic solutions initiated with a random starting point.
- The computer processing time required for a heuristic that begins with high-quality relaxed linear solution is no different than the time required for randomly initiated heuristic solutions.
- The method that is used to convert linear solutions to an integer starting point does not affect the final solution quality.

CHAPTER 2

METHODS

2.1 Study Data

For this research, two different study areas will be used, reflecting southern and western United States (US) forest conditions. Since landowners often have different management priorities, we will characterize the regions with two different management emphases. For this work, the assumed management priority for the western study area is to maximize an even-flow timber harvest volume subject to final harvest adjacency and minimum harvest age constraints. The western study area (Figure 2.1) is 4,550 acres (1,841 hectares) in size and is composed of 87 stands. The coniferous forest is mostly composed of Douglas-fir (*Pseudotsuga menziesii)* and western hemlock (*Tsuga heterophylla*), and is located in western Oregon. For this problem, the time horizon is 30 years long, and is divided into 6 five-year time periods. The minimum final harvest age is assumed to be 30 years. The unit for volume per acre is expressed in thousand board feet (MBF). For the western study area, the target harvest volume is 12,555 MBF for each time period. The target harvest volume was initially calculated using the Hanzlik formula (Hanzlik, 1922), which suggests a sustainable harvest level. Our harvest target volume assumption is conservative, and 10% below the Hanzlik estimate. Final harvest sizes are limited to 120 acres (State of Oregon, 2015). The area restriction model (Murray, 1999) is used to accommodate this concern. The green-up period is 5 years (one-time period).

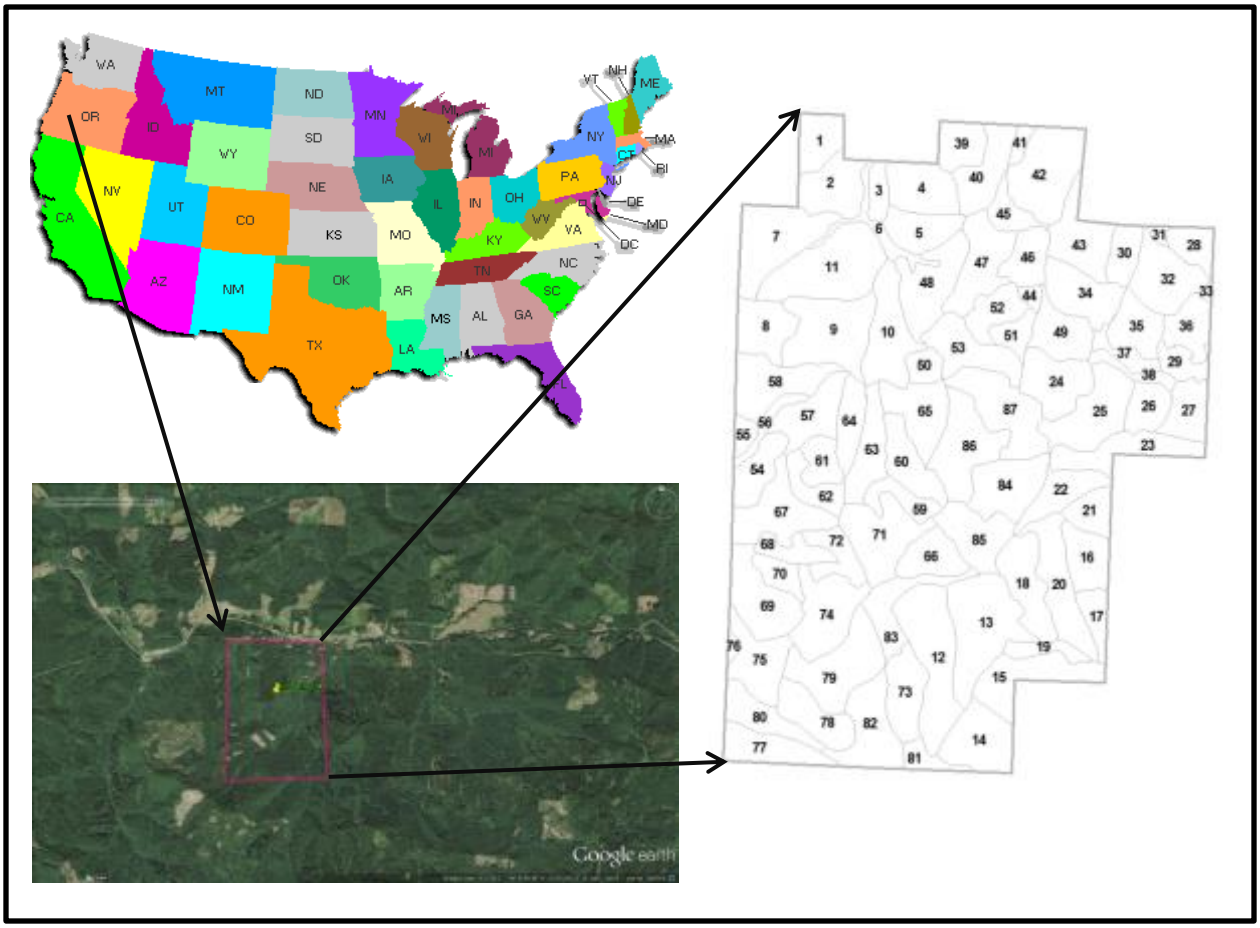

Figure 2.1. The layout of stands in western study area in Oregon (USA)

The southern study area (Figure 2.2) is a 39,087 acre (15,818 hectare) forest located in South Carolina with numerous (1,109) small stands, typical of a corporate southern forest district. Of these, 272 stands are considered riparian areas. Hence, the forest plans are developed using only 837 of the stands (32,365 acres, 13,098 hectares). Loblolly pine (*Pinus taeda*) is assumed to have been planted mainly in the plantations. Site indices (SI_{25} 60 and 70, base age 25) were randomly assigned to each stand.

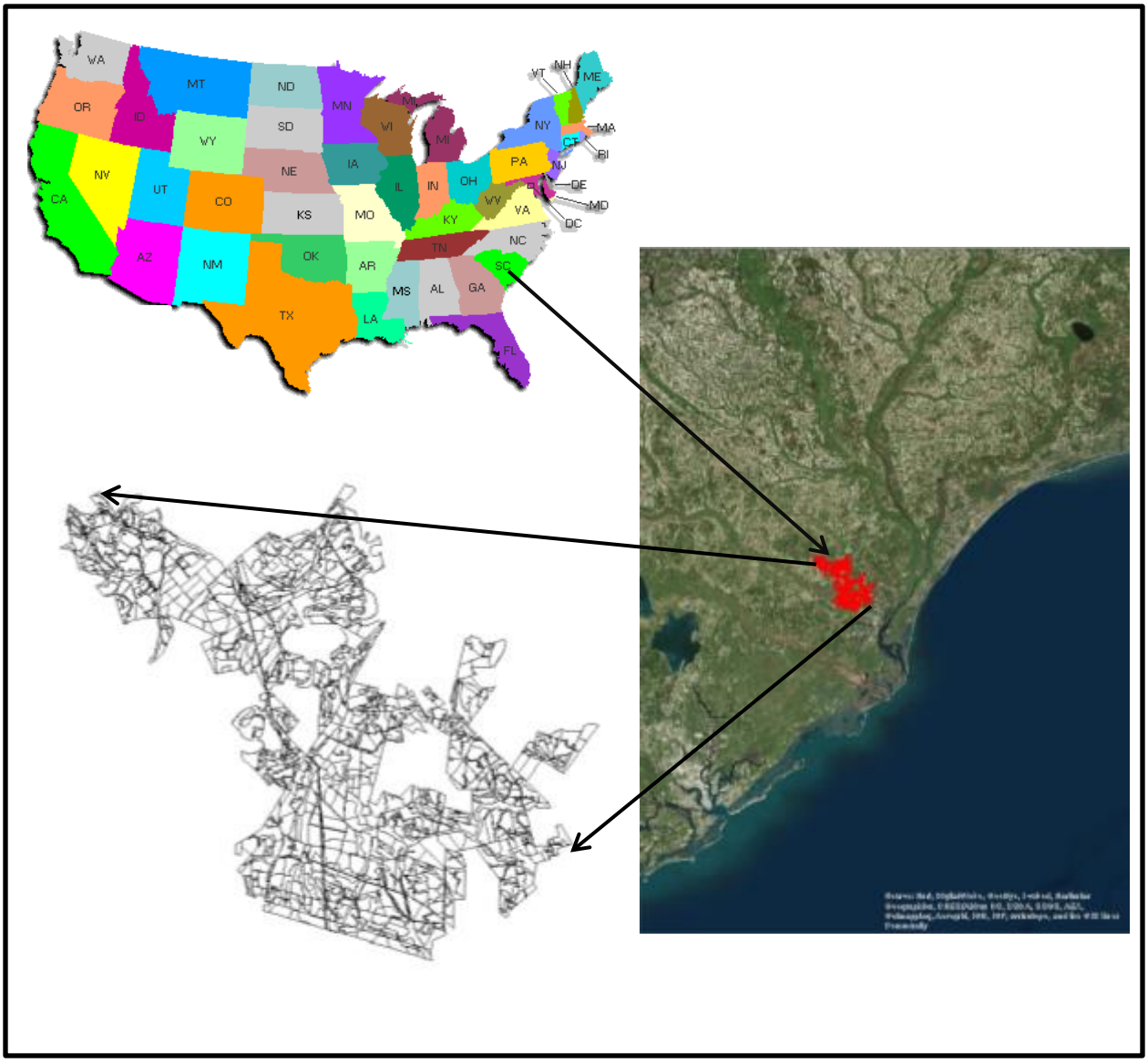

Figure 2.2. Stand map of southern study area in South Carolina (USA)

The assumed management priority for the southern study area is to maximize net present value subject to final harvest adjacency, green-up, wood flow, and minimum harvest age constraints. Here, the time horizon is 20 years long which is a typical tactical plan for southern United States forests, and is divided into 20 one-year time periods. For the southern forest, the scheduled total harvest volume is desired to be within 10% from one period to the next. The volumes represent the potential tonnage per acre in each time period. The data presents one joint

product that is timber in tons per acre; however, for the calculation of net present value, sawtimber, chip-n-saw and pulpwood products are acknowledged. The stumpage prices for the forest products are $25.60/ton for sawtimber, $17.46/ton for chip-n-saw, and $10.11/ton for pulpwood (Timber Mart-South, 2015). On the other hand, the establishment costs for the property are $67/acre for machine planting, $25/acre for seedlings, $123/acre for bedding, and $10/acre for herbaceous weed control (Barlow and DuBois 2011; 2015). The assumed discount rate is 6% for the southern problem. The minimum harvest age for the study area depends on stand conditions; however; it begins at age 27. Stands with ages over 90 years are assumed (and verified) to be riparian areas and cannot be scheduled to cut. Final harvest sizes are limited to 120 acres. The area restriction model of adjacency (Murray, 1999) is used to potentially group stands together for this purpose. The green-up period is 3 years.

2.2 Mathematical Problem Formulations

Two different forest management planning problems were designed since the assumed management priorities are different for both western and southern study areas. For the western forest, a spatial forest planning problem was developed with the objective function of maximizing an even-flow of wood volume. This is accomplished by minimizing the deviations between scheduled wood volume harvest and the target volume. A wood flow objective was selected in order to locate a solution to closest to the target volume. There are many different ways to formulate final harvest adjacency constraints in forest management problems. For our work, we used area restriction constraints (ARM) (Murray, 1999) to formulate the adjacency constraints. The area restriction model basically does not allow adjacent stands to be scheduled a final harvest if when combined they exceed a specified size limit.

For this study, a 120 acre (48.6 ha) clearcut size limit has been assumed for the adjacent stands, to be consistent with the state law in Oregon.

The problem formulation for the western forest is:

Minimize:

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

Subject to:

$$X_{it}A_i + \sum_{z \in N_i \cup S_i} X_{zt}A_z \leq MCA \qquad \forall i,t \tag{2}$$

$$\sum_{i=1}^{N}(X_{it}V_{it}A_i) - H_t = 0 \qquad \forall t \tag{3}$$

$$\sum_{i=1}^{T} X_{it} \leq 1 \qquad \forall i, \;\; X_{it} \in \{0,1\} \tag{4}$$

Where:

A_i= area of management unit *i*

i, j= an arbitrary management unit

MCA= maximum clearcut area

N= total management units

N_i= the set of all units adjacent to unit *i*

t= a planning period

T= the total number of planning periods in the planning horizon

H_t= total scheduled harvest volume for time period *t*

V_{it}= the available timber harvest volume per unit area during time period *t*, from management unit *i*

X_{it}= a binary decision variable, which = 1 if management unit *i* is scheduled for harvest in time period *t*, 0 otherwise

z= a neighboring management unit to management unit *i*

Equation 1 is the objective function, which is to minimize the deviation of periodic planned harvests from a harvest target. Equation 2 describes the area restriction model (ARM) adjacency constraint. Equation 3 is an accounting row that adds up the planned harvests for each time period. Equation 4 represents the resource constraints, which suggests that each stand could only be harvested once during the 30-year planning horizon.

For the southern study area, a spatial forest planning problem was designed with a management objective of maximizing net present value of timber harvested. The area restriction model will also be applied in this problem to formulate the adjacency constraints. The decisions are different than the western model, however. Here, a stand is assigned a management regime (thinning, final harvest), rather than the final harvest period.

