AN ABSTRACT OF THE THESIS OF

Brian K. Sharer for the degree of Master of Science in Forest Resources presented July 30, 1999. Title: Heuristic Solution Techniques for a Spatial Harvest Scheduling Problem Involving Wildlife Habitat and Timber Income.

Abstract approved:______________________________________

J. Douglas Brodie

Three heuristic techniques: simulated annealing (SA), tabu search (TS), and tabu search with strategic oscillation (TSSO), were used to schedule silvicultural activities designed to accelerate development of older forest structure at both stand and landscape scales over a 2450 acre forest located in northwestern Oregon. Goals for the forest over a 100-year planning horizon included reaching at least 500 acres of older forest structure with at least one contiguous 200-acre (or larger) block as soon as possible. The configuration and location, but not the amounts, of the older forest structure acres and the contiguous block were then free to move about the forest through time while best meeting the goal of producing a high, steady revenue flow over the entire planning horizon subject to restrictions on maximum clearcut patch size.

The heuristic techniques were able to provide feasible tactical schedules fulfilling the strategic goals over the entire horizon in ways which traditional forest

planning tools cannot. Of the three techniques examined, TSSO produced schedules with the best, most consistent objective function values. SA yielded a wider range of values which were always slightly worse but required only a fraction of the computing time. Straightforward TS produced relatively poor objective function values, most likely because of its inability to search the infeasible regions of the diverse solution space. Estimation of the globally optimal objective function value using Weibull distributions suggested that all TSSO solutions were within 1.8% of the optimum, the best being within .03%, while all SA solutions were within 7.6%, the best being within 1.7%. However, 95% confidence intervals of the Weibull location parameter estimates for the SA and TSSO distributions did not overlap, despite the fact that both distributions of results failed to be rejected as fitting a Weibull distribution. This disparity again suggests that statistical inference by itself of global optima for heuristic results may be an inadequate means of assessing how "good" a heuristic is.

Heuristic Solution Techniques for a Spatial Harvest Scheduling Problem Involving Wildlife Habitat and Timber Income

by

Brian K. Sharer

A THESIS

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Science

Presented July 30, 1999
Commencement June 2000

Master of Science thesis of Brian K. Sharer presented on July 30, 1999.

APPROVED:

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Major Pro

Redacted for privacy

Chair of Department of Forest Resources

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

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Brian K. Sharer, Author

ACKNOWLEDGMENTS

This research would not have been possible without the help of many people. Dr. John Sessions developed the framework for the harvest scheduling model and the simulated annealing algorithm to solve it. Without his original work, guidance, effort, and help along the way, it is safe to say this thesis research would not even have been attempted. Debora Johnson and Janet Ross of the College of Forestry Research Forests staff worked tirelessly to generate, update, modify, and organize the prescription, inventory, GIS, and cost data during the development of the Blodgett Plan, and provided me with invaluable assistance in understanding, organizing, and interpreting the prescription data with which the harvest scheduling models were run. I would especially like to thank my advisor, Dr. Doug Brodie, for his constant support and guidance in allowing me the opportunity to acquire skills and do research in this fascinating field. I thank Dr. Darius Adams, my original advisor at Oregon State, for first giving me an opportunity here as a student, and for being a reliable source of expert information on all matters economic through my time here. Dr. Claire Montgomery helped me through a transitional time with funding support and an interesting summer project, for which I am very grateful. Dr. Pete Bettinger provided valuable advice, software (and hardware!) loans to assist me in understanding validation of heuristics through extreme value theory. Finally, I would like to thank the ever-changing community of graduate students I worked with during my time here in the Harris Computer Laboratory and elsewhere for putting up with me and my griping all these years.

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INTRODUCTION

Overview

The purpose of this research is to develop and demonstrate methodologies that can assist forest managers in making tactical harvest plans which require explicit and complex spatial and temporal detail. As social and potentially legal pressures to include wildlife habitat and other amenity considerations in forest planning increase, managers need to understand and be able to demonstrate how these requirements will be met through time on a landscape scale and to do so in ways that best meet the objectives of stakeholders. For individuals, firms, or public agencies attempting to maximize profits while fulfilling legal requirements and other initiatives to reduce habitat impacts of harvesting practices, piecemeal harvest planning may be impractical and financially risky. Improper planning may leave unnecessarily large areas of timberland unavailable for current and/or future harvest due to the spatial constraints imposed by regulations (Boston 1996). For some industrial and public land managers, demonstrating how scheduled management activities will affect landscape characteristics through time will likely become increasingly important. Under recently adopted California law, for instance, large landowners are required to develop long-term sustained yield plans which address, among other things, the habitat needs- including patch size, patch shape, and distribution of habitat- of threatened, endangered, and sensitive plants and their relation to growth and yield projections and harvest schedules (Boston 1996). Recent threatened species listings of the marbled murrelet, *Branchyrampus mamoratus,* and the northern spotted owl, *Strix occidentalis*, have prompted some large landowners, such as the State of Oregon, to develop habitat conservation plans which consider the spatial arrangement of forest stands through time to promote the development of desirable wildlife habitat on a landscape scale to mitigate negative impacts of harvesting (Oregon Department of Forestry 1998a 1998b).

The recently completed Blodgett Forest Plan (Oregon State University Research Forests 1999) represents an attempt to show how wildlife associated with older forest stands in the Pacific Northwest might be considered in a framework of active commercial management. The Plan's mission is to "develop the Blodgett Tract as a biologically diverse and sustainable forest to demonstrate efficient timber production under a non-reserve based strategy" (Oregon State University Research Forests 1999 p. 5). To fulfill this mission, specific management objectives were formulated by the Blodgett planning team which defined measurable levels of achievement at both the stand and forest (landscape) level. These levels formed the goals and constraints of the harvest scheduling model described in this thesis. The modeling framework, and the solution methods described herein, represent a methodology for forest planning with complex spatial and temporal detail that might be required in many different scenarios. This introductory chapter attempts first to synthesize the rationale and context of the stand and landscape goals developed for this particular plan. Traditional forest planning tools, it turns out, are insufficient for accurate financial and tactical analysis of long-term forest plans such as the Blodgett plan which have detailed spatial and temporal requirements, or for projecting the effects of management activities on the landscape through time. Newer approaches to handling complex combinatorial problems with applications to forest management are then presented as an alternative, including the heuristic solution techniques used in this research and methods available to validate their performance.

Wildlife potential of commercially managed forests

Background

In western Oregon, the wildlife species that are currently of prominent concern from a forest management perspective are those associated with old growth stands and stands that have key structural and compositional attributes of old growth (Oregon Department of Forestry 1998a). These structures include large trees of several species, vertical and horizontal heterogeneity within and among stands, large snags and logs, and deep forest floor litter (Ruggiero 1991). At the landscape scale, wildlife species associated with mature forest type differ in spatiotemporal habitat requirements, but their natural histories in the Pacific Northwest are reported to be associated with conditions of an older forest matrix (perhaps 40-60% of the landscape) where disturbance resulting in stand replacement typically occurred on intervals of 150-500 years (Hansen et al. 1995, McComb et al. 1993). In these conditions, stand-replacing disturbance was uneven in intensity, timing, and scale, leaving a mosaic of stands in differing age and size, the largest single component being old growth (Hansen et al. 1991).

In contrast, relatively little forest with late seral stage characteristics remains on nonfederal lands in western Oregon (Oregon Department of Forestry 1998b). Many commercially managed stands in western Oregon and the rest of the Pacific Northwest contain few tree species, are managed on short rotations with high tree density and slow diameter growth, have a single canopy layer with little or no understory, and contain few snags and little down woody debris (Curtis and Carey 1996; Hayes et al. 1997). If left to develop naturally as reserves, many stands currently under commercial management in the Pacific Northwest could require an exceedingly long time span to provide structural and compositional features used by species associated with older forest structure (Carey et al. 1996, Curtis and Carey 1996, Carey and Curtis 1996). It is possible that some currently very densely stocked stands will never achieve old-growth conditions (Tappeiner et al. 1997). Reserve-based approaches to wildlife habitat provision can be very costly, and fear of impending regulatory activity to protect late seral stage species can act as an incentive to remove timber that may have provided habitat on private land (Lippke et al. 1996, Greber 1990).

Stand-level potential of commercially managed forest

The prohibitive costs of reserve based systems and long times necessary to reach stands with late seral stage structure has prompted inquiry into accelerated habitat possibilities of the mainly early and mid-seral stage (0-50 years old) forests that comprise most state and private lands. With the hypothesis that wildlife may respond primarily to stand structure, not stand age (Hayes etal. 1997), these studies have suggested that active commercial management might produce stand structure with more features typical of older forest stands at an accelerated rate in young stands. Extended rotations (> 70 years) have been proposed in combination with commercial thinning activity to produce stands with larger trees and deep crowns (Curtis and Marshall 1993; Carey et al. 1996; Hayes et al. 1997; Barbour et al. 1997). In these scenarios, commercial thinning acts to increase diameter growth in remaining trees which, with minimum understory shrub cover, allows coniferous understory development and the growth of multiple age cohorts. Combined with active snag recruitment and management of legacy structures, silvicultural prescriptions utilizing commercial thinning have been simulated and found to produce structural and compositional patterns typical of older forests at a greatly reduced time scale. Economic loss associated with the longer rotation ages of these regimes is in part mitigated by the larger amounts and quality of wood that results at harvest and by greater volume and financial returns compared to reserve-based systems (Lippke et al. 1996; Barbour et al. 1997).

As an example of this approach, McComb et al. (1993) developed and simulated prescriptions for a prototypical young managed plantation with high stocking (319 tpa) that featured active snag recruitment and a heavy thinning to 81 tpa at age 40 and additional thinning from below at age 90. At stand age 115, they found predicted similarity in diameter distribution between the manipulated plantation stand and an unmanaged 300-year old stand was 79%, using an adaptation of Morisita's community similarity index (McComb et al. 1993). Carey et al. (1996) modeled prescriptions for the Western Olympic peninsula in Washington that were able to create functional old-growth habitat characteristics in as little as 70 to 90 years on high site lands. These "biodiversity management pathways" featured precommercial thinning to forestall early canopy closure, early heavy commercial thinnings (age 30) to maintain tree growth and promote understory development, and subsequent variable-density thinnings to further increase diameter growth and add coarse woody debris to the ecosystem. Less intensive site preparation and snag, woody debris, and understory hardwood retention were also components of these pathways. Different commercial thinning regimes were also modeled in this study. These simulations showed increased understory development relative to similarly-aged PCT-only rotations (Carey et al. 1996). In a western Oregon example, Barbour et al. (1997) modeled Douglas-fir (Pseudotsuga mensziesii) regimes featuring early heavy thinnings at 15 (PCT) and 30 (CT) years and found that tree diameter, crown depth, and limb diameter, all positively correlated with older forest structure, were greatly increased at 80 and 100 years relative to unthinned treatments.

Although theory and these simulation results suggest that thinning will accelerate the development of characteristics typical of older forests, empirical studies are limited. Recently, in studies in western Oregon, Hayes et al. (1998) found that while the numbers of a few wildlife species declined in the first few years following commercial thinning, others increased, and none were extirpated. Newton and Cole (1987) studied two Douglas-fir stands (120 and 140 years of age) of natural fire origin that were selectively logged in 1914 to residual densities of 31 and 29 tpa, respectively, and had hardwoods killed standing in 1959. They found that average stand diameter was 7.5 and 10.8 inches greater than the largest diameters of trees in a normal stand of the same age and that neither mean annual increment nor periodic annual increment had culminated.

Landscape-level potential of commercially managed forest

While stand-level approaches using thinning to create habitat more favorable to wildlife species associated with later seral stage conditions are well established theoretically and through simulation modeling, few concrete ideas exist for methods of providing older habitat on a landscape scale. Although older forest structure is considered generally in shortest supply, the range, amounts, and configuration of older forest structure through time needed within a landscape to achieve optimal levels of biodiversity is poorly understood (Hunter 1997). Recent approaches have suggested designing landscapes based on historical patterns with special attention to maintaining or enhancing interior forest habitat area in older forest conditions and the habitat needs of species at higher risk of extinction (Hunter 1990; Cissel et al. 1998; Oregon Department of Forestry 1998b).