The problem formulation for the southern forest is:

Maximize:

$$\sum_{i=1}^{N}\sum_{r=1}^{R} X_{ir} A_i NPV_{ir} \tag{5}$$

Subject to:

$$\sum_{r=1}^{R} X_{ir} \leq 1 \qquad \forall \boldsymbol{i},\ X_{ir} \in \{0,1\} \tag{6}$$

$$\sum_{r=1}^{R}\sum_{t=1}^{T} Fh_{irt} \leq 1 \qquad \forall \boldsymbol{i},\ Fh_{irt} \in \{0,1\} \tag{7}$$

$$lw_{ir} = t(Fh_{irt}) - [(g-1)(Fh_{irt})] \qquad if\ \ lw_{ir} \leq 1,\ lw_{ir} = 1 \tag{8}$$

$$uw_{ir} = t(Fh_{irt}) + [(g-1)(Fh_{irt})] \qquad if\ \ uw_{ir} > 1,\ uw_{ir} = T \tag{9}$$

$$\sum_{r=1}^{R}\sum_{t=1}^{T} Fh_{irt} A_i + \sum_{z \notin Ni \cup Si} \sum_{r=1}^{R}\sum_{lw}^{uw} Fh_{zrt} A_z \leq MCA \qquad \forall i \tag{10}$$

$$\sum_{i=1}^{N}\sum_{r=1}^{R} X_{ir} A_i V_{irt} - H_t = 0 \qquad \forall t \tag{11}$$

$$H_t \geq 0.9 H_{t+1} \qquad \forall t = 1, \ldots . T-1 \tag{12}$$

$$H_t \leq 1.1 H_{t+1} \tag{13}$$

Where:

A_i= area of management unit *i*

C_{it}= regeneration cost per ton for unit *i* harvested in time period *t*

Fh_{irt}= 1 for time periods (*t*) where final harvest of stand *i* managed under regime *r* is possible; 0 otherwise

g= green-up window (years)

i= a management unit

lw_{ir}= lower end of green-up window (time period) for management unit *i*, management regime *r*

MCA= maximum clearcut area

N= the total number of management units

N_i= the set of all management units adjacent to unit *i*

NPV_{ir}= net present value per unit area associated with management unit *i* scheduled under management regime *r*

R= number of management regimes

S_i= the set of all management units adjacent to these management units adjacent to management unit i

t= a planning period

T= the total number of time periods in the planning horizon

uw_{ir}= upper end of green-up window (time period) for management unit *i*, management regime *r*

V_{irt}= the available timber harvest volume per unit area during time period *t*, from management unit *i*, scheduled with management regime *r*

X_{ir}= a binary variable, which = 1 if management unit *i* is scheduled management regime *r*, 0 otherwise

z= a neighboring management unit to management unit *i*

Equation 5 is the objective function of the problem that is to maximize the net present value. Equation 6 indicates that each stand could only be assigned one management regime. Equations 7, 8, 9 and 10 maintain the maximum clearcut size using the ARM final harvest adjacency method (assuming the green-up period is 2 years). *Green-up windows* are necessary references to *time* in association with final harvests. Equation 7 simply notes the specific time period in which a final harvest is scheduled for management unit *i*, when managed under regime *r*. Equation 8 defines the lower end of the green-up window for management unit *i*, when scheduled under regime *r*. Equation 9 defines the upper end of the green-up window. Equation 10 controls the area scheduled for final harvest. Equation 11 acts as an accounting row to add up scheduled harvest volumes in each time period. Equations 12 and 13 constrain the volume harvested in each time period. This model formation represents a Model I (Johnson and Scheurman 1977), mixed integer programming problem.

2.3 Heuristic Processes

Threshold Accepting

Threshold accepting is a directed search method, and was introduced by Dueck and Scheuer (1990). The threshold accepting search process tries to locate the best solution to a problem through random moves by transitioning a current feasible solution to a new feasible

solution. The parameters that need to be defined for threshold accepting are the initial threshold, the iterations per threshold, the threshold change, and the unsuccessful iterations per threshold.

As an overview, threshold accepting starts with a large threshold (in objective function value units) and narrows it down during the search process (Figure 2.3). A large initial threshold allows threshold accepting to search widely throughout the solution space during the early stages of the search. As the threshold decreases, finding a solution between the best solution value and the threshold becomes more difficult. The program first develops an initial random solution. Then, it starts to randomly check for better solutions or solutions with objective function values within the threshold. When it selects a potential new solution, it determines whether it is feasible with respect to the constraints, and whether it is the best overall solution. If so, the solution is saved in memory as the best solution. If feasible but not the best overall solution, the heuristic checks whether the potential solution (objective function value) is within the threshold. If the objective function is in the threshold, the potential solution will be saved as the current solution. Otherwise, the process returns to select a new potential solution from the solution space. The current solution replaces the best solution if necessary. After a certain number (user-defined) of changes to the current solution, the threshold contracts. Further, if there are a certain number (user-defined) of unsuccessful changes to the current solution, the threshold contracts. When the threshold is very small (user-defined), the search process terminates. Nearing this condition, the heuristic acts as a greedy search process.

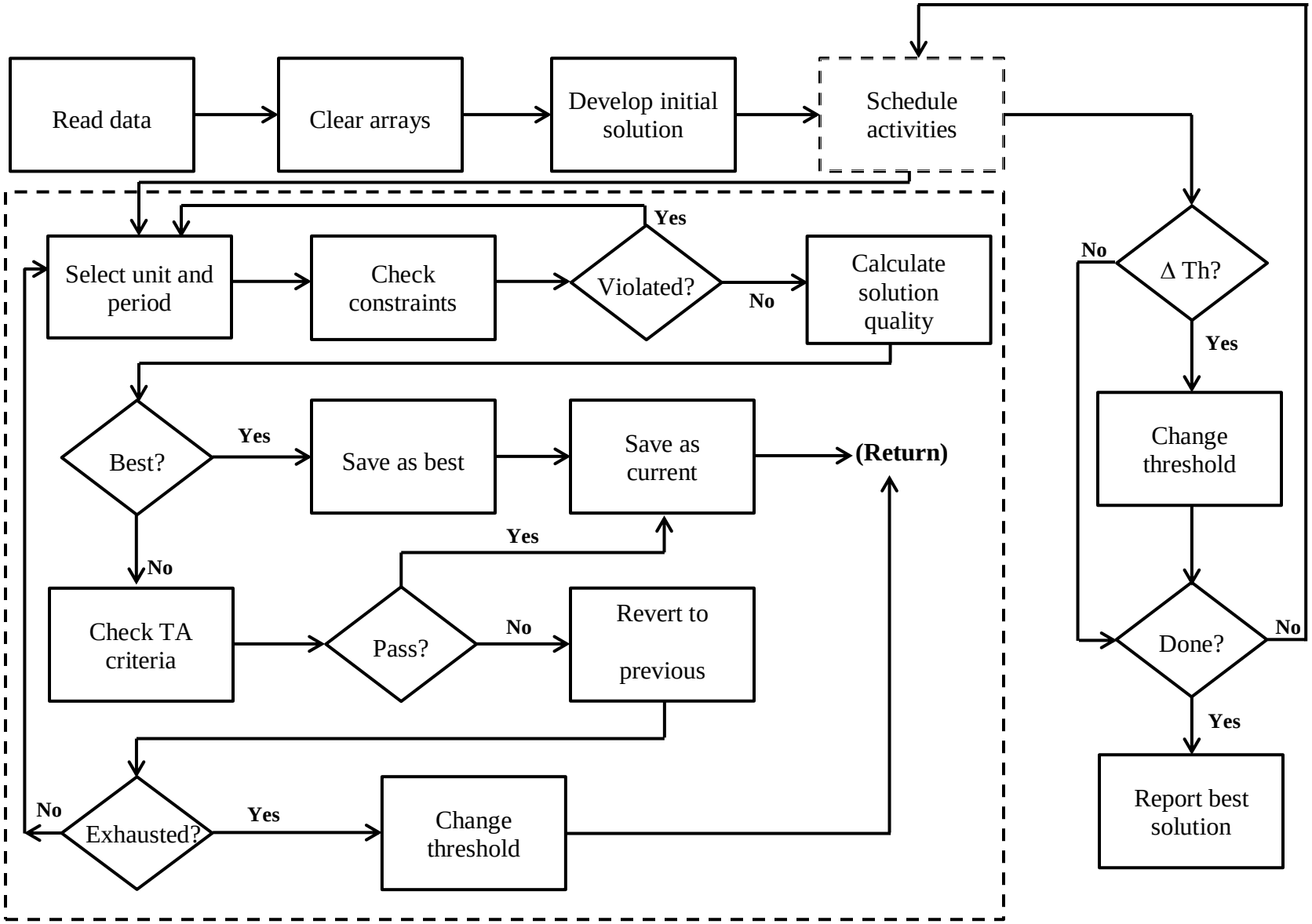

Figure 2.3. Working process of threshold accepting

In our study, the required parameters for threshold accepting are defined differently for western and southern study areas. For application to the western forest, the parameters were set according to Bettinger et al. (2015), who illustrated that these parameters provided the best solution for the threshold accepting method when applied to this property. For the southern forest, we developed trial runs to determine the appropriate threshold accepting parameters. In accordance this purpose, we tested 100,000 to 1,000,000 dollars for the initial threshold, 100 to 1,000 dollars for the threshold change, 25 to 100 for the iterations per threshold, 100 to 1,000 for the unsuccessful iterations per threshold, and 5 to 10 iterations for reversion rate. Based on those trials, parameters that we determined for western and southern study areas are shown in Table 2.1. For both forest management scenarios, these sets of parameters will be utilized. In this algorithm a reversion rate is employed (Bettinger et al., 2015), as are 2-opt moves (Bettinger et al., 1999). The Heuristic Algorithm Teaching Tool (HATT) software (Bettinger, 2013) is used for the western problem. The Scheduling of Forest Investment Endeavors (SOFIE) software (Bettinger, 2016) is used for the southern problem.

Table 2.1. Threshold accepting parameters

Forest Plan	Initial threshold	Iterations per threshold	Threshold change	Unsuccessful iterations per threshold	Reversion rate	Pattern of moves
Western study area	10,000,000[a]	10	100[a]	2,000	3	100 1-opt 10 2-opt
Southern study area	500,000[b]	100	1,000[b]	100	10	100 1-opt 10 2-opt

[a]= MBF^2
[b]= Dollars

Tabu Search

Tabu search was developed by Glover (1989, 1990) and is often considered a deterministic directed search algorithm. The tabu search algorithm uses memory to constrain the changes made to possible solutions. The latest move made during the search transition is considered tabu, and unavailable for a certain number of moves until the tabu tenure expires (Figure 2.4). Aspiration criteria can be used to override this aspect of the search process. Here, if a move is tabu, but will result in the best solution located during the search (up to that point in the search), the move is deemed acceptable. Moves are generally selected deterministically: the best choice for transitioning the current solution (positively or negatively affecting the objective function value) is made after assessing all options. In this process, a neighborhood of potential changes to the current solution is assessed. Tabu states are randomly assigned for each move selected, from 1 to the maximum specified using an equal probability selection process. This is unconventional with respect to typical tabu search implementations, yet through tests does seem to improve solution quality (perhaps by reducing the cycling of solutions). A tabu search process requires defining two parameters: the total number of iterations and the tabu state. In this algorithm, a reversion rate is employed (Bettinger et al., 2015), as are 2-opt moves (Bettinger et al., 1999).

In this research, the tabu search parameters for western and southern study areas are determined differently. For the southern study area, we developed a number of trial runs in order to specify the required parameters. For this purpose, we tested 25,000, 50,000, 75,000 and 100,000 iterations to define total number of iterations. Also, we examined the values 100, 150, 200 and 250 for the tabu state, and values between 5 and 10 for the reversion rate. All of the aforementioned parameters were run systematically to find the best combination.

The required parameters for the western study area were again determined according to Bettinger et al. (2015) as they were in the threshold accepting method. Based on these trials and assumptions, the specified parameters are presented in Table 2.2.