In the draft Western Oregon State Forests Habitat Conservation Plan, the Oregon Department of Forestry applied the concept of more closely matching the historical composition of stand types across the landscape. To promote biodiversity consistent with their other goals, they proposed a landscape design whereby targeted percentages of forest stands in different structural conditions were to be developed on state forest lands as quickly as possible and maintained in these percentages more or less for perpetuity. The proposed percentages of older forest structure, to be achieved through active silvicultural manipulation, were designed to more closely approximate historical conditions. Once the targeted percentages are achieved,

> "...individual stands on the landscape will continue to change once the range of stand types in the targeted amounts is achieved, but at that point, the relative abundance of the types will be reasonably stable. At some point decades or centuries in the future, a dynamic balance will be achieved of the stand types in the desired percentages, and individual stands will move into and out of the various structure types at a relatively even rate." (Oregon Department of Forestry 1998b, p. IV-8)

Under this scenario, a 20-year time scale for moving blocks of habitat was suggested, where older forest structure stands could "blink" on and off across the landscape provided overall patch goals were met over the landscape consistent with other goals during the planning horizon (Oregon Department of Forestry 1998a; Oregon Department of Forestry 1998b). An independent scientific review of this proposed landscape plan questioned if this strategy would be adequate for late seral stage species with limited vagility such as salamanders and lichens. These species may not be able to disperse to new areas of older forest structure in response to its positional change on the landscape in such a short time period. As an alternative approach, one reviewer suggested that "anchors" of older forest structure be used for such species to provide adequate interior habitat and longer time to disperse to new areas. These "anchors" would consist of contiguous older forest structure stands that remained this way longer than 20 years (Hayes 1998).

Forest planning for wildlife habitat

Introduction

Planning for forest landscape designs favorable to wildlife habitat is a relatively new concept in forest management coinciding with concepts in landscape ecology that have developed over the last two decades. Such planning requires detailed spatial and temporal analysis historically not considered in forest planning efforts (Boston 1996). One approach recently used is to schedule timber harvests and other silvicultural activities by trial and error secondary to establishing landscape conditions spatially and temporally favorable for wildlife throughout the planning horizon. Cissel et al. (1998) present a landscape plan for the Augusta Creek watershed in Western Oregon based on historical fire regimes. The watershed is broken up into “landscape areas”, including upland and aquatic reserves, and areas suitable for timber harvest where rotation ages, clear cut patch sizes and overstory retention levels are derived from fire history. To transform the harvestable areas from their current to desired future condition, harvest units were first delineated by hand according to ranked mapping criteria. Next, prescriptions for these harvest units were applied by trial and error over the planning horizon (400 years, with 20 year planning periods) until a spatially acceptable pattern and the future landscape conditions for the harvestable areas were achieved (Cissel et al. 1998). The authors note the "complexity and judgment required to interpret the four [spatially acceptable] criteria required several modifications and partial iterations to achieve a satisfactory pattern" (Cissel et al. 1998 p. 40). This observation suggests the potential utility of decision support models capable of scheduling resource allocation under such detailed spatial and temporal conditions.

Hierarchy of forest planning

While Cissel et al. (1998) did not use an optimization model to guide the harvest scheduling, it may be because traditional decision support tools used in forest planning are ill-equipped to handle detailed spatial and temporal analysis. Evolving primarily in response to the need to meet a sustainable flow of timber objectives from large forest properties over long time periods, the forest planning process has traditionally been hierarchical in nature. The levels of forest planning are strategic, tactical, and operational (Richards 1997; Martell et al. 1998). Strategic planning considers the forest (or forests) as a whole and attempts to allocate entire resources over long (>1 rotation length) planning horizons. Tactical planning attempts to produce spatially and temporally feasible schedules of activities over a shorter time horizon in keeping with targets calculated from the strategic level. Operational planning schedules the results of the tactical plan "on the ground" in the best possible way during a very brief planning horizon- typically one year or less (Richards 1997). The entire planning process is typically carried out in tiers, so that the outputs of one level are "fed" down to the next level as goals to be achieved.

Differences in the amount of spatial detail, the length of planning horizon, and the aggregation of data at these different levels cause predicted and actual values of various outputs to differ between levels. For instance, since strategic planning models do not recognize stand boundaries, it may be impossible at the tactical planning level to find a combination of discrete stands of type a during period t to clear cut which fulfills the strategic planning model's recommended acres of a to clear cut during period t. Output divergence is magnified when additional temporal and spatial constraints, such as restrictions on maximum clear cut size and the requirements for feasible road networks, are part of the problem. In summary, the aggregation necessary for analysis at the strategic level effectively changes the forest planning problem to a slightly different problem than the disaggregated tactical and operational problems (Bettinger 1996).

Solution methods

LP and extensions

Linear programming (LP) models have been widely employed to solve strategic level planning problems. At this level, stand level data are aggregated into "macro-stands" or strata; time is aggregated into multiple-year planning periods, and overall levels of output to produce per period are determined (Weintraub and Cholaky 1991; Martell et al. 1998). The variables are continuous and the objective function and constraints must be linear. The planning horizon is long, usually greater than one rotation length. Output levels are expressed in terms of the volume and acreage of timber by type and silvicultural activity (e.g. thin, clear-cut) to cut each period. In industrial settings, the objective of strategic planning is typically to maximize present net worth subject to harvest flow stability and availability of resources (Martell et al. 1998). Provisions for wildlife habitat, or other non-commodity objectives are represented in the formulation as constraints and expressed in the solution, like other outputs of the LP model, as aspatial strata amounts such as acres of a potential cover type (Richards 1997; Davis and Johnson 1987). LP is amenable to designating fixed acres, which have spatial reality, through the aggregate emphasis technique (Davis and Johnson 1987). In general, areas so designated would remain fixed for the planning horizon and are not able to respond dynamically in keeping with other optimal activities.

Planning results at the strategic level are generally aspatial, however. Since the LP solution mix is continuous, and discrete harvest units with the spatiotemporal requirements which may restrict their assigned activities are usually not part of the problem formulation, attempting to achieve harvest levels tactically during the strategic planning horizon as specified in the strata-based plan is impossible. One way around this dilemma is to include discrete decision units such as stands and road segments as 0/1 integer variables in the LP formulation, making the problem an integer programming (IP) or mixed-integer programming (MIP) formulation (Yoshimoto 1990). However, without even considering explicit spatial restrictions on harvest units and road building, solution time for such formulations increases exponentially with the number of integer variables due to the solution algorithms necessary to find integral solutions (Bettinger 1996, Dykstra 1984). Adding spatial and temporal constraints on the integer variables further increases the size and complexity of the problem past that which can be formulated and solved in a reasonable amount of user or computer time unless the original problem size is extremely small (Lockwood and Moore 1993; Yoshimoto et al. 1994).

A more common approach to incorporating spatial detail in forest planning models is to use the output of the strategic model as goals for a shorter period of the strategic planning horizon and solve a smaller problem (Weintraub and Cholaky 1991, Richards 1997). IP and MIP can be applied to these tactical planning efforts and produce optimal solutions, but problem size is still limited by the number of integer variables and the number and complexity of constraint rows specifying the spatial restrictions (Boston and Bettinger 1999). Furthermore, besides possibly leading to tactically infeasible schedules later in the planning horizon (Yoshimoto et al. 1994), the method of combining strategic goals with segmented tactical planning efforts is likely to produce revenue and volume levels far below that estimated by the disaggregated strategic plan (Nelson et al. 1994).

Heuristics

The difficulty in formulating and solving realistically sized planning problems has led in recent years to the development and application of heuristic programming (HP) techniques in forestry. Heuristics have an advantage over other mathematical programming approaches in that 1.) they do not require that all combinations of integer variables and their constraints be stated *a priori*, which allows for fast and flexible constraint formulation; 2.) they are well-suited to the combinatorial nature of problems with adjacency restrictions among stands; 3.)feasible solutions can be determined from the data structures embedded in the heuristic algorithms; and 4.) they can produce good solutions in a reasonable amount of computing time (Boston and Bettinger 1999; Bettinger 1996; Lockwood and Moore 1993). The disadvantage of heuristic techniques is that there is no guarantee of optimality associated with the algorithms used (Boston and Bettinger 1999). Performance may be measured against a relaxed LP formulation of the problem at hand, which generates a theoretical upper bound value, compared with the results of another heuristic, which only provides relative comparison, or measured by estimation of the optimal solution value which is developed using extreme value theory (Boston and Bettinger 1999; Bettinger 1996).

There have been numerous applications of HP to forest planning problems. Many of the algorithms were specifically developed for the scheduling problem at hand (e.g. Weintraub and Cholaky 1991; Elwood and Rose 1990; Yoshimoto et al. 1994); however, recent years have seen several applications in forestry of two generalized heuristic algorithms, simulated annealing (SA) and tabu search (TS). Both of these are based on neighborhood search. In neighborhood search procedures, an initial starting solution to a problem is designated. This solution may be either feasible or infeasible, depending on the search technique used. At each iteration, moves which would alter the current solution slightly are considered and evaluated. Eventually, after a certain number of iterations which alter the solution slightly, the neighborhood search algorithm terminates and reports the best solution found during the search. In that only a small portion of the total solution space is examined at each iteration, neighborhood search techniques are also known as local optimization techniques (Reeves 1993). The pitfall of neighborhood search techniques is that there is no guarantee the locally optimal solution the algorithm finds will be the globally optimal solution. Locally optimal areas of the solution space have been referred to as "attraction basins" (e.g. Battiti and Tecchioli 1994b) because in order to achieve solution structures that are even better, despite the attractiveness of the local optima relative to its immediate neighbors, a neighborhood search algorithm may be required to accept a series of worse solutions in order to "jump" into a better area of the solution space. Two examples of strategies to accomplish overcoming local optimality, simulated annealing and tabu search, rely on very different methodologies to prevent entrapment in local optima.

Simulated annealing

Simulated annealing is a stochastic optimization technique which seeks to mimic the behavior of liquid metal as it is cooled in a water bath to a stable solid state, a process known as annealing (Reeves 1993). SA techniques tentatively perturb the arrangement of a solution, evaluate the associated change in the objective function, then conditionally accept or reject the new arrangement depending on an acceptance criterion. If the new objective function value is better, the solution is accepted. If the new objective function is not better, the new solution is accepted or rejected depending on a criterion which becomes more stringent as the solution progresses, or "cools". A typical form of this criterion is:

$$p(\Delta) = \exp - \left(\frac{E_2 - E_1}{c} \right)$$

where:

$p(\Delta)$ is the probability $(0 \leq p(\Delta) \leq 1)$ of an inferior solution being accepted

c is the acceptance control, or "temperature" parameter

E_1 is the objective function value before the proposed change

E_2 is the objective function value after the proposed change

In process, the parameter c is reduced gradually- "cooled"- according to a schedule consisting of beginning and terminating "temperatures" and a simple temperature reduction function. By allowing the possibility of non-improving moves, especially early on in the process, SA is able to escape entrapment in local optima (Lockwood and Moore 1993; Bettinger 1996).

Nelson and Liu (1994) developed a simulated annealing algorithm to schedule a 431-unit forest over 12 and 15 periods with minimum harvest ages and green up adjacency restrictions. They found that their SA algorithm outperformed a random start hill-climbing algorithm. Lockwood and Moore (1993) used SA to schedule both 6148 and 27,458 unit problems over 12 periods with minimum harvest block constraints and adjacency delay restrictions. They used a series of penalty functions to achieve harvest blocks in the desired range of 100-200 ha and to deter solutions from picking adjacent units for harvest within 20 years of each other rather than setting these as hard constraint boundaries (Lockwood and Moore 1993). They found the algorithm was able to provide consistently good feasible solutions.

Tabu search

Tabu search is a directed, rather than random, search technique, unlike SA (Glover and Laguna 1998). Tabu search encompasses a series of strategies designed to take advantage of the search history to avoid entrapment in local optima while identifying and exploring regions of the solution space which have good characteristics. The effectiveness of tabu search depends on achieving the proper mixture of diversification and intensification in the search routine so that enough of the solution space is explored but very good solutions are not missed. Diversification of the search procedure is achieved through memory structures which prevent the search from cycling repeatedly back to previously explored regions of the solution space. Lists keep track of specific elements which have recently or frequently been part of solutions considered by the search algorithm and assign "tabu" status to them based on user-specified rules. The tabu status assigned to frequently or recently administered moves prevents the search from cycling back to previously explored regions of the solution space, forcing it instead into unexplored areas. Intensification is achieved by always picking the neighborhood solution which results in the best improvement of the objective function value or the least deterioration, and by utilizing memory structures that keep track of "good" solution elements (Richards 1997; Boston 1996). *Aspiration criteria* may be intelligently defined by the modeler, so that tabu status may be overridden at appropriate times to intensify searches in promising regions of the solution space (Glover and Laguna 1998).

Most tabu search implementations make use of a short-term memory structure in the form of a list which prohibits recent moves (of solution elements into or out of solution) from re-occurring. In many instances, modelers have found this structure sufficient for effecting ample diversification to avoid local optima and produce good solutions. However, there are many modifications possible with tabu search to improve algorithm performance. A long-term, frequency based tabu memory structure may be employed. The attributes which determine tabu status may be changed, or more than one tabu list based on different attributes may be maintained (e.g. Boston 1996). Neighborhoods may be searched completely, randomly, or systematically using elaborate candidate list strategies (Glover and Laguna 1998). Neighborhoods may include only feasible or infeasible moves. Short term tabu tenure may be fixed, random, or determined dynamically through a feedback mechanism during run time (Battiti and Techiolli 1994a 1995). These represent only a partial list of possible modifications; for a thorough discussion of tabu search extensions and topics, see Glover and Laguna (1998). It is clear that picking the best combination of approaches to use can be very problem-specific and time-intensive for the modeler. Perhaps for this reason, most implementations of tabu search in forest planning, as in other applied problems, have relied on simple fixed tenure short-term tabu lists and occasionally on a frequency-based long-term memory structure. Even so, the task of finding the right short-term tabu list length to find the best solutions can expend significant amounts of the modeler's time without yielding clear results about the optimal size to use (Paulli 1993; Richards 1997; Brumelle et al. 1998).

Tabu search has been applied in forest planning both to solve industrially-motivated tactical problems and to address complex multiple objective problems concerning wildlife habitat and environmental quality. Murray and Church (1995) applied tabu search to schedule clear cuts and road building on a 45 unit, 52 road-linkage forest over 3 periods subject to road connectivity requirements, same period adjacency restrictions, and even-flow limits. Tabu search outperformed simulated annealing and Monte Carlo integer programming approaches. The mean objective function value difference between simulated annealing and tabu search as implemented was less than 2%; however, solution time for their tabu search procedure was 82.60 seconds per solution vs. 30.86 seconds for simulated annealing on a 386/33 personal computer (Murray and Church 1995). Brumelle et al. (1998) solved 219 unit problem with 6 and 12 periods, and a 491-unit problem over 12 periods scheduling clear cut harvests subject to green-up adjacency restrictions and even-flow requirements. They found that tabu search outperformed another heuristic algorithm (Brumelle et al. 1998).

Boston (1996) used tabu search to solve a 50-year, 10-period tactical harvest scheduling problem for 218 units and a variety of prescription alternatives to meet volume, landscape aggregation, and closed-canopy cluster shape goals subject to maximum clear-cut opening restrictions and minimum closed canopy coverage goals. Using extreme value theory, Boston found that in one scenario, one solution produced by tabu search was within 2% of the estimated global optimum and 75% of all TS solutions were within 80% of the estimated optimum. For another scenario, one solution was within 6% of the estimated optimum, and all other solutions were within 83% of the estimated optimum (Boston 1996). Bettinger et al. (1997) demonstrated the applicability of tabu search to schedule timber harvests subject to providing wildlife habitat for elk, and meeting clear-cut adjacency rules and even-flow requirements. The spatial habitat goals were not possible to solve using non-linear programming but all solutions produced by the TS procedure were spatially and temporally feasible (Bettinger et al. 1997). Another complex problem, intractable by mathematical programming techniques, was also solved by Bettinger using TS techniques (Bettinger 1996). This problem involved scheduling timber harvests and road construction or obliteration activities subject to meeting stream sediment goals, stream temperature goals, and even-flow restrictions for a 14,000+ acre watershed in eastern Oregon (Bettinger 1996).

Tabu search with strategic oscillation

The aforementioned forestry applications all limit admissible solution transitions to within the feasible region, or use static penalty functions with fixed weights to allow consideration of infeasible solutions during the search. Recently, Richards (1997) warned about the possible pitfalls of using straightforward applications of tabu search in forest planning problems. Using a data set for a 1039 stand forest with 135 road links and a variety of tabu search approaches, Richards scheduled clear cut harvests subject to green-up adjacency constraints and road construction for a 20-year planning horizon with 5-year periods. The tabu search approaches used included fixed-tenure tabu search, fixed-tenure tabu search with random diversification, the reactive tenure tabu search method of Battiti and Tecchioli (1994a 1995), tabu search with strategic oscillation, and combination approaches using several strategies (Richards 1997). In the fixed tabu tenure applications, Richards experimented extensively with different short-term tabu list lengths. The best results were found with a combination of strategic oscillation, reactive tabu tenure and a stochastic diversification process when chaotic cycling of solutions was detected during the search process. Of all the approaches tested, Richards found that the most important strategy for improving results was the use of strategic oscillation. Use of different fixed tenure lengths, stochastic diversification routines, and reactive tabu tenure modifications alone did not improve results predictably, but incorporating the strategic oscillation strategy in all instances resulted in significant gains in objective function average and best values, suggesting that researchers need be wary of results from straightforward TS implementations (Richards 1997).

In some combinatorial integer problems, the constraint structures may be such that to progress from one feasible solution to another that is better, a region of infeasibility must be crossed. There are may be no sequences of feasible moves, or the sequence of neighborhood moves within the feasible region may be extremely obtuse, so that the transition of one feasible solution to one that is markedly better may be impracticable. Richards (1997) recognized this structure in the tactical forest planning problem. A simple example can be visualized in Figure 1 which represents a feasible solution to a harvest scheduling problem with restrictions on clear-cut patch sizes greater than 120 acres. If the current solution includes non-adjacent units 1 and 2, which are, say, 50 and 60 acres each, for harvest in the first period, there may be no sequence of feasible moves that could schedule unit 3, which is 75 acres, although scheduling unit 3 may be part of the optimal solution. Scheduling unit 3 would increase the size of clear cut opening to greater than 120 acres as long as unit 1 or 2 were scheduled. An aggressive search procedure which only considers moves in the feasible region would not be very likely to find a sequence of feasible moves which would end up scheduling unit 3 if scheduling units 1 and 2 represent a relatively high value. Strategic oscillation has been proposed by Glover (1990) in conjunction with tabu search as a means of smoothing solution trajectories between feasible regions of the search space.

Following Gendreau et al's (1994) application for the vehicle routing problem, Richards (1997) induced oscillation in tabu search procedures by augmenting the objective function with penalty terms with self-regulating coefficients for each of the constraint sets. The objective function, f(x), was modified to $f_{pen}(x) = f(x) + \sum_{j=1}^{k} c_j P_j(x)$ where there are k

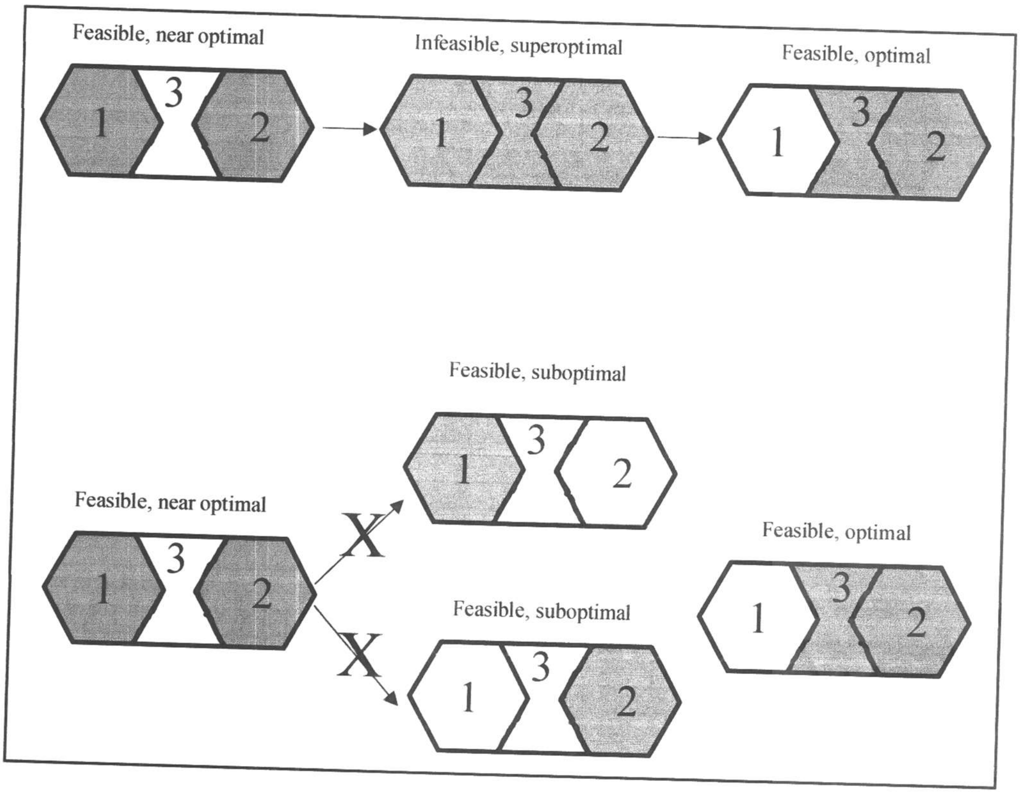


Figure 1. Effects of adjacency restrictions on move transitions. In the upper example, if the search is allowed to move through infeasible regions, the optimal solution is found. In the lower example, if the search is restricted to the feasible region, a search trajectory leading to an optimal solution may be difficult or impossible to find.

constraints, a coefficient c_j for each penalty function, P_j which measures the amount by which a solution x violates constraint j. A dynamic feedback mechanism is used to vary the constraint parameters. If the last M solutions were feasible with respect to constraint *j*, then the penalty coefficient is halved. If the last M solutions were infeasible with respect to constraint *j*, then c_j is doubled. Thus, when the search trajectory has moved away from a constraint boundary towards the "interior" of the feasible region, penalty reduction allows the search to progress out of the feasible region by making infeasible solutions look more attractive. Conversely, the search is pulled back towards the feasible region for a constraint when it has violated the constraint too long. The overall effect is to bias the search "near" the boundaries of the feasible region, and a continuous mix of feasible and infeasible solutions is achieved (Richards 1997; Gendreau et al. 1994). In Richards' formulation, the constraints on the problem were even flow of volume, maximum opening size, and road network feasibility (Richards 1997).

Heuristic validation and extreme value theory

Golden and Alt (1977) and Los and Lardinois (1982) developed procedures for estimating optimal value based on the results of heuristic procedures. The results from a heuristic are considered as a sample from a population of local optima which may or may not contain the global optimal solution. As the sample size increases towards infinity, the distribution of these samples is assumed to approach a three-parameter Weibull distribution (Los and Lardinois 1982):

$$F(x) = \mathrm{Exp}\{-((a - x)/b)^{c}\}$$

where

a = location parameter

b = scale parameter

c = shape parameter.

Using this information, the estimated location parameter, a, becomes an estimate of the global optimum (Bettinger 1996; Boston 1996, Golden and Alt 1977, Los and Lardinois 1982).