Table 2.2. Tabu search parameters

Study area	Total number of iterations	Maximum tabu state	Reversion rate	Pattern of moves
Western study area	1,000,000	200	6	100 1-opt 10 2-opt
Southern study area	25,000	100	10	100 1-opt 10 2-opt

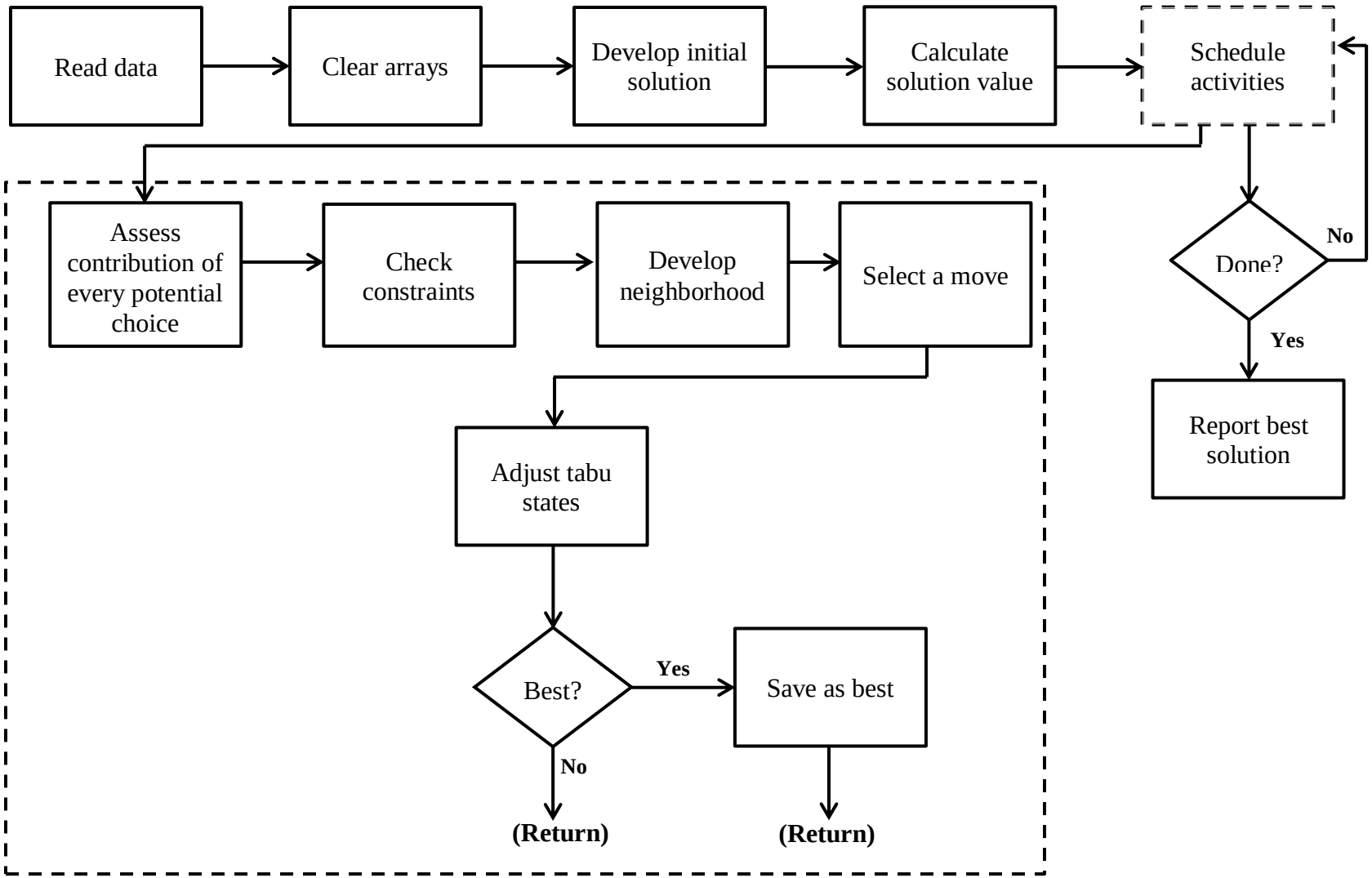

Figure 2.4. Working process of tabu search

Linear Programming Solution Conversion

Besides randomly starting the heuristics, we also seeded each with a specified starting point that was based on a relaxed linear programming (LP) solution. For this purpose, the problems for western and southern study areas were solved using linear programming solver LINGO 15.0 (Lindo Systems, Inc., 2015). These problems do not include adjacency constraints. The relaxed solution from linear programming was uploaded to the heuristic problem solvers and converted to an integer starting point, represented as a feasible solution. In doing this, the heuristic problem solvers converted the LP solution using one of 18 different processes (Table 2.3). The 18 scenarios along with a random starting solution provided 19 different approaches to the use of threshold accepting and tabu search methods for solving the management problems. Each conversion method therefore represents a scenario for the research.

Of the scenarios, there are three groups that each includes 6 treatments applied to the linear programming solution. The groups, here, represent the order of processing of stands. In the first six scenarios, the treatment is to use an ascending stand order which means that the heuristic processes the stands starting from number 1, and searches for a split final harvest assignment. A split harvest assignment schedules part of a stand's final harvest to one-time period, and part of it to another time period(s). Scenarios 7 to 12 repeat the same process, but consider stands from the last stand to the first. Scenarios 13 to 18 process stands randomly. As soon as a stand is found to have a split final harvest in the relaxed LP solution the second step offers two options: unscheduling the final harvest assignment associated with the stand or selecting the majority assignment. If a stand did not have a split final harvest assignment in the linear programming solution, and the assignment was whole (i.e., to harvest the stand in a specific time period), the adjacency constraints were assessed. The same held when a split final assignment was converted

to a majority assignment. If a final harvest adjacency violation occurs, a third step offers three options: unscheduling the final harvest, selecting a random feasible assignment, or selecting the next-best feasible assignment. It should be noted that selecting a random feasible assignment or the next-best assignment may ultimately lead to unscheduling the final harvest assignment for a stand by chance, or if these lead to harvest adjacency violations. Further, the random assignment could represent the next-best assignment.

Processing Considerations

In our model, the total number of variables for relaxed linear programming problems was 456 for the western problem and 11,097 for the southern problem, and the number of constraints were respectively 83 and 1,210. However, these problems do not include adjacency constraints as stated before. The software (LINGO 15.0) was run on a PC with 2.50 GHz Intel® Xeon® processor and 8 GB of RAM.

For the heuristic problems, two different PCs were used. The western problem and associated scenarios were processed using a PC with 2.50 GHz Intel® Xeon® processor and 8 GB of RAM. On the other hand, the southern problem and scenarios were processed using a PC with 3.40 GHz Intel® Core™ i7 processor and 32 GB of RAM.

One hundred feasible solutions were created with the heuristics for each scenario. In most scenarios, each of the one hundred solutions can be considered an independent sample from a large population of potential forest plans (Golden and Alt 1979, Los and Lardinois 1982). Hence, there are 1,900 solutions (18 scenarios and one random set) for each study area. The total number of solutions generated was 7,600 (1,900 solutions x 2 heuristic methods x 2 study areas).

Table 2.3. LP-conversion methods

				If a stand has a split final harvest assignment [b], how is the integer assignment handled?		If final harvest adjacency violations occur, how is the integer assignment for the stand handled?		
	Stand order[a]							
Scenario	Ascending	Descending	Random	Unschedule the stand [c]	Select majority assignment [d]	Unschedule the stand [c]	Select random assignment [e]	Select next best assignment [f]
1	✓			✓		✓		
2	✓			✓			✓	
3	✓			✓				✓
4	✓				✓	✓		
5	✓				✓		✓	
6	✓				✓			✓
7		✓		✓		✓		
8		✓		✓			✓	
9		✓		✓				✓
10		✓			✓	✓		
11		✓			✓		✓	
12		✓			✓			✓
13			✓	✓		✓		
14			✓	✓			✓	
15			✓	✓				✓
16			✓		✓	✓		
17			✓		✓		✓	
18			✓		✓			✓

[a] The order in which stands are addressed in the linear programming solution conversion process, using stand number as the criterion.
[b] A split harvest assignment schedules part of a stand's final harvest to one-time period, and part of it to another time period(s).
[c] No final harvest is assigned.
[d] Of the final harvest assignments, select the period that contains the greatest proportion of the stand; if infeasible, unschedule the assignment.
[e] Schedule a final harvest randomly, ensuring feasibility; unscheduling the assignment is a choice.
[f] The next best final harvest assignment for a stand is based on the contribution to the objective when the decision is needed; if infeasible, the next best is attempted. The last resort is to unschedule the assignment for the stand.

2.4 Statistical Methods

When using heuristic techniques to solve a problem, we do not generally know whether the global optimum solution will be located, or that the solutions generated are within some minimum distance to the global optimum solution (Boston and Bettinger, 1999; Bettinger et al., 2009; Dong et al., 2015). Statistical tests can be applied to heuristic results in some cases to allow understanding of the quality of solutions generated (Bettinger et al., 2009). As Golden and Alt (1979) and Los and Lardinois (1982) summarized, if the starting point for the heuristic search was selected randomly, the results of a search can be considered as independent samples from a larger population, and then can be used in statistical tests. Ten of the 18 LP-conversion processes include a random component for developing the starting solution. Further, threshold accepting involves random selection of moves and tabu search includes a random tabu state. While not perfectly conforming to earlier ideas regarding the independence of solutions, these processes ensure diverse and unique searches for the global optimum solution.

The solutions generated using threshold accepting and tabu search are compared in several ways. As Bettinger et al. (2009) reported, there are several ways to assess the performance of heuristics. First, the minimum, maximum, mean, and standard deviation of 100 independent runs from each of the 19 scenarios to serve as a self-validation of the results (Bettinger et al., 2009). We use the statistical results (i.e., mean, standard deviation) to evaluate heuristic solution quality (Level 2), and we use other heuristic solutions to compare results (Level 3). Second, the Kruskal-Wallis and Mann-Whitney U tests were employed to evaluate the quality of the solutions that are produced by different search techniques and to determine whether they are significantly different. Finally, we use mathematical programming techniques for comparison (Levels 5 and 6).

The best course of action is to compare the results from a heuristic procedure with the global optimum solution that was generated using a traditional mathematical programming technique (e.g., mixed integer programming).

Normality tests showed that the data sets (both in western and southern study area) are non-normally distributed. Therefore, non-parametric statistical methods were employed for the analysis. First, a Kruskal-Wallis test was used to check whether there is a statistically significant difference among the 19 scenarios. Hereupon, the Mann-Whitney U test was employed to check the statistical relationship between each pair of two scenarios.

Mathematical programming approaches have been employed in assessments of the quality of heuristic (e. g. Bachmatiuk et al., 2015), but the use of them is highly dependent on the size and complexity of the planning problems. We developed the linear and mixed integer programming formulations for the western study area since the planning problem is less complicated than the one in the southern study area. The western mixed integer problem consisted of 480 variables where the 474 of them were integers, and the total number of constraints was 2,170. We did solve the linear programming solution for the southern forest but we did not develop the mixed integer programming formulations because the number of adjacency constraints made the formulation complicated; however, a relaxed linear programming solution can be used in association with spatial forest planning problems to describe the relationship of heuristic solutions and an upper bound on the problem (e.g., Boston and Bettinger, 1999, 2002; Bettinger et al., 2007).

CHAPTER 3

RESULTS

3.1 Western Study Area

The 19 sets of 100 solutions (1 random starting scenario + 18 LP-conversion scenarios) from tabu search, when assessed for the solution quality, demonstrate that scenario 11 and scenario 17 produced the highest quality forest plans with respect to the objective function value (Table 3.1). Therefore, if a planner were in a position to generate 100 heuristic solutions, the best course of action would be to use a seeding system that selected the majority assignment for each stand from an LP solution, then perhaps randomly change it when adjacency constraints arise. However, once the statistical summaries are considered, one can see that scenario 4 produced the best forest plans in general (lowest minimum objective function value, lowest average objective function value, and lowest standard deviation value). This is similar to scenarios 11 and 17, except when adjacency constraints arise, the final harvest of a stand is unscheduled. In addition, scenario 8 and 11 resembled scenario 4 in two respects (minimum and variation) although the mean solution values were higher (i.e., worse). On the other hand, scenario 15 generated the worst forest plan, with the highest maximum objective function value, mean and standard deviation. Even though its minimum objective function value was closer to the best scenarios (0.04), the average results made it the worst overall. The other lower-quality scenarios are scenarios 1 and 2, which were similar to scenario 15. Based on these results, using a random starting point is not necessarily the best alternative for generating solutions.

Despite the fact that its minimum objective function value is 0.03, which is close to the overall best solution, the accumulation of other results is not good as scenarios 4 and 8.

Table 3.1. Western study area tabu search results

Search process	Scenario	Reversion interval (iterations)	Minimum (best) solution value (MBF^2)	Maximum (worst) solution value (MBF^2)	Average solution value (MBF^2)	Standard deviation of solution values (MBF^2)	Average time required (sec)
TS12	Random	6	0.03	17.37	1.57	2.76	362.23
TS12	1	6	0.07	68.42	4.15	7.99	333.90
TS12	2	6	0.03	53.93	4.38	7.77	351.81
TS12	3	6	0.11	17.57	2.39	3.32	339.56
TS12	4	6	0.03	11.29	1.30	2.36	340.41
TS12	5	6	0.04	24.24	2.04	3.83	348.79
TS12	6	6	0.07	18.49	1.45	2.84	352.94
TS12	7	6	0.06	25.72	2.67	4.46	358.13
TS12	8	6	0.04	12.08	1.72	2.44	339.35
TS12	9	6	0.05	16.33	1.64	2.81	340.74
TS12	10	6	0.05	16.83	1.43	2.60	341.31
TS12	11	6	0.02	25.28	1.46	3.30	341.13
TS12	12	6	0.04	16.72	1.57	2.92	335.03
TS12	13	6	0.08	67.34	3.57	7.56	337.63
TS12	14	6	0.04	23.85	2.65	3.69	352.52
TS12	15	6	0.04	66.65	4.22	9.33	334.20
TS12	16	6	0.05	19.18	1.93	3.60	351.95
TS12	17	6	0.02	19.02	1.72	3.07	339.59
TS12	18	6	0.04	19.23	1.77	2.89	340.79

To determine whether these results were significantly different, statistical analysis was performed with the data for each heuristic method (the 18 LP-conversion scenarios and the random starting solution). For the overall collection, a Kruskal-Wallis test was used instead of an ANOVA analysis since the data was non-normally distributed. The tabu search model used in the western study area was significantly different at the level of $p=0.0001$ which indicated that at least one of the scenarios modeled with tabu search had significantly different mean values than

the others. To assess the statistical relationship among pairs of two scenarios, once again a non-parametric statistical method, the Mann-Whitney U test, was employed. These tests indicated that the best scenario when using tabu search, scenario 4, was not significantly different than the random scenario ($p<0.154$). Although the results from the random starting scenario were not as good as scenario 4, there was no statistically significant difference between these two scenarios. When the best and the worst scenario, scenario 15, were compared, we found that they were significantly different ($p=0.0001$). The random starting scenario was also significantly different than scenario 15 ($p=0.001$). Full results can be found in Appendix A.