If an assortment of randomly generated initial starting solutions is used and the number of possible solutions is large, the necessary conditions for using Weibull information of statistically independent local optima and a continuous distribution may be met in practice (Golden and Alt 1977; Los and Lardinois 1982; Bettinger 1996). However, because distributions are not truly continuous and heuristic results are not truly independent (*i.e.* good heuristics all attempt to reach the same globally optimal location), it becomes imperative to test the goodness-of-fit of heuristic solution samples to justify using the Weibull distribution parameters for inference. Tests suggested for testing goodness of fit to a Weibull distribution include the chi-square test, Kolmogorov-Smirnov test, and the Anderson-Darling test (Boston and Bettinger 1999).

Using the Anderson-Darling test for goodness of fit, Boston and Bettinger (1999) rejected in 10 of 12 cases the hypothesis that heuristic solution values were distributed as a Weibull distribution. For the two sets that were not rejected, one estimated optimal value, from simulated annealing, was within 99.8% of the known optimum while the other (Monte Carlo integer programming) set's estimated optimal value was only within 86.8% of the known optimum. The authors conclude that even where the Weibull assumption has not been rejected, the location parameter estimates "are dependent on the quality of the estimates" (Boston and Bettinger 1999 p. 300).

The reliability of the location parameter estimate, $\hat{a}$, is directly related to the estimate of the range parameter, $\hat{b}$, and the shape parameter, $\hat{c}$. As $\hat{b}$ and $\hat{c}$ increase, the spread of the data increases, rendering the point estimate of the optimal value less precise, or within a larger "confidence interval" (Golden and Alt 1977; Los and Lardinois 1982)

Los and Lardinois (1982) developed a method of determining the approximate confidence interval for the location parameter estimate from sample data based on the methodology of Golden and Alt (1977) and extreme value theory. Their estimate of the confidence interval for a minimization procedure is:

$$\text{Prob}\left\{ x_{(1)}^{hd} - \frac{\hat{b}}{S} \leq x^{*} \leq x_{(1)}^{hd} \right\} \cong 1 - \alpha$$

;

$$\text{S} = \left(-\frac{\text{R}}{\ln \alpha} \right)^{1/\hat{c}}$$

where

$1 - \alpha$ is the desired confidence level for the interval

R is the sample size

$x_{(1)}^{hd}$ is the best distinct local optimum found (duplicate values not allowed)

x^{*} is the true global optimum, estimated by $\hat{a}$

Using confidence intervals estimated from this equation, the reliability (precision) of the parameter estimate, $\hat{a}$, of x^{*} may be better judged.

CASE STUDY: THE BLODGETT TRACT

Site description and history

The Blodgett Tract is an approximately 2450 acre forest located in the hills immediately above the Columbia River in Columbia County, northwest Oregon, 46° 4' latitude, 123° 21' longitude (Figure 2). The tract was extensively railroad logged in the 1910's and 1920's. In 1928, the tract was acquired by Oregon State University (then Oregon State College) College of Forestry as mostly cutover land. Some artificial regeneration was done on site in the 1940's, but most vegetation came back as natural regeneration of Douglas-fir and Western hemlock (*Tsuga heterophylla*). During the past 15 years there have been 24 million board feet (MMBF) removed through thinning and clear-cut harvests by the College of Forestry Research Forests (Oregon State University Research Forests 1999).

Current conditions

1. Vegetation The Blodgett Tract currently consists of mainly 40-80 year old stands of Douglas-fir and Western hemlock on upland areas, while riparian areas are dominated by red alder (*Alnus rubra*) that is mixed in some areas with Douglas-fir, western redcedar (*Thuja plicata*), and Sitka spruce (*Picea sitchensis*). There are approximately 50.6 MMBF of Douglas-fir and 29.1 MMBF of Western hemlock on the site according to the most recent inventory (Oregon State University Research Forests 1999). Distribution of volume by age class and species is given in Table 1. Geographic distribution by age class over the site is depicted in Figure 3.

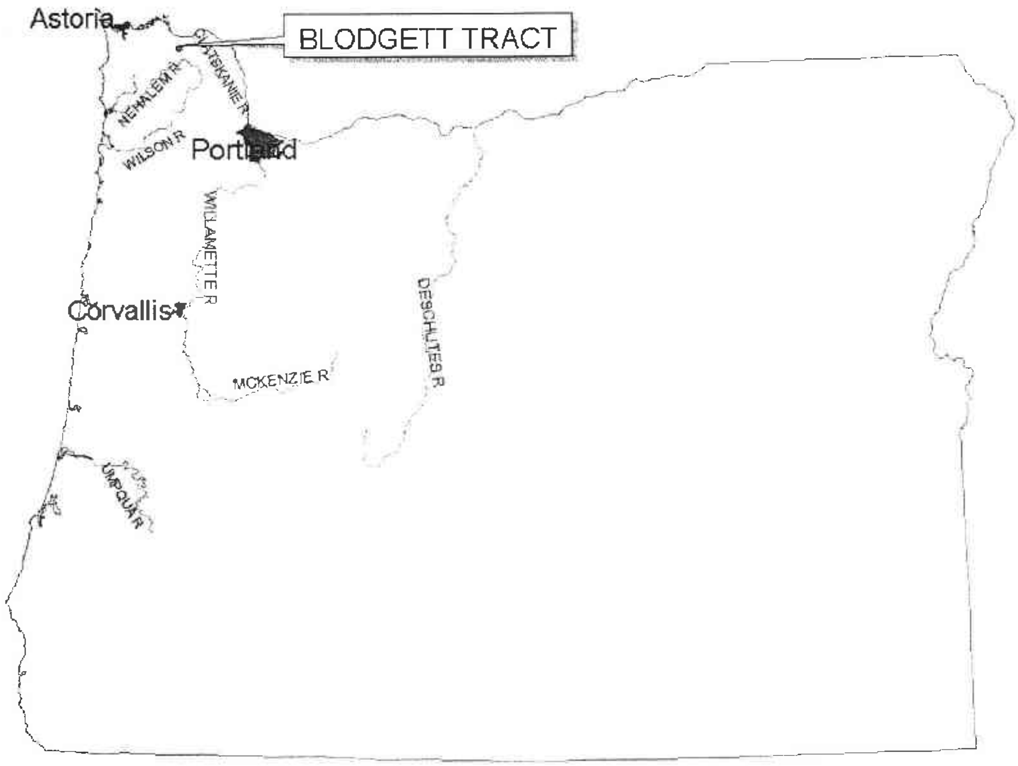


Figure 2. Location of the Blodgett Tract

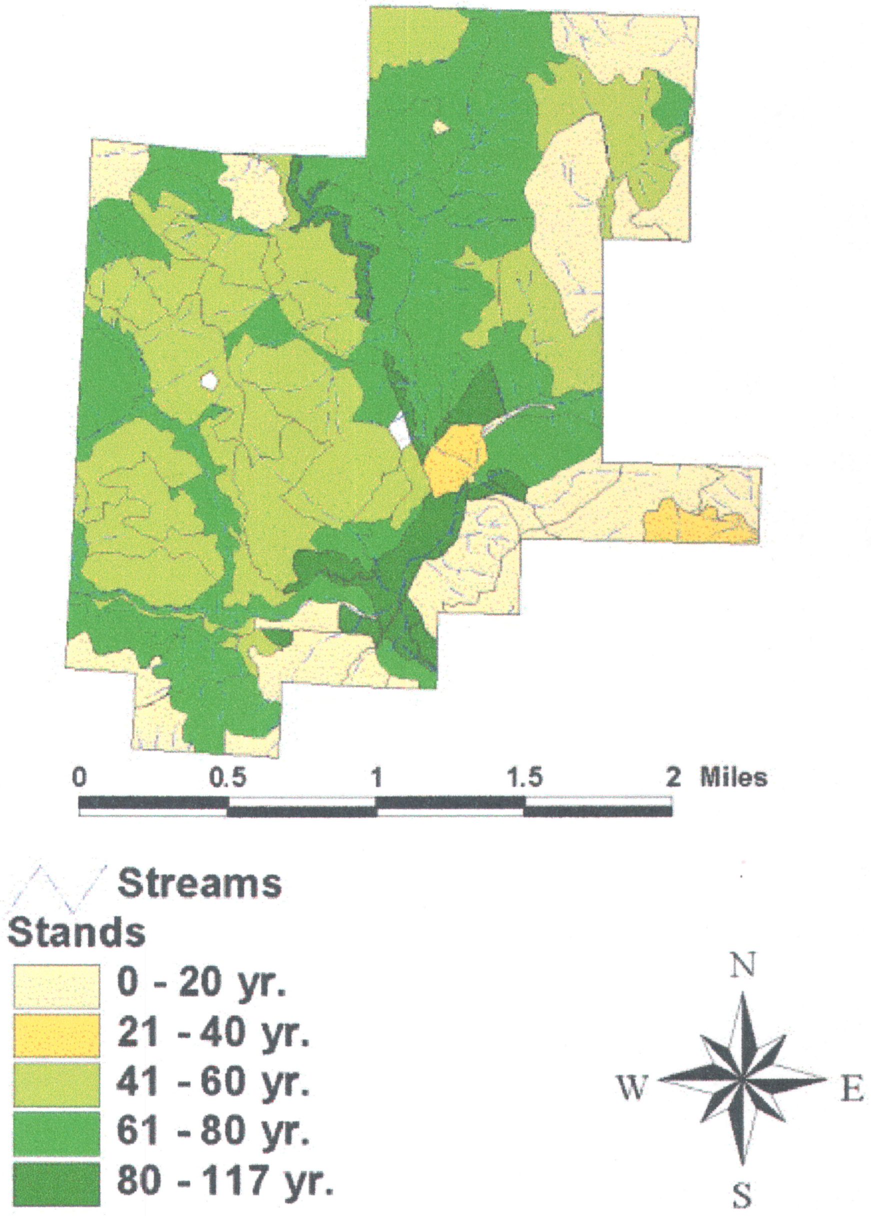


Figure 3. Initial age class distribution of the Blodgett Tract

Table 1. Existing forest inventory (MMBF). From Oregon State University Research Forests (1999).

Age Class	Total Douglas-fir	Total Western Hemlock
0-20	0.02	0.01
21-40	0.34	0.30
41-60	6.21	4.35
61-80	41.24	21.89
81-120	2.74	2.55
Total	50.55	29.11

2. Wildlife Currently, the Blodgett Tract has no reported population of Northern spotted owl or Marbled murrelet (*Brachyramphus marmoratus*) although the tract is located within the home range of both species. The tract has areas which may be suitable for spotted owl nesting, roosting, and foraging, but there are few suitable nest trees at present for murrelets. Survey information on other vertebrates, invertebrates, fungi, and lichens is not currently available but is assumed to reveal an assemblage of organisms typically associated with the native forests in the area.

The Fishhawk drainage system, which runs through the Blodgett Tract, was identified as a Core Salmon Area in the Oregon Plan (State of Oregon 1997) and has habitat that is regarded as fair to good for Coho salmon (*Onchorhyncus kisutch*) (Oregon State University Research Forests 1999).

Forest plan

In September 1997 it was decided by Oregon State University's Dean of the College of Forestry that a long-term comprehensive plan for the Blodgett Forest should be developed that demonstrated "economic efficiency while meeting public goals for environmental protection, especially fish and wildlife habitat" (Oregon State University Research Forests 1999 p. 3). A planning team was convened from the College of Forestry consisting of wildlife biologists, silviculturists, hydrologists, economists, and research forests staff. The planning team elaborated that the mission of the plan would be to "develop the Blodgett Tract as a biologically diverse and sustainable forest to demonstrate efficient timber production under a non-reserve based strategy" (Oregon State University Research Forests 1999 p. 5). Following some of the principles described earlier for achieving wildlife habitat compatible with active commercial management, the planning team developed general and specific objectives to fulfill this mission. Goals were developed for individual upland and riparian stands, the landscape as a whole, revenue flow through time, and other areas such as demonstration and education.

Goals developed by the planning team included:

1. Upland stands:

A. General: Implement a high yield, intensive silviculture on longer rotations (75+ year) which does not rely on a reserve based system for providing fish and wildlife habitat.

B. Specific: Develop and implement even-age prescriptions for existing and future stands that reach a target diameter distribution where the 20 largest trees per acre average 30.0" dbh or greater as soon as possible and remain in this state for at least 20 years prior to harvest. Determine and maintain levels of down woody debris in these stands for biodiversity through an adaptive approach. Such stands, structurally accelerated through silvicultural manipulation to provide mature forest characteristics, were dubbed "mature young growth" (MYG) by the planning team (Sessions et al. personal communication).

2. Riparian stands:

A. General: Actively manage riparian areas to maintain and enhance fish habitat.

B. Specific: Develop and implement prescriptions to convert the overall mix of riparian stands to a 50/50 mix of conifer-dominated and hardwood-dominated through even-age management with stream buffers.

3. Landscape:

A. General: Provide fish and wildlife habitat over the forest through time while not relying on a reserve-based system.

B. Specific:

1. Upland.

a. Provide a mosaic of stands in structure and composition ranging from early seral, open stages to mature forest conditions, with at least 20% (>=500 acres) of the forest at any given time in mature forest condition. Mature forest condition has the 20 largest trees per acre averaging 30" dbh or greater and adequate levels of down woody debris.

b. Maintain at least 1 large contiguous block of habitat of at least 200 acres in mature forest condition at any given time, which will be allowed to move across the landscape as management activities proceed.

c. Reach goals a and b as quickly as possible.

2. Riparian: Provide hardwood riparian stands within 1000' of conifer riparian stands over the entire forest by establishing an alternating conifer/hardwood stand structure along streams.

4. Revenue:

A. General: Provide a dependable supply of revenue to the College of Forestry.

B. Specific:

1. As close to (or above) $1.0 M per year as possible over the 1st 15 years of the plan consistent with other goals.

2. Revenue not to deviate more than 50% between successive 5 year periods over entire planning horizon.

Other goals of maintaining good neighbor relations, research, demonstration, and extension activities were defined but not anchored to measurable goals.

As spelled out by the planning team, the Blodgett Plan goals represent a working attempt to implement the principles of managing commercial stands for wildlife habitat as earlier described. The task at hand was to develop a strategic and tactical planning model which would show the best combination and timing of silvicultural treatments over the entire forest to achieve the measurable landscape and revenue goals. Specifications for the model included a 100-year planning horizon, divided into 20 5-year periods of analysis, corresponding with the 5-year periodic output of the growth and yield model used for stand projections in this case: ORGANON, SMC version (Hann et al. 1995).

DATA COLLECTION AND VARIABLE CALCULATION

Inventory data

From OSU Research Forests' inventory data for the Blodgett Tract, 66 upland and 15 riparian stand types were initially defined for the existing forest based on homogeneous overstory species composition and stocking. Four additional upland stand types were defined for young stands based on the years to wait until they had reached 20-years old and could be modeled in ORGANON. Five of the 15 existing riparian stand types were designated as types that could be converted to either alder- or conifer-dominated stands following regeneration harvest, depending on their position along forest streams. For the scheduling analysis, alder and conifer conversions were accounted as separate stand types. Thus a total of 70 upland stand types and 20 riparian stand types were considered.

OSU Research Forests engineers delineated 130 management units using slope class information developed from recent and historic aerial photos, existing and proposed road locations, stream information, logging patterns used in previous entries, and field reconnaissance. The boundaries of these units were designed to ensure that solutions from harvest scheduling simulation could be feasibly logged and were intended to provide a framework for operational logging plan development. Stand types were intersected with management units to produce sub-units so that stand differences within the management units could be recognized in the yield projections developed for the harvest scheduling analysis. This created a set of 200 harvest scheduling units. Within their larger management units, the individual harvest scheduling units needed to have thinning and final harvest operations synchronized.

Growth and yield and prescription generation

For the upland stand types, the silviculture planning team members designed prescriptions to accelerate thinnable harvest units towards the MYG goal. Prescriptions were modeled in ORGANON, SMC version (Hann et al. 1995). These prescriptions featured an initial heavy thinning from below (to 110-120 sq. ft. basal area) in the first 20 years from present, with an additional entry 15 years afterwards to 120 sq. ft. BA, to promote diameter growth of the 20 largest tpa so that the target of average dbh of 30" would be met as soon as possible. Some harvest units on slopes exposed to wind and which had not been thinned before were designated as "high risk" for windthrow. For stand types associated with these units, additional light thinning prescriptions were modeled which would not remove more than 40% of the basal area in the first entry, and residual basal area would always be near or above 150 $ft.^2$. Additional grow-only yields for all existing upland stand types were also projected in ORGANON. Harvest units deemed not thinnable by OSU Research Forests engineers could only receive no-thin prescriptions with a regeneration harvest. High windthrow risk harvest units could be assigned light or no thin prescriptions. Low windthrow risk harvest units could be assigned heavy, light, or no thin prescriptions. For both light and heavy thinning options a set of four prescriptions with timing of the first entry occurring in one of the first four periods (five years each) – or 20 years- were presented to permit flexibility in harvest scheduling.

A graphic example expressed in basal area and trees per acre of a heavy thinning prescription with the first entry occurring in the 3rd 5-year period for existing stand type "101" is shown in Figure 4. Corresponding diameter growth of the 20 largest trees per acre are shown in Figure 5. Future upland stands were all assigned the same prescription featuring an initial planting of Douglas-fir following clear-cut harvest. This prescription was modeled the same way as the existing stands except that an additional pre-commercial thinning from below to an SDI of 110 occurs at 18 years, or 2 years after crown closure at age 16. The stand trajectory of the future stand prescription and the growth of the 20 largest trees per acre is shown in Figure 6.

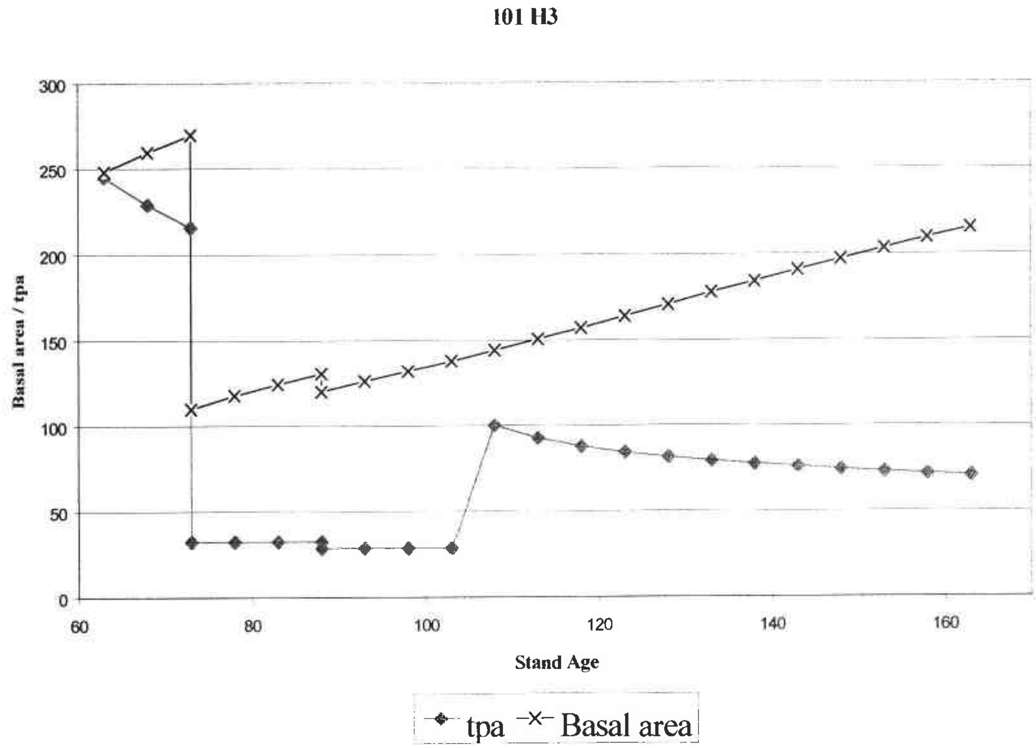


Figure 4. Silvicultural prescription for stand type 101, thinned in the 3rd period (10-15 years from present). Initial stand age is 63 years.

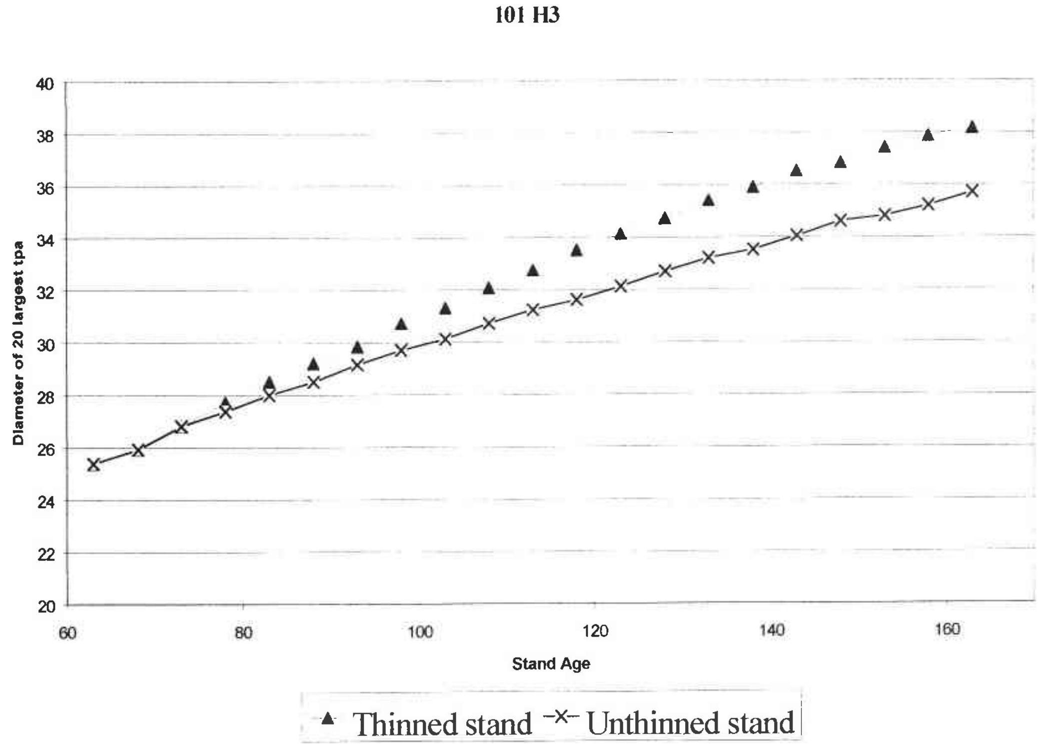
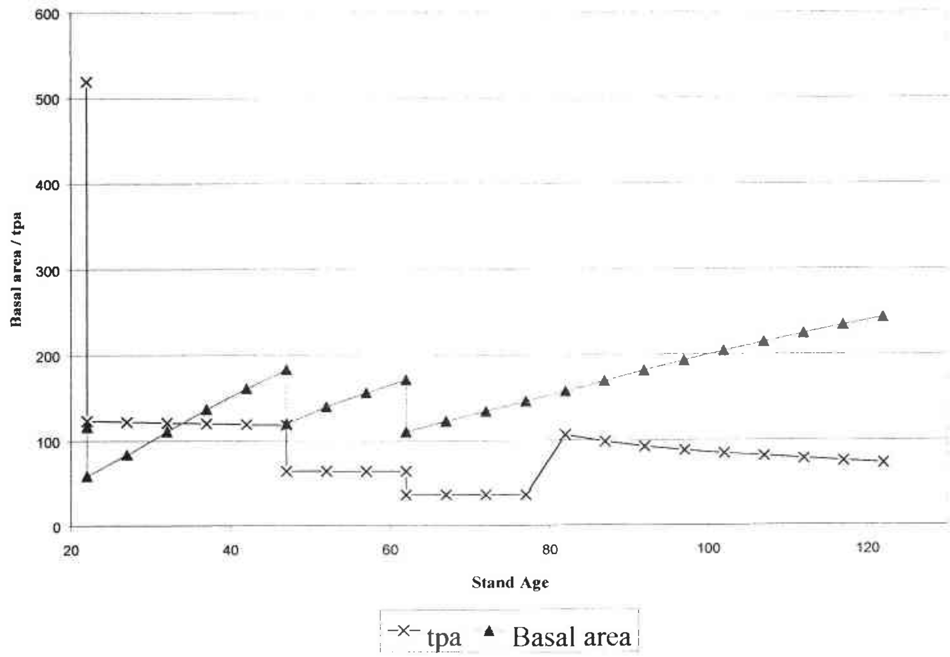


Figure 5. Diameter growth of the 20 largest trees per acre for thinning prescription "101H3"

For riparian stand types, the riparian team members designed prescriptions to accelerate diameter growth of current stands as in the upland stand prescriptions. These prescriptions also featured strategies to meet certain levels of woody debris for delivery to streams and maintain or enhance bank stability (Oregon State University Research Forests 1999). Depending on a riparian harvest unit's size and location, future stands would either be planted to conifer- or alder- dominated stands. This choice was predetermined by riparian planning team members to meet forest-level goals for improving fish habitat through wood delivery to streams. Both existing and future riparian stands were modeled in an independent growth and yield model and the results formatted as ORGANON output for use in the harvest scheduling model.