In order to understand the improvement of solutions generated by the LP-conversion process, we should examine at the converted solution objective function value and assess how much this value was improved by the heuristic method. Table 3.2 shows the change for each scenario from the linear programming converted solution value to the final tabu search solution.

In this table, the change represents the average final solution value improvement for each scenario. Since this is a minimization problem, the lowest average starting values might be assumed to lead to the identification at the best scenario (as in scenario 9); however, it might not (as in scenario 10), since the average solution value is not the only criteria to be used to assess as the best scenario. In this case, scenario 4 has the lowest average final solution value that is mentioned as the best scenario before. However, scenario 10 started with the lowest LP-converted solution value. On the other hand, scenario 8 (one of the better scenarios) made the greatest progress when the LP-converted solution value and the average final solution values are considered.

Table 3.2. Change in the starting solution value in western tabu search method

Scenario	Average starting point (MBF^2)	Average ending solution value (MBF^2)	Change (MBF^2)
1	35,410,486.62	4.15	35,410,482.47
2	34,734,653.69	4.38	34,734,649.31
3	25,991,961.57	2.39	25,991,959.18
4	18,134,783.64	1.30	18,134,782.34
5	26,148,578.29	2.04	26,148,576.25
6	28,203,654.39	1.45	28,203,652.94
7	37,542,895.21	2.67	37,542,892.54
8	45,956,684.12	1.72	45,956,682.40
9	41,567,158.98	1.64	41,567,157.34
10	7,818,644.29	1.43	7,818,642.86
11	35,900,660.99	1.46	35,900,659.53
12	32,963,830.64	1.57	32,963,829.07
13	36,711,662.72	3.57	36,711,659.15
14	38,652,599.57	2.65	38,652,596.92
15	35,662,851.20	4.22	35,662,846.98
16	13,119,739.58	1.93	13,119,737.65
17	29,343,516.24	1.72	29,343,514.52
18	27,450,612.27	1.77	27,450,610.50

With threshold accepting, scenario 1 produced the best forest plan based on minimum objective function value (Table 3.3). This process involved unscheduling the final harvest of a stand with a split schedule arising from the LP solution, and further unscheduling the fina harvest when no split schedule was detected, but adjacency constraints arose. However, scenario 4 had the lowest maximum (worst) objective function value, lowest mean objective function values and lowest standard deviation that illustrates that it generated the better forest plans, as was found with tabu search. Moreover, scenario 15 and scenario 16 provided results that were similar to scenario 4.

Conversely, scenario 1 developed some of the worst overall solutions using the parameters selected. This suggests that scenario 1 may be among the worst scenarios unless a

high number of solutions are generated. Scenario 9 also can be categorized in a similar manner. According to Table 3.3, solutions generated from the random starting point scenario were not necessarily better than solutions starting with an LP-converted starting point.

Table 3.3. Western study area threshold accepting results

Search process	Scenario	Reversion interval (iterations)	Minimum (best) solution value (MBF^2)	Maximum (worst) solution value (MBF^2)	Average solution value (MBF^2)	Standard deviation of solution values (MBF^2)	Average time required (sec)
TA12	Random	3	22.19	2,997.67	608.21	547.80	612.30
TA12	1	3	6.87	7,070.66	671.68	842.39	688.21
TA12	2	3	21.53	4,664.50	508.13	611.78	699.81
TA12	3	3	7.84	3,012.48	571.72	576.24	662.86
TA12	4	3	13.38	1,551.75	406.80	331.25	611.54
TA12	5	3	16.60	3,493.69	581.16	716.88	674.82
TA12	6	3	19.09	3,901.22	444.41	522.41	600.97
TA12	7	3	21.15	3,345.78	663.60	580.64	552.00
TA12	8	3	29.90	3,159.32	624.80	689.39	632.12
TA12	9	3	15.90	6,374.19	681.22	823.85	651.95
TA12	10	3	31.91	4,118.63	474.80	528.29	603.94
TA12	11	3	24.84	2,730.28	420.70	475.17	650.93
TA12	12	3	9.01	4,887.68	577.37	787.05	664.14
TA12	13	3	58.22	2,816.72	549.75	540.47	631.68
TA12	14	3	20.87	2,266.43	554.69	472.37	640.51
TA12	15	3	13.40	1,855.45	502.05	430.19	687.76
TA12	16	3	15.42	2,047.25	455.83	452.07	568.35
TA12	17	3	19.29	4,692.67	481.04	610.73	646.85
TA12	18	3	26.81	5,605.16	526.64	689.36	641.58

The overall collection of threshold accepting solutions associated with the western study area were also significantly different at the level of $p=0.0001$, which meant that at least one of the scenarios had significantly different mean objective function values. We employed statistical tests among the pairs of scenarios, and found that the best scenario, scenario 4, was significantly different than the random starting scenario ($p= 0.002$). When those two scenarios were compared to the worst scenario, which was scenario 1, statistical results showed that scenario 4 was

significantly different than scenario 1 (*p=0.003*); however, the random starting scenario was not significantly different than scenario 1 (*p=0.949*). Full results of these statistical analyses can be found in Appendix B.

The improvement of the solutions that began with LP-converted starting points using threshold accepting is similar to what we found using tabu search (Table 3.4). The best scenario, scenario 4, had the lowest average final solution values although the converted solution value (initial starting solution) was not necessarily the lowest. With threshold accepting, scenarios 10 and 16 did not produce better average solution values than scenario 4 even though their average converted solution value (starting point) was much lower (better) than scenario 4. The best progress was made by scenario 8, as when using the tabu search method.

Table 3.4. Change in the starting solution value in western threshold accepting method

Scenario	Average starting point (MBF^2)	Average ending solution value (MBF^2)	Change (MBF^2)
1	35,410,486.62	671.68	35,409,814.94
2	35,416,176.92	508.13	35,415,668.79
3	25,991,961.57	571.72	25,991,389.85
4	18,134,783.64	406.80	18,134,376.84
5	24,636,942.85	581.16	24,636,361.69
6	28,203,654.39	444.41	28,203,209.98
7	37,542,895.21	663.60	37,542,231.61
8	46,700,210.27	624.80	46,699,585.47
9	41,567,158.98	681.22	41,566,477.76
10	7,818,644.29	474.80	7,818,169.49
11	32,292,513.72	420.70	32,292,093.02
12	32,963,830.64	577.37	32,963,253.27
13	36,498,017.32	549.75	36,497,467.57
14	40,885,561.82	554.69	40,885,007.13
15	36,226,160.55	502.05	36,225,658.50
16	13,365,926.29	455.83	13,365,470.46
17	31,147,047.13	481.04	31,146,566.09
18	28,827,693.50	526.64	28,827,166.86

Compared to the tabu search results, threshold accepting results are worse; however, scenario 4 stands out again as the best scenario with respect to the lowest maximum, the lowest average and the lowest standard deviation values. When both sets of results are juxtaposed, the striking difference is that the maximum objective function value (i.e., worst solution) generated by tabu search was better than the minimum objective function value (i.e., best solution) generated by threshold accepting. As stated before, the harvest volume target was 12,555 MBF for each time period; hence, the total harvest target was 75,330 MBF. To illustrate, the best, the worst and the average 30-year scheduled harvest volumes for each scenario were compared (Table 3.5).

Table 3.5. Best target harvest volume in tabu search and threshold accepting methods

Search process & scenario	Minimum (best) solution value (MBF)	Maximum (worst) solution value (MBF)	Average solution value (MBF)
TS Scenario 4	75,329.92	75,325.43	75,328.49
TA Scenario 4	75,323.29	75,352.47	75,316.63

According to Table 3.5, the best threshold accepting solution (i.e., minimum objective function value) in scenario 4 provided 75,323.29 MBF volume for the entire planning horizon. This amount is not better than the worst solution (i.e., maximum objective function value), 75,353.43 MBF, generated by tabu search scenario 4 which is a dramatic difference. Although the results indicate that tabu search can more reliably provide a solution that has the most even scheduled harvest volumes, on a practical level the difference between average solutions generated by both methods amounts to about three truckloads of wood, or about $6,000 US dollars (12 MBF x $500 per MBF).

Interestingly, when using threshold accepting, the worst solution value seems to provide the highest amount of scheduled harvest volume; however, the criteria to assess these results centers on the distance from the target volume (the closer is the better) (Fig. 3.1 and Fig. 3.2).

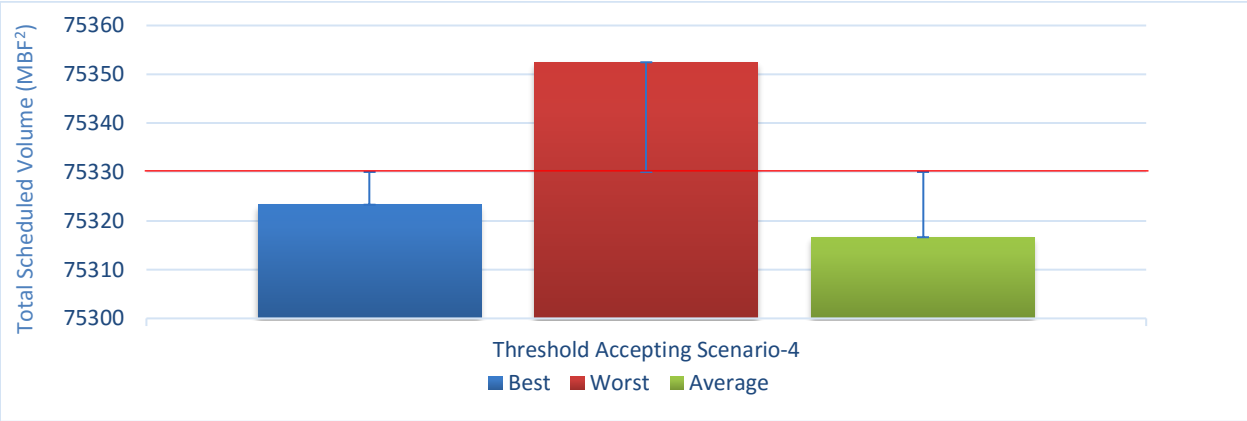

Figure 3.1. The distance between the threshold accepting (TA) results and the target volume

In line with the tables and figures presented so far, one can see that the tabu search algorithm produced better solutions. In order to see if this difference is statistically significant, we performed a test between the best scenarios of each method. The results indicated that the difference between the best scenarios of each method is statistically significant at the level of $p=0.0001$. The same test was also employed among the worst scenarios of each method, and the results were the same, ($p=0.0001$). Lastly, the difference between the random starting scenarios of both methods were also statistically significant at the level of $p=0.0001$.

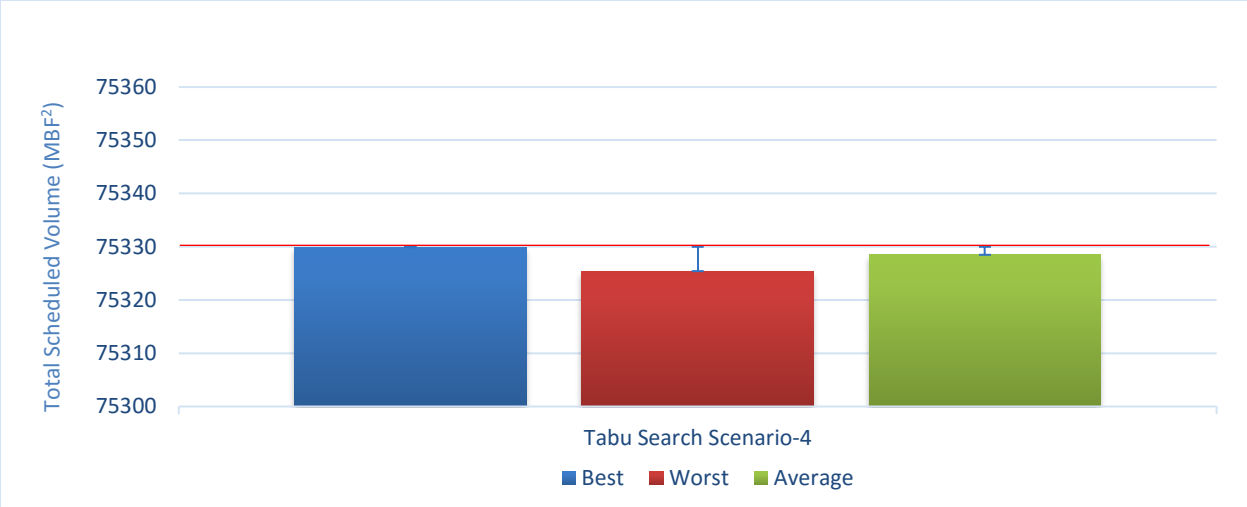

Figure 3.2. The distance between the tabu search (TS) results and the target volume

Based on the results, we obtained better results initiating the search with a relaxed (converted) linear initial solution before using the tabu search and the threshold accepting methods. The difference between the results generated with a random starting solution and the best solutions generated using a converted linear programming solution as the initial solution was not statistically significant when using tabu search, while it was statistically significant when using threshold accepting. Therefore, we partially reject the null hypothesis that heuristic solutions developed with a converted (seeded) linear programming initial solution are no better than heuristic solutions developed when initiated from a random starting point.