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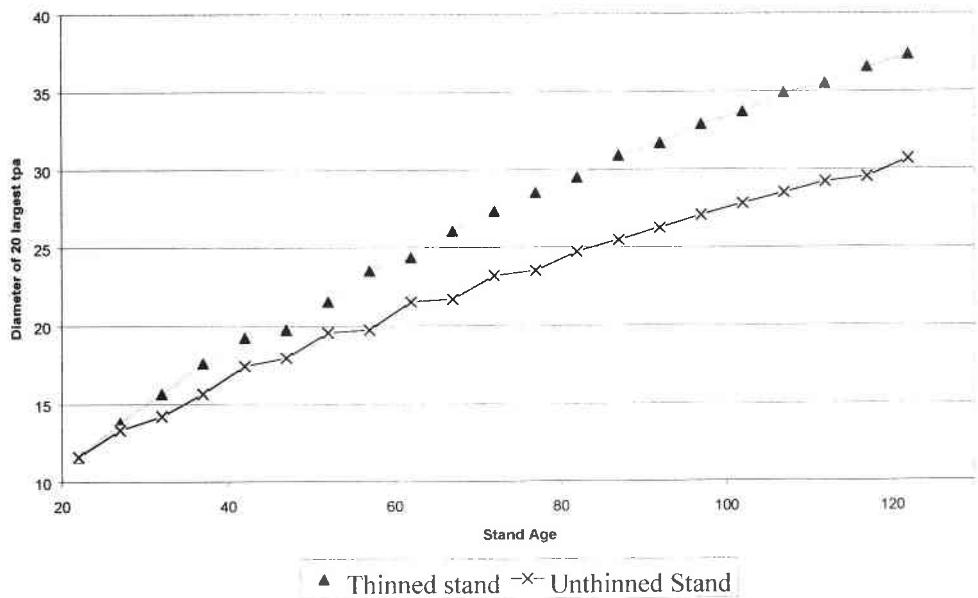

Figure 6. Silvicultural prescription for future stands (above) and corresponding diameter growth of the 20 largest trees per acre (below)

Existing stands and their prescriptions representing the upland and riparian stand types were projected for at least 20 five-year periods as were the future stands and their prescriptions in ORGANON. Relevant per acre information about growth, yield, inventory, age, and diameter of the 20 largest trees per acre for the existing stand types was extracted from the ORGANON output and spliced together with the corresponding information from ORGANON projection output for future stands to create the data arrays for the possible prescriptions that could be assigned to the harvest units in the harvest schedule. There were 335 stand projections in ORGANON representing no-thin, light thinning, and heavy thinning regimes for the 90 existing stand types. One stand projection was used for all future upland stands, and two stand projections, representing either conifer or alder conversion, were used for riparian future stands. For each 5-year period over the 100-year horizon, information from the future stands was spliced together to the information from the existing stands, to represent a clear-cut harvest and regeneration in that period. For each existing stand projection, this yielded a total of 20 prescriptions representing 20 possible periods for a clear-cut harvest and regeneration, plus one prescription where future stand information was not appended to existing stand info, representing no clear-cut of the existing stand over the planning horizon. A prescription thus consisted of thinning activities (if any) on an existing stand and a clear-cut harvest occurring in one of the 20 five year periods, followed by immediate regeneration and establishment of the future stand, and the thinning activities, if any, (designed to reach the MYG goal as quickly as possible) to be implemented on the future stand during the rest of the projection period. The future stand is not allowed a second clear-cut harvest in these prescriptions. The process of creating prescriptions yielded a total of 7297 prescriptions representing the 90 existing stand types which were represented in the 200 harvest units.

The harvest units were divided amongst 130 management units as previously described. Since these management groups are the basis of future operational activity on the forest, coordination of activities assigned to their constituent individual harvest units is critical in developing feasible plans. For those groups with more than one harvest unit, an index of coordinated prescriptions for individual harvest units within these groups was created ensuring that thinning and final harvest operations would occur in the same 5-year periods during the entire planning horizon. Each index number referred to a coordinated set of individual harvest units' prescriptions for a particular management group. Within each coordinated set, thinning activities could be of different intensity, but had to occur in the same five-year period as thinning activities for all harvest units represented by the set, as did final harvest and regeneration. For those management units with more than 1 member, a total of 3108 coordinated prescription sets was created and indexed using spreadsheets and programs coded in BASIC. When choosing prescriptions for management groups with more than one harvest unit, the solution algorithms described later refer to appropriate ranges of index numbers to assign prescriptions to management groups' component harvest units.

Costs and revenues

Log prices are based on Oregon Department of Forestry log prices for domestically processed logs and are presented in Table 2. They are constant over the planning horizon. OSU Research Forests engineers determined which harvest units could be harvested by tractor and which required cable logging. For skyline logging systems, stump-to-mill

Table 2 . Log prices used in harvest scheduling analysis

Log Grade	Douglas-fir	Western Hemlock
#2 saw	590	475
#3 saw	530	430
#4 saw	445	355

logging costs were developed by OSU Research Forests engineers (Oregon State University Research Forests 1999). Costs include felling, delimbing, bucking, yarding, loading, and hauling. Total stump to mill costs for thinning and clear-cut skyline harvest operations are given in Table 3. Costs were interpolated for average log sizes and volumes per acre falling between the listed table parameters. Some harvest units were unable to be thinned for at least 30 years due to inadequate stump or tree anchors for guylines or skyline. For thinning or clear-cut to occur in the first 30 for these units, additional costs were added to include an extra rigging slinger, tipping plate anchors and installation gear, and an additional tractor. These extra logging costs are given in Table 4. Costs were again interpolated as necessary. For harvest units that could be tractor logged, stump-to-mill logging costs were assumed to be 85% of the same costs for skyline (Oregon State University Research Forests 1999).

Research forests staff estimated road construction, reconstruction, and maintenance costs to be $50 / MBF. Sale preparation and administrative costs were $17.57 / MBF on clear-cut harvest units and $42.20 / MBF on thinning harvest units. Average discounted regeneration costs were estimated to be $500 / acre for all treatments (College of Forestry Research Forests 1999). Defect was estimated to average 3% of the gross volume, with an

Table 3. Skyline stump to mill costs ($ / acre) for thinning and clear-cut operations

Log MBF	Log Size	MBF Cut Per Acre						
		3	5	10	15	20	40	60
0.07	8" x 34'	339.90	273.42	224.93	206.92	198.25	---	---
0.13	10" x 34'	285.47	218.97	169.29	152.45	146.33	137.17	134.81
0.17	12" x 34'	272.49	210.95	161.25	144.44	135.76	124.71	120.31
0.24	14" x 34'	270.64	204.13	153.92	137.63	128.95	118.79	114.39
0.34	16" x 34'	266.80	200.30	150.61	133.78	125.12	113.99	109.62
0.45	18" x 34'	---	---	---	---	---	111.5	107.13

additional 2% gross volume left on the ground from breakage, so all yields in the harvest scheduling prescriptions were reduced by 5% (College of Forestry Research Forests 1999). The real discount rate used was 4%. This rate represents the average opportunity cost of capital in the private economy (Row et al. 1981). All revenues and costs were discounted from the middle of each five-year period.

Table 4. Thinning and clear-cut logging costs ($/acre) with and without artificial anchors.

MBF cut / acre	3	10	20
With anchors	303.66	178.13	150.53
Without anchors	285.47	163.29	146.33
Difference	18.19	8.84	4.20

METHODS

Problem formulation

To assess the goals of the Blodgett Plan, a harvest scheduling problem may be formulated as follows:

Maximize:

$$\sum_{i=1}^{n}\sum_{t=1}^{u} r_{ijt}x_{ijt} \quad ; \ j \in \text{ (allowable prescriptions for stand type i)}$$

Where:

$\mathbf{r_{ijt}}$ = discounted net revenue from harvesting or thinning unit i assigned prescription j in period t

$\mathbf{x_{ijt}}$ = 1 if unit i is harvested following prescription j or thinned in time t

0 otherwise

n = total number of harvest units

u = total number of time periods

Subject to:

1. 500 acres at any time has 20 largest tpa averaging >= 30” dbh
2. At least 200 acres with 20 largest tpa averaging >= 30” dbh contiguous at any time
3. All x_{ijt} must have all activities synchronized with other x_{ijt} in same operational unit
4. Maximum clear-cut patch size <120 ac.
5. Periodic deviation from average net revenue not to exceed 50%
6. Goals 1 & 2 must be reached at earliest t possible

In that each 0/1 decision variable in this formulation tracks a unique geographic area of the forest throughout the planning horizon, in an LP framework, this would be a Model 1 formulation. This might be formulated as a mixed integer programming problem where the prescription assigned to each harvest unit is a 0/1 decision variable. There are on average (7297 / 90) ≈ 81 prescriptions per stand type, or about 16,200 0/1 integer variables in the hypothetical objective function representing prescriptions that could be assigned to the 200 harvest units. Additional integer decision variables would have to be added to account possible "blobs" of MYG that could occur each period- *i.e.*, combinations of contiguous harvest units whose area totals more than 200 acres and with the 20 largest trees per acre greater than 30" dbh. The combinations of harvest unit acreages having MYG that total at least 500 acres per period represent even more integer variables to be accounted in the constraint matrix. Other constraint rows would also be numerous and complicated to form. One example would be restrictions on combinations of harvest units with harvest occurring in the same period having adjacent acreages greater than 120 acres. Another complexity of this problem in IP formulation would be how to determine the earliest time period possible to meet the landscape goals and hold this as a constraint at the same time of problem solution.