When the tabu search and threshold accepting methods are compared using the computer processing time, it can be seen that the results are parallel with the solution values. However, these results may be highly associated with the programming logic employed and parameters chosen, as one should expect that tabu search to be slower. According to the required available time for one single run on Table 3.1 and Table 3.3, one can see that tabu search solved the problem approximately two times faster than threshold accepting. Thus, the required time might be changed by adjusting the search parameters; however, this may in turn affect the solution

quality. Moreover, the least required time for a single run using tabu search was 333.90 seconds in scenario 1, and the greatest amount of time was 362.23 seconds in the random starting scenario. This result shows that the scenarios initiated with a relaxed linear solution are faster to process than the random starting scenario. This assumption is valid for threshold accepting too. The fastest time for one single run took 552.00 seconds in scenario 7, and the greatest amount of required time was 669.81 seconds in scenario 2. The random starting scenario, in this case, took 612.30 seconds, which was longer than what was required by most scenarios that were started with relaxed linear solution scenarios. Therefore, we reject our null hypotheses that the required amount of time to solve a random starting scenario is not different than the time required for scenarios initiated with a relaxed linear solution.

As stated before, the best course of action is to compare the results from a heuristic procedure with the global optimum solution that was generated using a traditional mathematical programming technique. We solved the same problem by using the mixed integer linear programming method to compare the results. The running time limit for this procedure was 86,400 seconds (one day), after which the solver (LINGO 15.0) was interrupted and asked to report the current, best, feasible solution. The mixed integer programming results, and a comparison with the tabu search and the threshold accepting methods are presented on Table 3.6.

Table 3.6. Comparison between the heuristic and the mathematical programming technique

Search Algorithm	Total volume scheduled (MBF)	Required time (seconds)	Best solution value (MBF^2)
Tabu search method	75,328.49[a]	340.41[a]	1.42
Threshold accepting method	75,316.63[a]	611.54[a]	416.74
Mixed integer programming	75,326.79[b]	86,400.00[b]	2.30

[a] Average of 100 solutions
[b] One solution

The tabu search method generated the highest amount of wood and required the least amount of time between the methods (Table 3.6). Although the mixed integer programming method could not converge upon the global optimum solution, the one that it produced was better than the best threshold accepting method solution. However, the time it required was the highest among the methods. Even the time for threshold accepting methods represented one single solution, the entire set of 100 solutions only required 61,154.00 seconds which is still lower than the mixed integer programming required.

3.2 Southern Study Area

The 19 sets of 100 solutions (1 random starting scenario + 18 LP-conversion scenarios) generated for the southern study area using threshold accepting and tabu search all represent a maximization problem. In this case, the lowest objective function value represents the worst solution value, and the highest objective function value represents the best solution, which was the exact opposite of the western study area. This is related to the change of the assumed management priority. In the southern study area, our management objective involved maximizing the net present value. Thus, one can assume that the maximum objective function value represents the greatest economic return from the land.

When the threshold accepting results were assessed for the solution quality, scenario 18 generated the highest quality forest plan with respect to the objective function value ($49,442,898.84) (Table 3.7). However, once the other parameters (the minimum and the average objective function value, and standard deviation of solution values) were considered, one can see that scenario 9 produced the best overall quality forest plans. Scenario 9 produced the highest minimum and average objective function values, and the lowest standard deviation values.

This process involved unscheduling a stand's management regime if a split schedule was detected from the linear programming solution, and otherwise scheduling the next best (in terms of net present value) management regime when adjacency violations were found. Scenario 3 had several processing characteristics in common with scenario 9, had the lowest standard deviation as well, but the other results were not as favorable as the result of scenario 9. In addition, scenario 6 also produced good results; however, the values it generated were not better than those produced by scenarios 9 and 6. Despite the fact that scenario 18 produced the greatest single solution, the standard deviation of 100 solutions produced by this scenario was relatively large.

Table 3.7. Southern study area threshold accepting results

Search process	Scenario	Reversion interval (iterations)	Minimum (worst) solution value (USD)	Maximum (best) solution value (USD)	Average solution value (USD)	Standard deviation of solution values (USD)	Average time required (second)
TA12	Random	10	46,228,658.75	48,731,556.78	47,657,628.56	501,137.64	84.60
TA12	1	10	47,526,508.50	48,904,455.23	48,128,891.48	240,976.06	50.53
TA12	2	10	47,444,712.58	48,882,085.00	48,231,280.49	280,758.39	62.90
TA12	3	10	48,131,840.20	48,832,571.90	48,432,109.18	127,512.91	50.60
TA12	4	10	47,832,291.74	48,801,014.60	48,296,329.79	202,353.46	50.65
TA12	5	10	47,786,606.78	48,823,764.64	48,314,319.00	253,711.06	14.84
TA12	6	10	48,008,971.56	48,901,962.87	48,416,190.26	173,623.06	49.59
TA12	7	10	47,310,952.67	48,487,547.18	47,981,981.93	300,093.06	52.15
TA12	8	10	47,597,442.84	48,947,157.74	48,372,591.77	258,510.51	50.52
TA12	9	10	48,244,714.78	49,000,122.28	48,564,875.89	144,380.25	17.73
TA12	10	10	47,319,537.16	48,644,049.84	48,068,039.16	276,610.08	16.97
TA12	11	10	47,264,426.00	48,892,748.60	48,370,031.23	259,230.80	10.54
TA12	12	10	46,775,373.40	48,398,625.30	47,567,601.78	365,180.96	17.25
TA12	13	10	47,313,715.00	48,589,716.53	48,003,888.77	282,767.60	20.36
TA12	14	10	47,213,115.64	49,349,762.74	48,279,754.32	386,283.33	20.73
TA12	15	10	46,244,938.56	49,321,504.39	48,282,580.40	567,960.86	20.91
TA12	16	10	47,186,461.39	49,069,765.11	47,997,483.53	339,607.34	15.52
TA12	17	10	47,106,672.92	49,046,109.12	48,246,758.23	370,309.60	30.81
TA12	18	10	47,334,525.93	49,442,898.84	48,301,906.52	441,889.34	31.68

On the other hand, the random starting scenario produced the worst forest plan, as noted by the minimum objective function value ($46,228,658.75). However, this value represented only a single solution from a set of 100 runs hence this did not mean it was the worst overall scenario. The worst scenario seemed to be scenario 12 which had the lowest maximum and average objective function values. Although its minimum objective function value was not as bad as the minimum objective function value using a random starting point, it was not very good ($46,775,373.40). Scenario 15 and the random starting scenario had the greatest standard deviation of objective function values but the maximum and the average objective function values of scenario 15 did not seem so inferior as to be counted as one of the worst scenarios.

As stated above, the random starting scenario, in this case, was one of the two worst scenarios. All of the results it generated were far from the best scenario; however, in order to ensure that this assumption is correct, statistical tests should be used to verify these conclusions.

To determine whether the sets of results generated for each scenario were significantly different, a statistical analysis was performed. Even though half of the dataset, almost, was normally distributed, we used a non-parametric statistical test, Kruskal-Wallis, since the data included non-normally distributed samples. According to the overall collection of data, the threshold accepting model used in the southern study area was significantly different at the level of $p= 0.0001$ which meant that at least one of the samples (i.e., scenarios) had significantly different mean values than the other scenarios. To determine the relationship between the pairs of scenarios, another non-parametric statistical test, Mann-Whitney U test, was used. In line with the statistical results, the set of plans generated by the best scenario, scenario 9, was significantly different than all other scenarios, interestingly ($p= 0.0001$ for the all scenarios). This gripping result indicated that scenario 9 generated superior solutions. Another intriguing result was that

the random starting scenario, one of the two worst scenarios, was also significantly different than other scenarios except scenario 12 (*p= 0.156)*, which we suggested was the worst scenario. Thus, we can confidently state that our assumptions when viewing the results in Table 3.7 were confirmed with the statistical results. Full results of these analyses can be found in Appendix C.

In order to understand the improvement of an LP-converted solution provided by a heuristic method, we can examine the converted solution objective function value and assess how much this value was improved by the heuristic method. The improvement of each threshold accepting scenario from the LP-converted solution value to the average final solution value were shown in Table 3.8.

Table 3.8. Change in the starting solution objective function value for the southern forest problem, using the threshold accepting method

Scenario	Average starting point (USD)[a]	Average ending solution value (USD)[b]	Improvement (%)
1	43,174,323.68	48,128,891.48	11.48
2	45,097,784.66	48,231,280.49	6.95
3	47,066,249.64	48,432,109.18	2.90
4	43,748,685.53	48,296,329.79	10.39
5	45,466,830.10	48,314,319.00	6.26
6	46,743,236.22	48,416,190.26	3.58
7	41,897,253.21	47,981,981.93	14.52
8	44,586,335.46	48,372,591.77	8.49
9	46,495,203.93	48,564,875.89	4.45
10	43,339,193.42	48,068,039.16	10.91
11	45,010,709.58	48,370,031.23	7.46
12	26,647,086.23	47,567,601.78	78.51
13	42,163,108.62	48,003,888.77	13.85
14	44,289,741.99	48,279,754.32	9.01
15	43,563,979.01	48,282,580.40	10.83
16	42,025,547.79	47,997,483.53	14.21
17	44,656,505.90	48,246,758.23	8.04
18	43,080,307.66	48,301,906.52	12.12

[a] The average value of converted LP solutions prior to employing a heuristic method
[b] The average solution value after employing heuristic methods

Since this is a maximization problem, the highest average starting value (from the converted LP solutions) might be assumed to lead to the identification of the best average solution values (from the heuristic methods). However, this may not be the case, since the average solution value is not the only criteria to be considered when determining the best scenario. According to the results, scenario 12, the worst scenario, had the greatest improvement with 78.51%; however, this dramatic improvement was related to the low average starting point (Figure 3.3). Apart from that, the overall improvement rate changed between 2% to 15%. Scenario 7 and 16 also had a significant improvement with, respectively, 14.52% and 14.21%. The lowest improvement was made by scenario 3, 2.90%, which began with the highest average LP-converted solution and was one of the best overall scenarios after employing a heuristic method. The best scenario, scenario 9, had 4.45% improvement when the LP-converted solution value and the average final solution values are compared.

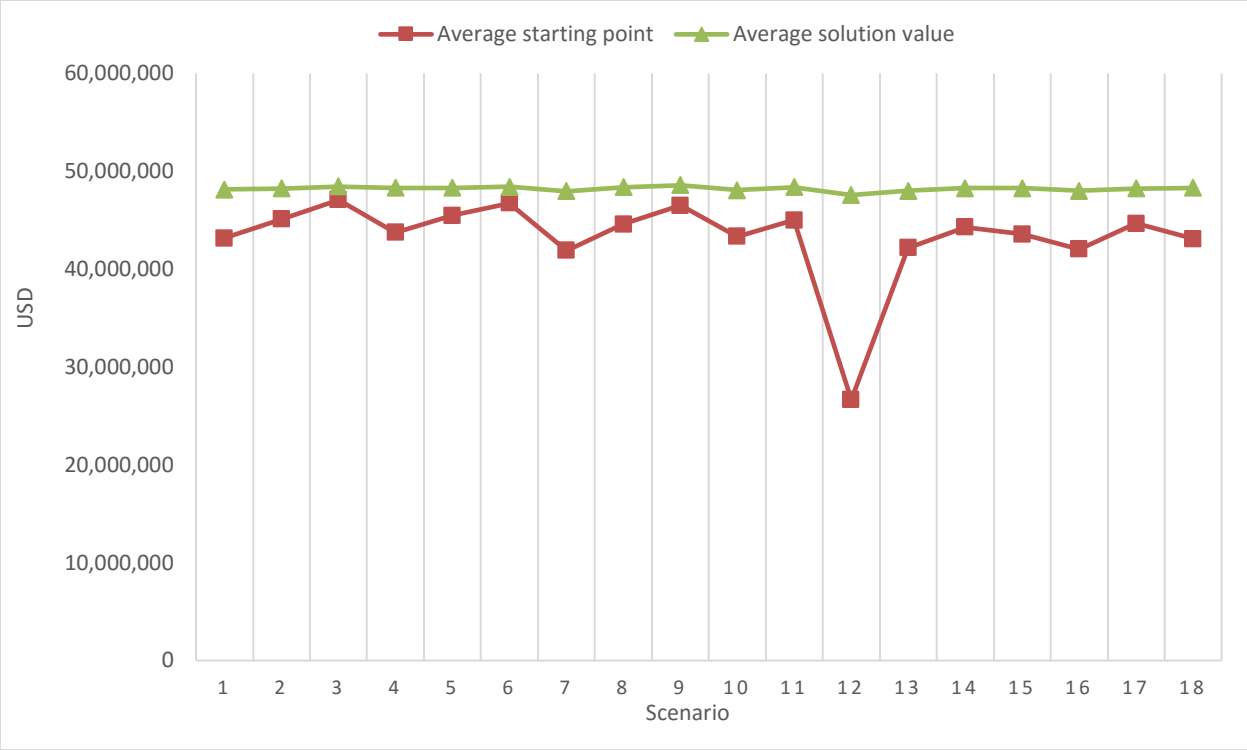

Figure 3.3. Graphical display of the change in objective function values using the southern forest and the threshold accepting method

With tabu search, the results followed exactly the same pattern observed with threshold accepting. The only difference was that tabu search provided better solutions (i.e., greater discounted net revenue plans). Scenario 18, as in threshold accepting, generated the highest quality forest plan as evidenced by the maximum objective function value ($49,535,229.30) (Table 3.9). However, to determine whether the scenario is the best overall, other results (the minimum and the average objective function value and standard deviation of solution values) should be considered, as stated before. After reviewing all the results, one can see that scenario 9 produced the best overall quality of forest plans, with the highest minimum and average objective function values, and the lowest standard deviation values. Scenario 3 and 6 were similar to scenario 9 with respect to some results (scenario 3 had a lower standard deviation than scenario 9); however, scenario 9 generated better solutions than those scenarios, in general.

Even though scenario 18 produced the best single solution (one of the 100 solutions generated), its standard deviation was the worst of all 19 scenarios.

Conversely, the random starting scenario produced the single worst forest plan, like in threshold accepting, with respect to the minimum objective function value ($46,520,319.38). The difference between the two heuristic methods was around $300,000.00, with tabu search providing higher valued plans. Thus, to decide the worst scenario, one should consider all of the results. Scenario 12 produced the lowest maximum and average objective function values, and the other parameters of this scenario were not very good. Hence, we can assume that scenario 12 was the worst scenario. For instance, there were no other scenarios that had average objective function values that were less than 48 million dollars (scenario 12 had $47,659,404.58). Scenario 18 had the greatest standard deviation value; however, it produced the greatest maximum objective function value, and its average objective function value was closer to the best one. Therefore, it might not be considered as one of the worst scenarios.

The improvement of the solutions using tabu search is similar to what was found using threshold accepting (Table 3.10). According to the table, the greatest improvement was made by scenario 12 (78.85%), yet this scenario had the lowest starting value (LP-converted solution value) and resulted in the worst solution values. Thus, this dramatic improvement was related to the lower level of starting point, as stated before.

Table 3.9. Southern study area tabu search results

Search process	Scenario	Reversion interval (iterations)	Minimum (worst) solution value (USD)	Maximum (best) solution value (USD)	Average solution value (USD)	Standard deviation of solution values (USD)	Average time required (second)
TS12	Random	10	46,520,319.38	48,829,873.16	48,033,847.00	395,190.14	472.14
TS12	1	10	48,115,883.56	48,659,807.60	48,214,693.44	86,652.96	401.37
TS12	2	10	47,892,165.46	49,123,557.82	48,521,671.26	240,819.84	407.95
TS12	3	10	48,583,237.29	48,908,084.74	48,741,390.37	63,874.09	347.81
TS12	4	10	48,394,524.70	48,902,282.61	48,649,500.83	73,560.75	361.81
TS12	5	10	47,968,040.74	49,158,983.58	48,702,316.54	251,468.11	356.92
TS12	6	10	48,530,225.28	48,809,183.25	48,594,807.59	72,114.62	360.66
TS12	7	10	47,927,934.78	48,654,048.06	48,302,656.94	180,134.18	416.93
TS12	8	10	48,014,850.52	49,440,653.27	48,723,061.28	223,739.18	404.84
TS12	9	10	48,780,900.74	49,091,994.09	48,901,040.99	82,880.10	402.49
TS12	10	10	48,488,193.58	48,868,645.97	48,619,135.30	89,130.96	377.63
TS12	11	10	46,749,298.19	49,194,867.71	48,612,551.82	386,117.44	401.76
TS12	12	10	47,290,314.12	48,058,752.33	47,659,404.58	181,409.92	448.16
TS12	13	10	47,605,926.59	49,203,968.76	48,448,601.31	309,650.75	399.34
TS12	14	10	47,549,522.07	49,477,223.24	48,637,703.81	319,274.47	390.12
TS12	15	10	47,318,796.68	49,443,485.74	48,603,588.08	434,292.87	394.78
TS12	16	10	47,590,277.39	49,312,710.70	48,464,947.02	334,080.50	384.43
TS12	17	10	47,928,059.22	49,432,291.66	48,660,461.08	311,555.19	389.28
TS12	18	10	46,895,406.76	49,535,229.30	48,562,296.63	483,040.82	379.87

The overall collection of tabu search results in the southern study area were significantly different at the level of *p=0.0001*. To assess the statistical relationships among the scenarios, we employed the Mann Whitney U test. According to the statistical tests, the results were parallel with the threshold accepting in southern study area. Scenario 9, which was the best scenario, was significantly different than all other scenarios (*p=0.0001*) which suggests plans generated by using scenario 9 were superior. The only difference in this data cluster was that the random starting scenario was also statistically different than all other scenarios. Thus, we can clearly state that it produced the worst solutions. Full results of these statistical analyses can be found in Appendix D.

Table 3.10. Change in the starting solution value for the southern forest problem, using the tabu search method

Scenario	Average starting point (USD)[a]	Average solution value (USD)[b]	Improvement (%)
1	43,174,323.68	48,214,693.44	11.67
2	44,893,229.83	48,521,671.26	8.08
3	47,066,249.64	48,741,390.37	3.56
4	43,748,685.53	48,649,500.83	11.20
5	46,096,746.53	48,702,316.54	5.65
6	46,743,236.22	48,594,807.59	3.96
7	41,897,253.21	48,302,656.94	15.29
8	44,693,109.05	48,723,061.28	9.02
9	46,495,203.93	48,901,040.99	5.17
10	43,339,193.42	48,619,135.30	12.18
11	44,005,691.40	48,612,551.82	10.47
12	26,647,086.23	47,659,404.58	78.85
13	42,156,285.69	48,448,601.31	14.93
14	44,458,112.25	48,637,703.81	9.40
15	43,445,093.77	48,603,588.08	11.87
16	42,135,118.82	48,464,947.02	15.02
17	44,666,858.61	48,660,461.08	8.94
18	41,777,075.19	48,562,296.63	16.24

[a] The average value of converted LP solutions prior to employing a heuristic method
[b] The average solution value after employing heuristic methods

The overall improvement of scenarios differed from 3% to 17% except scenario 12 (Figure 3.4). The greatest improvement was 16.24% by scenario 18, which had tolerable results when compared the other scenarios. The lowest improvement was made by the scenario 3, 3.56%, which was one of the best scenarios. The best scenario, scenario 9, had 5.17% improvement when considering the LP-converted solution value and the average final solution values are compared.

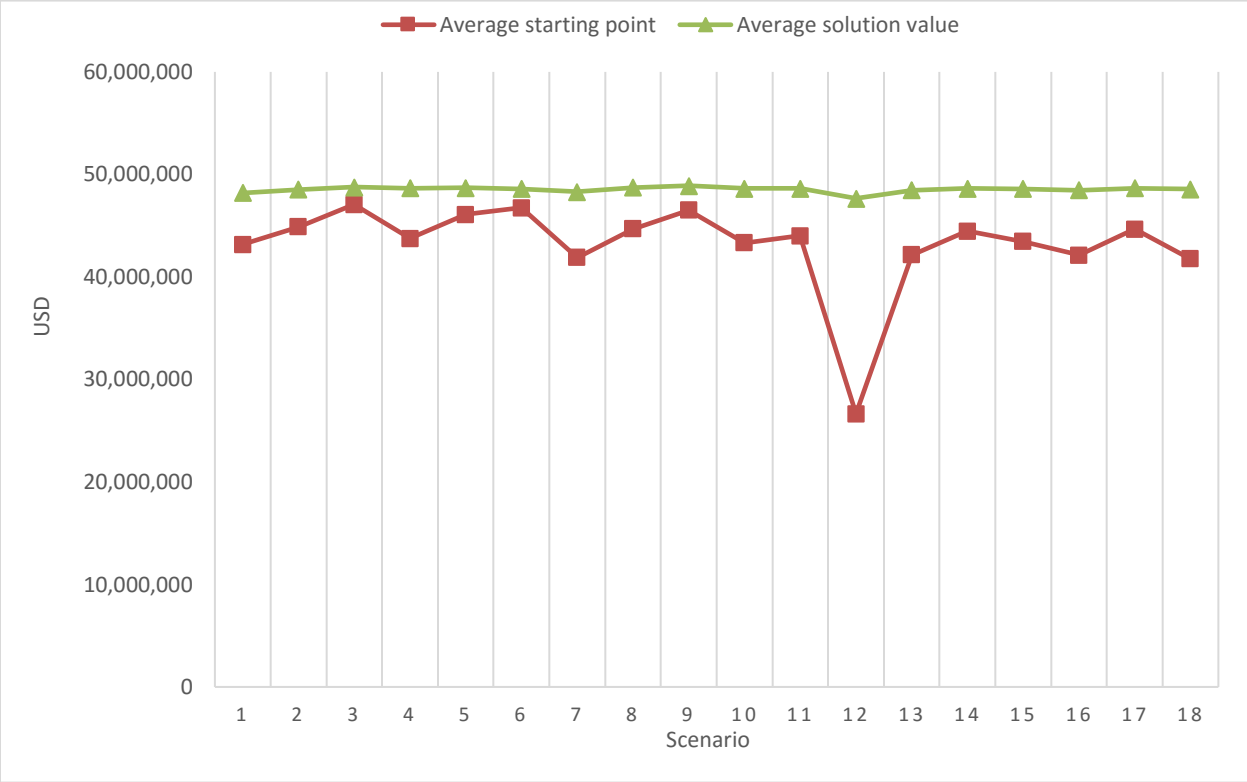

Figure 3.4. Graphical display of the change in objective function values using the southern forest and the tabu search method

When two heuristic methods were assessed by their improvement in LP-converted solution value, it can be noticed that some of the scenarios (scenario 1, 3, 4, 6, 7, 9, 10, 12) had the same LP-converted solution value (average starting point) in threshold accepting and tabu search. Since the conversion methods of those scenarios do not include any random feature (i.e.,

stand order, final harvest), the LP-converted solutions were the same in both methods. As a result of having the same starting points on these scenarios, the comparison between them might be more illustrative to understand how effective the heuristic algorithm was in generating solutions. Once those scenarios were compared, the tabu search made greater improvement than threshold accepting. However, this improvement was less than 1%, except scenario 10 where the improvement was 1.27%. If the improvement was presented by net present value, the least improvement, in scenario 1 (0.19%), corresponded to a $85,801.96 difference between tabu search and threshold accepting (tabu search is greater). On the other hand, the difference in net present value in scenario 10, in which the greatest improvement occurred, was $551,096.14. Lastly, these scenarios (not randomly started) included the best scenarios of each method, scenario 9, and the difference between their improvements was 0.72% that equaled to $336,165.10.

Compared to the tabu search results, threshold accepting results are not as good; however, scenario 9 stands out again as the best scenario. Unlike the results from the western study area, tabu search and threshold accepting methods generated solutions which were closer to each other in value. However, since the study area is larger, the difference, in objective function units, is also greater than the western study area. In order to understand that whether our assumption was correct, we employed a statistical test between the best, the worst and the random starting scenarios of the southern case study. The results indicated that the difference between the best scenarios for tabu search and threshold accepting was statistically significant at the level of $p=0.0001$. The difference between the worst scenarios was also statistically significant ($p=0.020$). Lastly, the random starting scenarios had statistically significant difference between each other ($p=0.0001$).

Based on the results, we attained better solutions by using converted linear programming solutions as starting points (seeds) for tabu search and threshold accepting. The results were both compared and corroborated by statistical tests. As a result, we reject our null hypothesis that heuristic solutions developed with a converted linear programming initial solution are no better than heuristic solutions developed when initiated from a random starting point.

When tabu search and threshold accepting methods are compared by computer processing time, one can see that the results, on the contrary, are not parallel with the solution values. While the tabu search solution values were better than the threshold accepting solutions, the average required computational time to solve the problem in tabu search is greater than what is required for threshold accepting (Table 3.7 and Table 3.9). However, these results may be highly associated with the programming logic employed and parameters chosen, as stated before. In the southern problem, threshold accepting solved the problem approximately ten times faster than tabu search, perhaps because the 1-opt and 2-opt neighborhoods are very large within tabu search. The required time might be changed by adjusting the search parameters; however, this may in turn affect the solution quality. The least required time for a single run in threshold accepting was 10.54 seconds in scenario 11. On the other hand, the best computer processing time (i.e., the least) for tabu search was 347.81 seconds. The results also indicated that the faster solutions were generated by the scenarios that initiated with relaxed (converted) linear solutions. The random starting scenarios had the greatest required computer processing time of each method, likely because these starting points were further away from the optimal solutions. In threshold accepting, the average required time was 84.60 seconds while it was 472.14 seconds with tabu search. Along with these results, one can conclude that scenarios initiated with a linear programming solution solve the problem faster than the random starting scenario in each method.

Therefore, we reject our null hypotheses that the required amount of time to solve a random starting scenario is not different than the time required for scenarios initiated with a relaxed linear solution.

Compared to the western problem, threshold accepting was faster in the southern problem while the required time was approximately the same for tabu search. The difference might be related to the parameters chosen and the constraints used in the problem, but more likely related to the size of the 1-opt and 2-opt neighborhoods within tabu search. However, the results, overall, are the same that relaxed linear solutions solved the problem faster than the random starting scenarios.

CHAPTER 4

DISCUSSION

Linear programming is often used to develop strategic and tactical forest plans. In general, spatial adjacency relationships are ignored in these problems. If these relationships are recognized, the problem is often solved in mixed integer programming. However, developing spatial adjacency relationships may be difficult in some large problems. Heuristic methods have been suggested to use for forest planning problems that involve complex spatial relationships for years. However, heuristic methods do not guarantee one can locate the global optimum solution for a problem even though they may solve the problem faster, and the final solution is relatively good. Traditional implementation of heuristics use random starting points. Here, we suggested a new approach to forestry to improve the quality of heuristic solutions by using a LP-converted solution as a starting point (i.e., a seed).