Because of the number of integer variables required, the complexity of constraint specification, and the evolutionary nature of the planning team's goals, formulation of an IP or MIP for this problem was impracticable. Instead, the problem was formulated as a two-phase combinatorial optimization problem to be solved with heuristic solution methods as shown in the hierarchical flowchart in Figure 7. The problem is to pick the best combination of eligible prescriptions to apply to each harvest unit that maximizes one

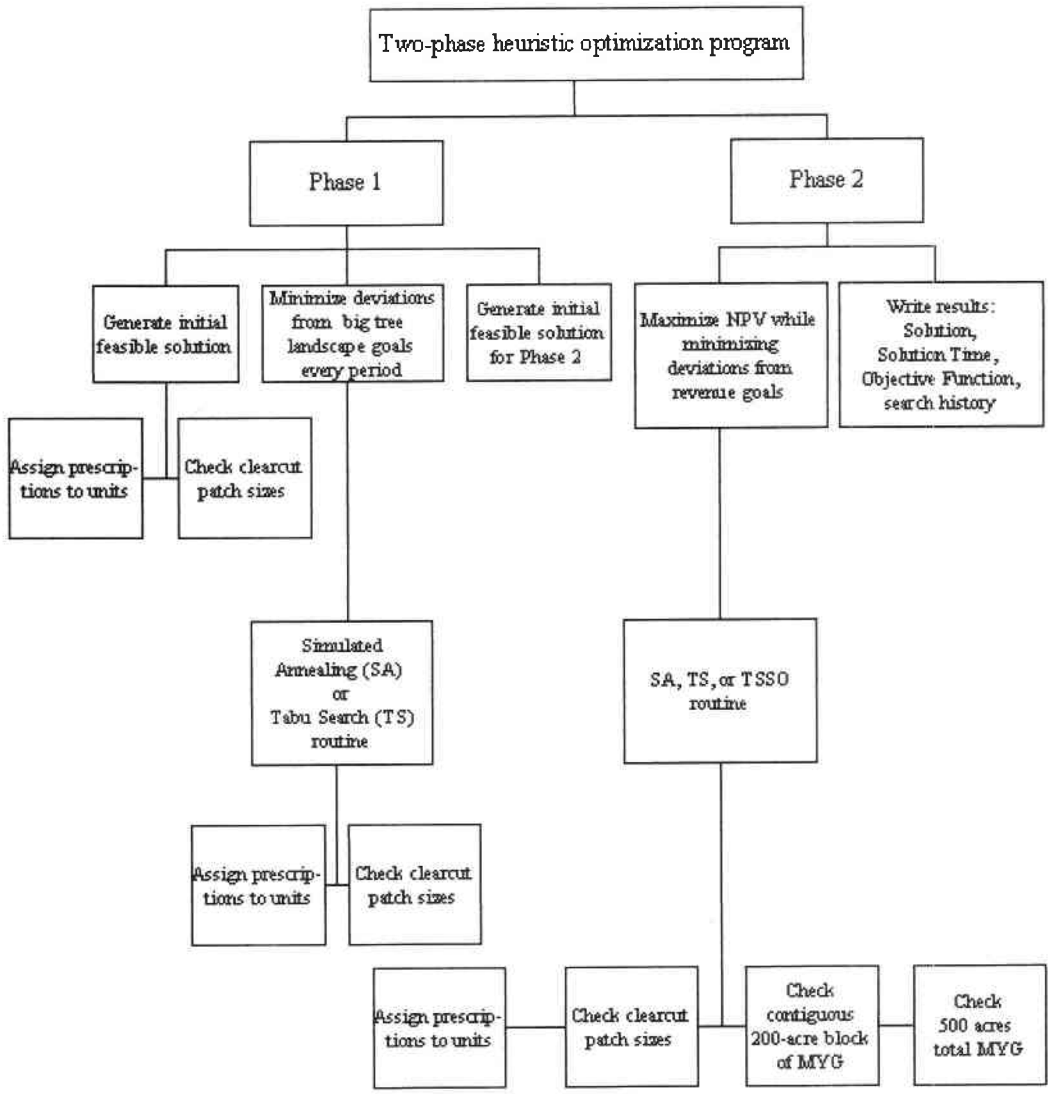

Figure 7. Hierarchical chart of two-phase optimization procedure

of two objective functions in a two-phase process. In the first phase of the model, the best combination of prescriptions for the harvest units is found that maximizes the number of harvest units meeting the MYG goal each period. The Phase I objective function is formulated as a least-squares minimization of deviation from a MYG target per period:

Minimize:

$$\sum_{t=1}^{u}(\mathrm{TARG}_t - \sum_{i=1}^{n} a_i x_{ijt})^2$$

where:

$TARG_t$ = target acreage in period t of forest in later seral stage structure;
a_i = the acreage of harvest unit x;
x_{ijt} = 1 if harvest unit i meets the late seral stage goal in period t associated with prescription j; 0 otherwise.

Subject to:
Maximum clear-cut patch size <120 ac.

The target acreage set in our formulation is the entire acreage of the Blodgett Forest in mature young growth condition.

The set of prescriptions resulting from Phase 1 produces a harvest schedule where the MYG landscape goals are reached in the earliest period possible, $\mathbf{t}^*$. This period is then used as a constraint in the second phase of the model, which seeks to maximize present net worth subject to revenue flow boundaries. In Phase 2, the landscape goals include maintaining 500 acres of mature forest present at any time and at least 200 contiguous acres of MYG during any 5-year period during the projection (in addition to restrictions on clear-cut patch size), beginning with the earliest period possible, in order to achieve the older forest structure landscape goals identified in Phase 1. Rather than a strict present net worth maximization, Phase 2 used a weighted goal programming objective function as follows:

Minimize

$$\sum_{t=1}^{t=u} PEN_t \left(TARG_t - \sum_{i=1}^{i=n} u_{ijt} x_{ijt}\right)^2 - \sum_{t=1}^{t=u} \sum_{i=1}^{i=n} r_{ijt} x_{ijt}$$

where:

r_{ijt} = discounted revenue from thinning or clear-cut harvesting unit i assigned prescription j in period t
u_{ijt} = undiscounted revenue from thinning or clear-cut harvesting unit i assigned prescription j in period t
x_{ijt} = 1 if unit i assigned prescription is thinned or clear-cut harvested in period t
PEN_t = scalar penalty term for period t.
$TARG_t$ = target revenue for period t

Subject to:

1. 500 acres at any time period at and after t* has 20 largest tpa averaging >=30"dbh
2. At least 200 acres with 20 largest tpa averaging >= 30" dbh contiguous at any time at or after t*
3. All x_{ijt} must have all activities synchronized with other x_{ijt} in same operational unit
4. Maximum contiguous clear-cut patch size <120 ac.

The weighted penalty formulation was used because early in the planning process, it was not immediately clear what the planning team's and the Dean of the College's preferences regarding revenue flow were. As the plan developed, the planning team and dean of the College of Forestry were presented with several alternatives showing different emphases on revenue flow created by varying the revenue targets per period and their scalar penalty terms. The planning team and Dean were then allowed to pick the schedule which appeared "best" to them.

Another reason for using such a target/penalty formulation is that, given the absence of shadow prices as in an LP formulation, including revenue goals as hard constraints does not provide information to the modeler about the tradeoff costs involved with setting the revenue flow boundaries. It is possible, for instance, that slight relaxations in hard revenue targets per period may produce huge gains in present net worth that may be desirable. Without shadow price information, this potential gain is less likely to be recognized by the modeler if revenue targets are set as hard constraints. Varying targets and penalties, however, provides a quick, if somewhat informal, means of exploring the solution space that might not otherwise be possible with heuristic techniques.

Solution methods

Three heuristic algorithms were developed to solve the two-phase combinatorial model and compared for performance, consistency, and efficiency. They were: simulated annealing (SA); tabu search with a short-term memory strategy only (TS), and tabu search with short-term memory and strategic oscillation (TSSO). To compare results among all three, a series of random feasible starting solutions for Phase 2 was created as follows. First, Phase 1 was initialized with a set of prescriptions which did not violate the maximum clear-cut patch size for any period. This was accomplished by randomly assigning prescriptions to each management unit from the subset of eligible prescriptions for that management unit, and checking all periods to see if the maximum clear-cut patch size had been violated. If a management unit had more than one harvest unit, a coordinated set of prescriptions was chosen for the management unit by randomly picking an eligible index number, described previously, and assigning the corresponding prescriptions. If the patch size were violated, the algorithm restarted and again randomly assigned prescriptions to the management units. This process continued until a mix of prescriptions was assigned which did not violate the maximum contiguous clear-cut patch size in any period.

Over 50 runs of phase 1 of the model using both TS and SA heuristics (but not TSSO) starting from a randomly assigned mix of prescriptions as described indicated that the earliest period possible for achieving the landscape MYG goals was period 4, or 15-20 years into the future. In fact, all runs yielded period 4 as the earliest period in which the MYG landscape goals could be reached. Therefore, period 4 was set as t*. Next, phase 1 was run by using the TS algorithm, described below, and checking solutions every 50 iterations until the landscape MYG goals had been met and maintained from period t* (4) to period 20. The results of this process were random feasible starting solutions for Phase 2 processes, which were then handled using the heuristic techniques described shortly. All three heuristic techniques relied on the same neighborhood structure and similar routines for determining if landscape constraints were being met.

Defining the neighborhood

For all solution methods used, the neighborhood, N, at each iteration is all potential moves, $\sigma_{m, (p1 \ldots pn)}$ from the current solution, s_c, which assign one management unit, m, 1.) if consisting of one harvest unit, an eligible prescription, p_1, different from that in the current solution, or, 2.) if consisting of n, *e.g.* more than one, harvest units, a different set of eligible prescriptions, $p_1 \ldots p_n$, while holding the prescriptions in the other management units constant.

Landscape constraints

All three heuristic models use similar subroutines to verify that the landscape goals of the problem were being met. For all 200 harvest units, an adjacency list was generated to identify all polygons which shared common arcs in the GIS. To check maximum clear-cut patch size of a proposed solution, for each 5-year period, the algorithms look at each prescription assigned to each harvest unit. If a harvest unit's prescription indicates a clear-cut harvest during that period, the algorithm records that unit as having been checked for that period, initializes a variable, *cc_patch size*, to the acreage of that harvest unit, and begins a recursive routine checking adjacent units for clearcuts in the same period. Each adjacent unit identified as having a clear-cut has its acreage added to *cc_patch size*. Units adjacent to these are then checked similarly and so forth. If *cc_patch size* is larger than 120 acres, the maximum clear-cut size constraint has been violated. Once all harvest units have been checked in a period, the algorithm moves on to the next period.

The existence of the 200 contiguous acres of MYG is checked in a similar fashion. Beginning period t*, the algorithm checks the "big tree array" associated with the prescription assigned to each harvest unit. The big tree array tracks the average diameter of the 20 largest tpa associated with the prescription assigned to the harvest unit. If this diameter is greater than or equal to 30.0" for the period and harvest unit being checked, the algorithm initializes a variable, *blob_size,* to the acreage of that harvest unit and begins a recursive routine checking adjacent units for largest tree average diameters >= 30.0". Each adjacent unit identified as having the largest trees averaging >=30.0" has its acreage added to *blob_size*. Units adjacent to these are then checked similarly and so forth. If the resulting acreage of *blob_size* is >=200, the 200 contiguous acres of MYG goal has been met for that period. If the resulting size is < 200 acres, the routine then continues examining the big tree status in the same period for prescriptions assigned to the harvest units that have not been identified as visited yet in the period. When the routine finds an average diameter >=30.0" associated with a harvest unit's prescription for the period, blob size is initialized to that harvest unit's acreage and the process resumes recursively as before. Please refer to Figure 8 for a detailed flow chart of this procedure.

If, during the period, the subroutine does not identify any contiguous "blobs" >=200 acres, the 200 contiguous acres of MYG goal has not been met for that period. As the algorithm checks for the existence of the 200 contiguous acres of MYG, it also tallies the total acres of older forest structure for the entire forest using the information from the big tree array. Once all harvest units' prescriptions have been checked in a period for big tree status, the subroutine moves on to the next period. If during any period at **t*** or later there are < 500 acres total of forest with the 20 largest tpa averaging >30.0", the 500 acre goal has not been met for the duration of the planning horizon as specified in the problem constraints. Similarly, if no "blob" >=200 acres with the 20 largest tpa averaging >=30.0" is found during any period at **t*** or later, the 200 contiguous acre constraint is not met.