The purpose of initiating heuristics with a LP-converted solution is to understand whether this new approach provides closer solutions to the global optimum than the traditional method. The results indicated that the best scenarios in western and southern study areas were LP-converted scenarios for both tabu search and threshold accepting. Although the random starting scenario was better than some of the LP-converted scenarios, we found that the LP-converted solutions, in most cases, are better than the random starting solutions. For example, LP-converted scenarios produced the best solutions in western and southern study areas both in tabu search and threshold accepting. The similarity among the heuristic methods in each study area was that the scenarios which provided the best solutions were the same (scenario 4 for the

western and scenario 9 for the southern TS and TA). However, the ranking of the other scenarios, including the random starting one, did not follow the same order in each method. Therefore, the type of seeding process may be problem-specific.

Once the effect of the conversion methods on the solution quality is assessed, one can see that there is a certain pattern between the conversion scenarios and the study areas. The remarkable finding is that each study area provided their best results with the same conversion treatments (Table 4.1). Moreover, in the western study area, threshold accepting and tabu search produced their best solutions when the linear programming solution was converted from ascending stand order. On the other hand, they provided best solutions descending order in the southern study area. If there was a split final harvest assignment on linear programming solution, heuristics in the western study area handled the integer assignment by selecting majority assignment where the heuristics in the southern study area handled by unscheduling the stand. When the final harvest adjacency violation occurred, heuristic methods in the western study area generated high quality solutions by handling the integer assignment with unscheduling the stand. On the other hand, both methods in the southern study area preferred to handle the integer assignment by selecting next best assignment.

Table 4.1. Pattern between the conversion scenarios and solution quality

Study area	Method	Stand order	If a stand has a split final harvest assignment, how is the integer assignment handled?	If final harvest adjacency violations occur, how is the integer assignment for the stand handled?
Western	TA	Ascending	Select majority assignment	Unschedule the stand
	TS	Ascending	Select majority assignment	Unschedule the stand
Southern	TA	Descending	Unschedule the stand	Select next best assignment
	TS	Descending	Unschedule the stand	Select next best assignment

The interesting finding is that we generally obtained better results initiating the search with a relaxed (converted) linear initial solution before using the tabu search and the threshold accepting methods in both study areas. However, in the western study area, the difference between the results generated by the random starting solution and the best solutions generated using a converted linear programming solution as the initial solution were not statistically significant when using tabu search, while they were statistically significant when using threshold accepting. This conflicting result may be related to the fact that the random starting scenario in western tabu search was one of the better scenarios which was fairly close to the best LP-converted scenario. On the other hand, the random starting scenario led to one of the worst solutions in western threshold accepting. In the southern study area, the random starting scenario produced one of the two worst sets of results. Here, the random starting scenario was significantly different than other scenarios except scenario 12 ($p= 0.156$), which we suggested that the worst scenario for both tabu search and threshold accepting. Thus, we can confidently state that the LP-converted solutions produce better results than the random starting scenarios supporting the first alternative hypothesis.

Once the heuristic methods are compared, tabu search produced better solutions than threshold accepting. This finding is also consistent with Bettinger et al. (2015) who found that tabu search often provides better solutions than threshold accepting, when enhanced with 2-opt moves and a reversion process. The improvement of the solutions using threshold accepting is similar to what was found using tabu search in both study areas. One of the most striking findings is that when both sets of results are compared, the maximum objective function value (i.e., worst solution) generated by tabu search was better than the minimum objective function value (i.e., best solution) generated by threshold accepting in the western study area. However,

for practical purposes, the difference between the average solutions of tabu search and threshold accepting in western study area is about 12 MBF which is worth about $6,000. On the other hand, the difference between the best and the second best solution in the southern study area is about $50,000.

To test the second hypothesis of this study, the required amount of time to solve a random starting scenario is not different than the time required for scenarios initiated with a relaxed linear solution, the required computer processing times for each method were compared. Results show that the scenarios initiated with a relaxed linear solution are faster to process than the random starting scenario for each method in both study areas. A conflicting finding is that tabu search results required less time than threshold accepting in the western study area. This finding is a very interesting one because it is not consistent with Bettinger et al. (2015) where the parameters for the western study area were acquired. In their study, tabu search required more time than threshold accepting with the same parameters. On the other hand, in the southern study area, the results related to computer processing time are parallel with their study that tabu search requires more time than threshold accepting. The parameters selected, and the computer code developed, obviously affect the time efficiency of search process.

To validate our results, we applied the self-validation of the results (Level 2), used other heuristic solutions (Level 3,) and used mathematical programming techniques (Levels 5 and 6) as reported in Bettinger et al. (2009) to compare with our results. The results were confirmed that LP-converted scenarios provided better solutions. All three levels of validation, stated above, applied to the results in the western study area; however, Level 6 validation could not be applied to the southern study area results since the number of spatial constraints did not allow to create the mixed-integer programming problem.

The only drawback in our study is that some of the LP-converted scenarios always started at the same place (not a random starting point for a set of 100 runs) in some cases. We are violating the assumption of Los and Lardinois (1979) that the samples need to be started with a different starting point to be considered as an independent. However, there was some randomness in threshold accepting methods since it is a stochastic search algorithm, and tabu search also includes random tabu state that mitigates this problem. In addition, as a result of having the same starting points on some scenarios, the comparison between them might be more illustrative to understand how effective the different heuristic algorithms on the solutions. Once those scenarios were compared, the tabu search made greater improvement than threshold accepting in both study areas.

There have been many research publications that attempt to improve the use of heuristic methods in forest planning. Bettinger et al. (2015) presented a study related to the effects of the reversion rates and change options. Moreover, Jin et al. (2016) suggested locating optimal parameters for some of the heuristic algorithms used in forest planning problems before applying those methods. The contribution of this study is that a new approach (seeding), which improves the quality of heuristic solutions, was introduced. The next step for further research would be to explore how other heuristic methods work with LP-converted starting points. With the optimum parameters for these heuristic methods, initiated LP-converted solution can be processed, and the results may be compared with this study to understand which heuristic method works better with the initiated solution.

CHAPTER 5

CONCLUSIONS

This study examined whether there might be differences in heuristic-generated forest plans when the heuristic employed begins with a random solution or when it begins with a relaxed linear programming solution. Two hypothetical forests were modeled, representing southern and western U.S. forest conditions. Two management objectives were assumed: maximizing an even-flow of scheduled timber harvest, and maximizing net present value of scheduled management regimes. Each problem was subject to final harvest adjacency, green-up, and minimum harvest age constraints. The southern problem also includes wood flow constraints. For this purpose, we formulated adjacency constraints using the area restriction model (Murray, 1999). The objective of the study was to determine whether a new approach (initiating a heuristic with a high-quality solution) might provide better solutions than the traditional assumption (initiate a heuristic with a random solution). The results suggested that in some cases using LP-converted solution as a starting point to the heuristic methods can provide higher quality solutions than the traditional random start of heuristic methods. Some findings of the study were statistically significant with respect to the objective function quality of spatially-constrained forest planning problems.

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APPENDIX A

(A1) Results (*p* values) of Tests of Statistical Significance Between Scenarios in Western Study Area Tabu Search Method

SN	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0		0.000	0.003	0.000	0.154	0.762	0.872	0.025	0.356	0.839	0.576	0.337	0.357	0.000	0.002	0.001	0.860	0.975	0.482
1	0.000		0.301	0.147	0.000	0.000	0.000	0.008	0.000	0.000	0.000	0.000	0.000	0.159	0.071	0.189	0.000	0.000	0.000
2	0.003	0.301		0.959	0.000	0.010	0.002	0.272	0.026	0.005	0.001	0.000	0.001	0.967	0.563	0.799	0.006	0.003	0.020
3	0.000	0.147	0.959		0.000	0.000	0.000	0.047	0.000	0.000	0.000	0.000	0.000	0.508	0.500	0.914	0.000	0.000	0.000
4	0.154	0.000	0.000	0.000		0.068	0.068	0.000	0.008	0.058	0.232	0.398	0.397	0.000	0.000	0.000	0.082	0.126	0.015
5	0.762	0.000	0.010	0.000	0.068		0.773	0.065	0.482	0.945	0.513	0.292	0.301	0.003	0.011	0.010	0.981	0.749	0.696
6	0.872	0.000	0.002	0.000	0.068	0.773		0.016	0.274	0.730	0.603	0.328	0.309	0.000	0.001	0.001	0.858	0.967	0.354
7	0.025	0.008	0.272	0.047	0.000	0.065	0.016		0.182	0.047	0.005	0.002	0.003	0.188	0.434	0.314	0.037	0.027	0.112
8	0.356	0.000	0.026	0.000	0.008	0.482	0.274	0.182		0.471	0.112	0.042	0.057	0.009	0.034	0.029	0.387	0.285	0.818
9	0.839	0.000	0.005	0.000	0.058	0.945	0.730	0.047	0.471		0.347	0.208	0.212	0.001	0.004	0.004	0.841	0.687	0.630
10	0.576	0.000	0.001	0.000	0.232	0.513	0.603	0.005	0.112	0.347		0.710	0.662	0.000	0.000	0.001	0.536	0.678	0.213
11	0.337	0.000	0.000	0.000	0.398	0.292	0.328	0.002	0.042	0.208	0.710		0.922	0.000	0.000	0.000	0.328	0.443	0.073
12	0.357	0.000	0.001	0.000	0.397	0.301	0.309	0.003	0.057	0.212	0.662	0.922		0.000	0.000	0.000	0.367	0.491	0.090
13	0.000	0.159	0.967	0.508	0.000	0.003	0.000	0.188	0.009	0.001	0.000	0.000	0.000		0.649	0.932	0.001	0.001	0.004
14	0.002	0.071	0.563	0.500	0.000	0.011	0.001	0.434	0.034	0.004	0.000	0.000	0.000	0.649		0.709	0.005	0.003	0.016
15	0.001	0.189	0.799	0.914	0.000	0.010	0.001	0.314	0.029	0.004	0.001	0.000	0.000	0.932	0.709		0.006	0.003	0.013
16	0.860	0.000	0.006	0.000	0.082	0.981	0.858	0.037	0.387	0.841	0.536	0.328	0.367	0.001	0.005	0.006		0.773	0.571
17	0.975	0.000	0.003	0.000	0.126	0.749	0.967	0.027	0.285	0.687	0.678	0.443	0.491	0.001	0.003	0.003	0.773		0.437
18	0.482	0.000	0.020	0.000	0.015	0.696	0.354	0.112	0.818	0.630	0.213	0.073	0.090	0.004	0.016	0.013	0.571	0.437	

SN= Scenario number

(A2) Symbolical Representation of Tests of Statistical Significance

SN	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0		✓	✓	✓	×	×	×	✓	×	×	×	×	×	✓	✓	✓	×	×	×
1	✓		×	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×	×	✓	✓	✓
2	✓	×		×	✓	✓	✓	×	✓	✓	✓	✓	✓	×	×	×	✓	✓	✓
3	✓	×	×		✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×	×	✓	✓	✓
4	×	✓	✓	✓		×	×	✓	✓	✓	×	×	×	✓	✓	✓	×	×	✓
5	×	✓	✓	✓	×		×	×	×	×	×	×	×	✓	✓	✓	×	×	×
6	×	✓	✓	✓	×	×		✓	×	×	×	×	×	✓	✓	✓	×	×	×
7	✓	✓	×	✓	✓	×	✓		×	✓	✓	✓	✓	×	×	×	✓	✓	×
8	×	✓	✓	✓	✓	×	×	×		×	×	✓	×	✓	✓	✓	×	×	×
9	×	✓	✓	✓	✓	×	×	✓	×		×	×	×	✓	✓	✓	×	×	×
10	×	✓	✓	✓	×	×	×	✓	×	×		×	×	✓	✓	✓	×	×	×
11	×	✓	✓	✓	×	×	×	✓	✓	×	×		×	✓	✓	✓	×	×	×
12	×	✓	✓	✓	×	×	×	✓	×	×	×	×		✓	✓	✓	×	×	×
13	✓	×	×	×	✓	✓	✓	×	✓	✓	✓	✓	✓		×	×	✓	✓	✓
14	✓	×	×	×	✓	✓	✓	×	✓	✓	✓	✓	✓	×		×	✓	✓	✓
15	✓	×	×	×	✓	✓	✓	×	✓	✓	✓	✓	✓	×	×		✓	✓	✓
16	×	✓	✓	✓	×	×	×	✓	×	×	×	×	×	✓	✓	✓		×	×
17	×	✓	✓	✓	×	×	×	✓	×	×	×	×	×	✓	✓	✓	×		×
18	×	✓	✓	✓	✓	×	×	×	×	×	×	×	×	✓	✓	✓	×	×	

SN= Scenario number
✓=Significant difference ($p \leq 0.05$)
×= No significant difference

APPENDIX B

(B1) Results (*p* values) of Tests of Statistical Significance Between Scenarios in Western Study Area Threshold Accepting Method

SN	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0		0.949	0.009	0.365	0.002	0.043	0.001	0.479	0.214	0.938	0.011	0.000	0.021	0.194	0.420	0.113	0.004	0.002	0.018
1	0.949		0.016	0.349	0.003	0.051	0.002	0.535	0.224	0.895	0.013	0.001	0.031	0.179	0.467	0.138	0.005	0.002	0.026
2	0.009	0.016		0.084	0.872	0.816	0.694	0.003	0.251	0.028	0.805	0.392	0.845	0.231	0.112	0.291	0.837	0.520	0.680
3	0.365	0.349	0.084		0.036	0.200	0.016	0.118	0.599	0.468	0.101	0.006	0.147	0.577	0.932	0.506	0.038	0.019	0.139
4	0.002	0.003	0.872	0.036		0.635	0.729	0.000	0.174	0.009	0.629	0.429	0.680	0.123	0.039	0.156	0.893	0.611	0.630
5	0.043	0.051	0.816	0.200	0.635		0.548	0.013	0.430	0.084	0.957	0.233	0.951	0.410	0.240	0.569	0.606	0.395	0.969
6	0.001	0.002	0.694	0.016	0.729	0.548		0.000	0.121	0.007	0.401	0.705	0.503	0.089	0.028	0.099	0.860	0.782	0.429
7	0.479	0.535	0.003	0.118	0.000	0.013	0.000		0.100	0.482	0.003	0.000	0.007	0.063	0.151	0.030	0.001	0.001	0.006
8	0.214	0.224	0.251	0.599	0.174	0.430	0.121	0.100		0.343	0.398	0.048	0.398	0.975	0.705	0.932	0.177	0.081	0.419
9	0.938	0.895	0.028	0.468	0.009	0.084	0.007	0.482	0.343		0.040	0.002	0.058	0.332	0.509	0.189	0.015	0.006	0.048
10	0.011	0.013	0.805	0.101	0.629	0.957	0.401	0.003	0.398	0.040		0.227	0.963	0.336	0.113	0.352	0.546	0.318	0.990
11	0.000	0.001	0.392	0.006	0.429	0.233	0.705	0.000	0.048	0.002	0.227		0.264	0.027	0.010	0.039	0.558	0.899	0.229
12	0.021	0.031	0.845	0.147	0.680	0.951	0.503	0.007	0.398	0.058	0.963	0.264		0.365	0.185	0.431	0.606	0.395	0.907
13	0.194	0.179	0.231	0.577	0.123	0.410	0.089	0.063	0.975	0.332	0.336	0.027	0.365		0.649	0.882	0.126	0.068	0.341
14	0.420	0.467	0.112	0.932	0.039	0.240	0.028	0.151	0.705	0.509	0.113	0.010	0.185	0.649		0.511	0.058	0.028	0.183
15	0.113	0.138	0.291	0.506	0.156	0.569	0.099	0.030	0.932	0.189	0.352	0.039	0.431	0.882	0.511		0.181	0.076	0.456
16	0.004	0.005	0.837	0.038	0.893	0.606	0.860	0.001	0.177	0.015	0.546	0.558	0.606	0.126	0.058	0.181		0.655	0.569
17	0.002	0.002	0.520	0.019	0.611	0.395	0.782	0.001	0.081	0.006	0.318	0.899	0.395	0.068	0.028	0.076	0.655		0.297
18	0.018	0.026	0.680	0.139	0.630	0.969	0.429	0.006	0.419	0.048	0.990	0.229	0.907	0.341	0.183	0.456	0.569	0.297	

SN= Scenario number

(B2) Symbolical Representation of Tests of Statistical Significance

SN	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0		×	✓	×	✓	✓	✓	×	×	×	✓	✓	✓	×	×	×	✓	✓	✓
1	×		✓	×	✓	×	✓	×	×	×	✓	✓	✓	×	×	×	✓	✓	✓
2	✓	✓		×	×	×	×	✓	×	✓	×	×	×	×	×	×	×	×	×
3	×	×	×		✓	×	✓	×	×	×	×	✓	×	×	×	×	✓	✓	×
4	✓	✓	×	✓		×	×	✓	×	✓	×	×	×	×	✓	×	×	×	×
5	✓	×	×	×	×		×	✓	×	×	×	×	×	×	×	×	×	×	×
6	✓	✓	×	✓	×	×		✓	×	✓	×	×	×	×	✓	×	×	×	×
7	×	×	✓	×	✓	✓	✓		×	×	✓	✓	✓	×	×	✓	✓	✓	✓
8	×	×	×	×	×	×	×	×		×	×	✓	×	×	×	×	×	×	×
9	×	×	✓	×	✓	×	✓	×	×		✓	✓	×	×	×	×	✓	✓	✓
10	✓	✓	×	×	×	×	×	✓	×	✓		×	×	×	×	×	×	×	×
11	✓	✓	×	✓	×	×	×	✓	✓	✓	×		×	✓	✓	✓	×	×	×
12	✓	✓	×	×	×	×	×	✓	×	×	×	×		×	×	×	×	×	×
13	×	×	×	×	×	×	×	×	×	×	×	✓	×		×	×	×	×	×
14	×	×	×	×	✓	×	✓	×	×	×	×	✓	×	×		×	×	✓	×
15	×	×	×	×	×	×	×	✓	×	×	×	✓	×	×	×		×	×	×
16	✓	✓	×	✓	×	×	×	✓	×	✓	×	×	×	×	×	×		×	×
17	✓	✓	×	✓	×	×	×	✓	×	✓	×	×	×	×	✓	×	×		×
18	✓	✓	×	×	×	×	×	✓	×	✓	×	×	×	×	×	×	×	×	

SN= Scenario number
✓=Significant difference ($p \leq 0.05$)
×= No significant difference

APPENDIX C

(C1) Results (*p* values) of Tests of Statistical Significance Between Scenarios in Southern Study Area Threshold Accepting Method

SN	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.156	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000		0.003	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.139	0.000	0.000	0.002	0.001	0.000	0.003	0.004	0.000
2	0.000	0.003		0.000	0.089	0.054	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.420	0.012	0.000	0.740	0.068
3	0.000	0.000	0.000		0.000	0.000	0.635	0.000	0.058	0.000	0.000	0.068	0.000	0.000	0.000	0.274	0.000	0.000	0.085
4	0.000	0.000	0.089	0.000		0.582	0.000	0.000	0.036	0.000	0.000	0.021	0.000	0.000	0.594	0.062	0.000	0.346	0.436
5	0.000	0.000	0.054	0.000	0.582		0.003	0.000	0.125	0.000	0.000	0.124	0.000	0.000	0.387	0.281	0.000	0.176	0.703
6	0.000	0.000	0.000	0.635	0.000	0.003		0.000	0.167	0.000	0.000	0.193	0.000	0.000	0.001	0.524	0.000	0.000	0.147
7	0.000	0.001	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.058	0.000	0.000	0.658	0.000	0.000	0.745	0.000	0.000
8	0.000	0.000	0.001	0.058	0.036	0.125	0.167	0.000		0.000	0.000	0.914	0.000	0.000	0.043	0.994	0.000	0.009	0.522
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10	0.000	0.139	0.000	0.000	0.000	0.000	0.000	0.058	0.000	0.000		0.000	0.000	0.161	0.000	0.000	0.134	0.000	0.000
11	0.000	0.000	0.000	0.068	0.021	0.124	0.193	0.000	0.914	0.000	0.000		0.000	0.000	0.032	0.940	0.000	0.007	0.502
12	0.156	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000
13	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.658	0.000	0.000	0.161	0.000	0.000		0.000	0.000	0.889	0.000	0.000
14	0.000	0.001	0.420	0.000	0.594	0.387	0.001	0.000	0.043	0.000	0.000	0.032	0.000	0.000		0.158	0.000	0.699	0.462
15	0.000	0.000	0.012	0.274	0.062	0.281	0.524	0.000	0.994	0.000	0.000	0.940	0.000	0.000	0.158		0.000	0.052	0.742
16	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.745	0.000	0.000	0.134	0.000	0.000	0.889	0.000	0.000		0.000	0.000
17	0.000	0.004	0.740	0.000	0.346	0.176	0.000	0.000	0.009	0.000	0.000	0.007	0.000	0.000	0.699	0.052	0.000		0.177
18	0.000	0.000	0.068	0.085	0.436	0.703	0.147	0.000	0.522	0.000	0.000	0.502	0.000	0.000	0.462	0.742	0.000	0.177	

SN= Scenario number

(C2) Symbolical Representation of Tests of Statistical Significance

SN	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓
1	✓		✓	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓
2	✓	✓		✓	×	×	✓	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	×	×
3	✓	✓	✓		✓	✓	×	✓	×	✓	✓	×	✓	✓	✓	×	✓	✓	×
4	✓	✓	×	✓		×	✓	✓	✓	✓	✓	✓	✓	✓	×	×	✓	×	×
5	✓	✓	×	✓	×		✓	✓	×	✓	✓	×	✓	✓	×	×	✓	×	×
6	✓	✓	✓	×	✓	✓		✓	×	✓	✓	×	✓	✓	✓	×	✓	✓	×
7	✓	✓	✓	✓	✓	✓	✓		✓	✓	×	✓	✓	×	✓	✓	×	✓	✓
8	✓	✓	✓	×	✓	×	×	✓		✓	✓	×	✓	✓	✓	×	✓	✓	×
9	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
10	✓	×	✓	✓	✓	✓	✓	×	✓	✓		✓	✓	×	✓	✓	×	✓	✓
11	✓	✓	✓	×	✓	×	×	✓	×	✓	✓		✓	✓	✓	×	✓	✓	×
12	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓
13	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	×	✓	✓		✓	✓	×	✓	✓
14	✓	✓	×	✓	×	×	✓	✓	✓	✓	✓	✓	✓	✓		×	✓	×	×
15	✓	✓	✓	×	×	×	×	✓	×	✓	✓	×	✓	✓	×		✓	×	×
16	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	×	✓	✓	×	✓	✓		✓	✓
17	✓	✓	×	✓	×	×	✓	✓	✓	✓	✓	✓	✓	✓	×	×	✓		×
18	✓	✓	×	×	×	×	×	✓	×	✓	✓	×	✓	✓	×	×	✓	×	

SN= Scenario number
✓=Significant difference ($p \leq 0.05$)
×= No significant difference

APPENDIX D

(D1) Results (*p* values) of Tests of Statistical Significance Between Scenarios in Southern Study Area Tabu Search Method

SN	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000		0.000	0.000	0.000	0.010	0.000	0.000	0.000	0.002	0.000	0.000	0.077	0.001	0.009	0.129	0.001	0.030
3	0.000	0.000	0.000		0.000	0.242	0.000	0.000	0.369	0.000	0.000	0.006	0.000	0.000	0.075	0.009	0.000	0.017	0.009
4	0.000	0.000	0.000	0.000		0.011	0.000	0.000	0.008	0.000	0.000	0.289	0.000	0.000	0.330	0.914	0.000	0.386	0.994
5	0.000	0.000	0.000	0.242	0.011		0.000	0.000	0.714	0.000	0.001	0.207	0.000	0.000	0.221	0.166	0.000	0.270	0.088
6	0.000	0.000	0.010	0.000	0.000	0.000		0.000	0.000	0.000	0.103	0.007	0.000	0.000	0.018	0.112	0.000	0.036	0.069
7	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
8	0.000	0.000	0.000	0.369	0.008	0.714	0.000	0.000		0.000	0.000	0.086	0.000	0.000	0.111	0.099	0.000	0.161	0.070
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10	0.000	0.000	0.002	0.000	0.000	0.001	0.103	0.000	0.000	0.000		0.050	0.000	0.000	0.086	0.261	0.000	0.124	0.318
11	0.000	0.000	0.000	0.006	0.289	0.207	0.007	0.000	0.086	0.000	0.050		0.000	0.000	0.975	0.803	0.000	0.916	0.653
12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000
13	0.000	0.000	0.077	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.738	0.000	0.003
14	0.000	0.000	0.001	0.075	0.330	0.221	0.018	0.000	0.111	0.000	0.086	0.975	0.000	0.000		0.813	0.000	0.830	0.589
15	0.000	0.000	0.009	0.009	0.914	0.166	0.112	0.000	0.099	0.000	0.261	0.803	0.000	0.000	0.813		0.001	0.658	0.751
16	0.000	0.000	0.129	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.738	0.000	0.001		0.000	0.007
17	0.000	0.000	0.001	0.017	0.386	0.270	0.036	0.000	0.161	0.000	0.124	0.916	0.000	0.000	0.830	0.658	0.000		0.379
18	0.000	0.000	0.030	0.009	0.994	0.088	0.069	0.000	0.070	0.000	0.318	0.653	0.000	0.003	0.589	0.751	0.007	0.379	

SN= Scenario number

(D2) Symbolical Representation of Tests of Statistical Significance

SN	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	×	✓	✓
3	✓	✓	✓		✓	×	✓	✓	×	✓	✓	✓	✓	✓	×	✓	✓	✓	✓
4	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	×	✓	✓	×	×	✓	×	×
5	✓	✓	✓	×	✓		✓	✓	×	✓	✓	×	✓	✓	×	×	✓	×	×
6	✓	✓	✓	✓	✓	✓		✓	✓	✓	×	✓	✓	✓	✓	×	✓	✓	×
7	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
8	✓	✓	✓	×	✓	×	✓	✓		✓	✓	×	✓	✓	×	×	✓	×	×
9	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
10	✓	✓	✓	✓	✓	✓	×	✓	✓	✓		✓	✓	✓	×	×	✓	×	×
11	✓	✓	✓	✓	×	×	✓	✓	×	✓	✓		✓	✓	×	×	✓	×	×
12	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓
13	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	×	✓	✓
14	✓	✓	✓	×	×	×	✓	✓	×	✓	×	×	✓	✓		×	✓	×	×
15	✓	✓	✓	✓	×	×	×	✓	×	✓	×	×	✓	✓	×		✓	×	×
16	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	✓	✓		✓	✓
17	✓	✓	✓	✓	×	×	✓	✓	×	✓	×	×	✓	✓	×	×	✓		×
18	✓	✓	✓	✓	×	×	×	✓	×	✓	×	×	✓	✓	×	×	✓	×	

SN= Scenario number
✓=Significant difference ($p \leq 0.05$)
×= No significant difference