Simulated annealing

The simulated annealing algorithm begins with a random starting solution as described above for the current solution. An initial temperature, **T**, is selected. The objective function is evaluated for this starting solution. Next, one of the 130 management units is chosen randomly. If the management unit has one harvest unit, a prescription is

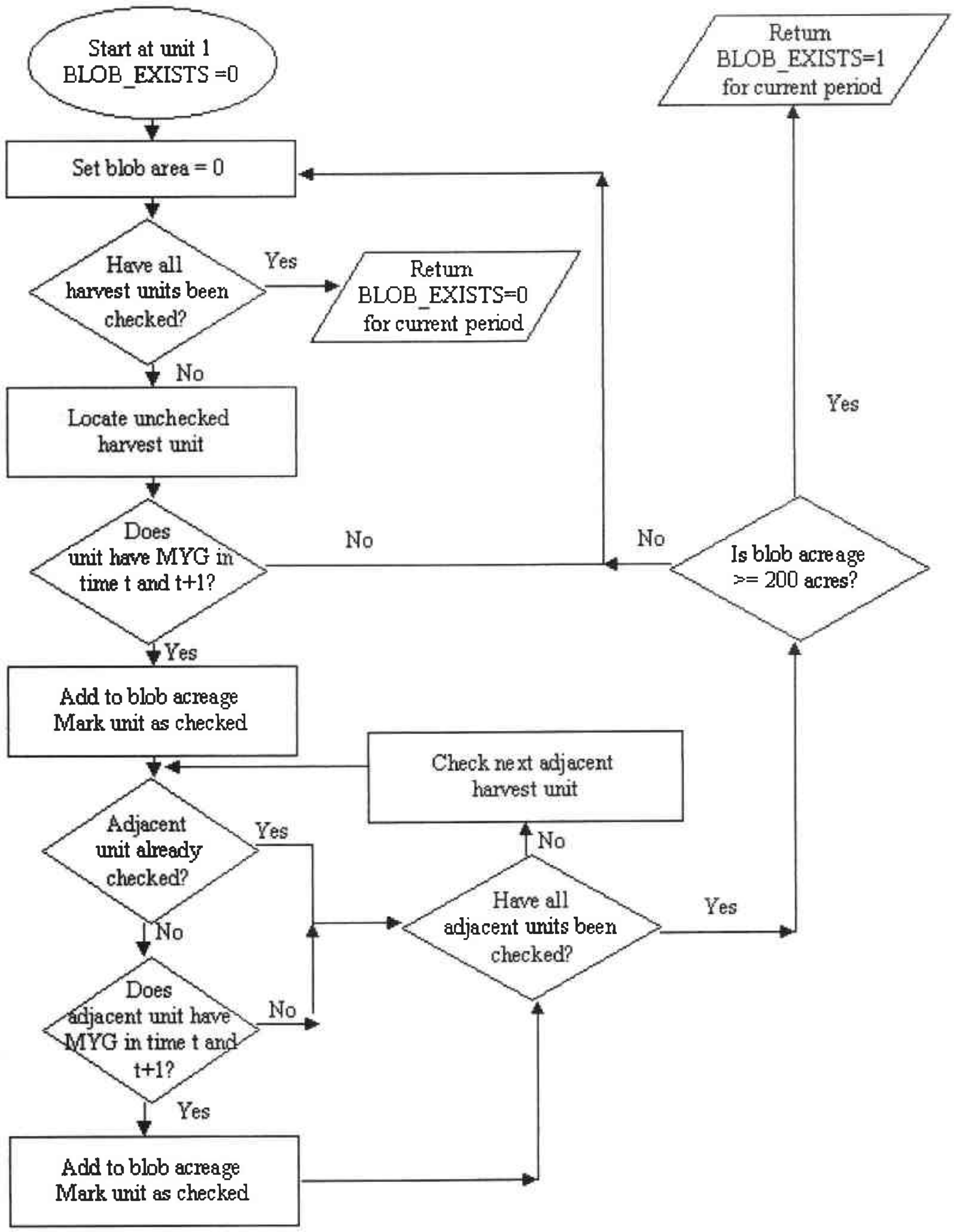

Figure 8. Subroutine used by heuristic procedures to check existence of 200-acre block of mature young growth each period.

randomly selected from the subset of eligible prescriptions for that unit's stand type. If the management unit has more than one harvest unit in it, a set of coordinated prescriptions is chosen using a randomly chosen index number from the eligible range for that management unit. The prescription or set of prescriptions is then assigned temporarily to the management unit and in Phase 1, a subroutine checks the resulting solution for maximum clear-cut patch size violations over the entire planning horizon. In Phase 2, subroutines check for clear-cut violations and the existence of both the 200 contiguous acres of MYG and the 500 acres of MYG total landscape goal from period **t*** to 20. The algorithm moves on to the next iteration in both Phase 1 and Phase 2 if the maximum clear-cut patch size is exceeded in any period. If the 200 contiguous acre goal or the 500 total acre goal is not met from period t* to 20, a penalty is assigned. Each penalty is assigned a very large value, allowing the possibility of infeasible solutions early in the solution process, but effectively prohibiting infeasibilities as the simulated annealing process cools down, as detailed below.

If the maximum clear-cut size in any period exceeds 120 acres, the temporary solution is rejected, and the original prescriptions from the current solution are restored. The algorithm then attempts again to assign a randomly chosen prescription or set of prescriptions to a management unit as just described. If not rejected because of clear-cut patch size restrictions, the temporary solution's objective function is evaluated. If the temporary solution is an improvement over the existing solution's objective function value, the temporary solution is selected as the current solution and the algorithm moves on to the next iteration. If the temporary solution is not an improvement, the following exponential function of the difference, Δ, between the temporary solution objective function value and the current solution objective function value is calculated:

$$f(\Delta) = e^{(-\Delta / T)}$$

A random number in the range 0-1 is generated. If the calculated value of the exponential function is greater than the random number, the temporary solution is accepted as the new current solution and the algorithm moves to the next iteration. In this way, non-improving solutions are allowed to be selected. The probability of accepting a non-improving solution decreases with the relative increase in the value of the objective function. A temperature cooling factor, α, reduces the temperature, T after a fixed number of iterations, NREP, at each T, so that the probability of accepting a non-improving solution also decreases as the algorithm progresses.

Tabu search

Neighborhood search procedures

The Tabu Search algorithm begins with a random feasible initial starting solution as previously described. Each iteration, every move $\sigma_{m, (p1 \ldots pn)}$ which changes a management unit's prescription or set of prescriptions while holding the prescriptions for all other management units constant is evaluated. That is, the entire neighborhood is searched per iteration. In the Tabu Search with short-term memory only application (TS), if feasibility is not maintained by a potential move, this move is no longer considered part of the neighborhood during the current iteration, and the algorithm moves on to check the

```
Initial feasible solution, s_c = Phase 1 solution;
Initial best solution, s_b = s_c;
Select initial temperature, T > 0 ;
Select ending temperature, T_end ;
Select temperature reduction factor, α ∀ 0 < α < 1;
Select number of iterations at each temperature, nrep;
iteration_count = 0;
Do until T = T_end
    Do until iteration_count = nrep
            Begin Loop:
            Randomly select a neighboring solution s_σ ∈ N (s_c)
            If maximum clearcut patch size for all periods for s is not ≤ 120 acres
                        Go to Begin Loop;
            Else
                        Check existence of contiguous 200-acre block of MYG for period t* to 20;
                        If block not present in all periods
                                    Calculate penalty, BLOB_PEN;
                        End if
                        Check existence of 500-acres total of MYG for period t* to 20;
                        If block not present in all periods
                                    Calculate penalty, ACRE_PEN;
                        End if
                        If (f(s_σ) > f(s_b)) and (BLOB_PEN = 0) and (ACRE_PEN=0) Then s_b = s_σ;

                        δ = [f(s_σ) - BLOB_PEN - ACRE_PEN] - f(s_c);
                        If δ > 0 then s_c = s_σ
                        Else
                                    Generate random x between 0-1;
                                    If x < exp ( δ / t ) then s_c = s_σ;
                        End if
            End if
            iteration_count = iteration_count + 1;
    Loop
    T = α * T;
Loop
```

FINAL s_b is approximation to optimal solution

Figure 9. Pseudocode for Simulated Annealing algorithm (Phase 2 example).

next candidate move. To check feasibility for each candidate move, subroutines check for maximum contiguous clear-cut acreage not exceeding 120 acres (Phase 1 and Phase 2), the existence of the contiguous 200 acre block of older forest structure from **t*** onward (Phase 2 only), and the existence of the 500 acres total of MYG over the landscape from **t*** onward (Phase 2 only). If a candidate move is feasible, it is added to the list of feasible potential moves, f_list where its identifying management unit, m, and prescription (p1) or prescription set, (p1...pn), are stored along with the value of the objective function that would result from implementation of the proposed move. The algorithm then goes on to check the next eligible prescription for the management unit, or, if all eligible prescriptions for a management unit have been evaluated, the algorithm starts evaluating prescription changes for the next management unit. The prescription currently in solution is not evaluated, since it is not a "move".

Once all prescriptions for all management units have been evaluated, the f_list is sorted (lowest to highest objective function in a minimization context) to identify the candidate move with the best improvement or least amount of degradation in the objective function value. If the 1st candidate move in the sorted f_list represents a better objective function value than the best feasible objective value function found yet, this move is accepted and the move's prescription or set of prescriptions is assigned to the appropriate management unit in the solution. In this case, the tabu status of the proposed move is not considered, and the move is implemented on the current solution. This modification produces the current solution for the next iteration, and a new best objective function is established. As an intensification strategy, when a new best objective function is found, all tabu restrictions, discussed below, which would prohibit the causative move from entering into the current solution are dropped. This strategy was thought to permit intense searching in "high quality" areas of the solution space. If the candidate move does not represent a better value than the best objective function value found yet, the candidate move's attributes are checked for tabu status on the short-term tabu list, described below. If the candidate move is tabu, the next best move on f_list is evaluated for tabu status, and so on, until a candidate move is identified that is not tabu. This move is then implemented on the current solution to produce the current solution for the next iteration. The tabu list, detailed below, is then updated with this move. The process then continues until a set number of iterations has passed with no improvement in the objective function or until nrep = maxrep, at which point the best solution is recorded along with its objective function value and CPU time before the application terminates.

Tabu restrictions

The attribute chosen to determine tabu status in short-term memory restrictions was management unit, m. If an m had a different prescription p assigned after an iteration, future $\sigma_{m,p}$ could not have the same m for the next z iterations unless the proposed $\sigma_{m,p}$ was feasible and improved the value of the best objective function found so far (which also triggered the release of all moves from tabu status). In other words, the short-term tabu list contains all feasible solution moves in the past z iterations that did produce improvements in the best objective function value. The effect of the short-term tabu list is to prevent the algorithm from cycling rapidly back to a locally optimal solution. In this application, after experimenting informally with different tenure lengths, a fixed tenure of 85 iterations for both the TS and tabu search with strategic oscillation (TSSO) was chosen as this gave the best results after an initial run from a fixed starting solution compared to tenures varying in length from 65 to 120 in increments of 5. Further testing of tenures 80-95 with 3 random starts apiece did not definitively prove 85 would be the best tenure length, but none of the nearest tenure lengths (80 and 90) performed better than 85 in these runs. All in all, choosing the best tenure length was based on best judgment and restricted in possible experimental approaches by the onerous solution times required. In choosing among possible move attributes to restrict by tabu status, management unit was chosen because the full neighborhood search as implemented required a great deal of computational time per iteration, and for most management units, there were many prescriptions whose interchange had little effect on the objective value of the entire solution. Therefore, strictly defining tabu attribute by integer variable status (unique management unit / prescription set combination) required too many iterations and was too costly in CPU time to consider. In our applications, no specific long-term memory strategy was used. Early efforts revealed inconsistent results experimenting with long-term frequency based memory based on different move attributes.

Tabu search with strategic oscillation (TSSO)

In the TSSO implementation, the objective function is augmented with one penalty term and penalty coefficient for each landscape constraint to form the following:

Minimize

$$\sum_{t=1}^{t=u} PEN_t \left(TARG_t - \sum_{i=1}^{i=n} u_{ijt} x_{ijt}\right)^2 - \sum_{t=1}^{t=u} \sum_{i=1}^{i=n} r_{ijt} x_{ijt}$$
$$+ \alpha \sum_{t=1}^{t=u} CC\_PEN_t + \beta \sum_{t=t^*}^{t=u} BLOB\_PEN_t + \gamma \sum_{t=t^*}^{t=u} ACRES\_PEN_t$$

where:

CC_PEN_t = penalty for violating maximum contiguous clear-cut patch size in period t.

```
Initial feasible solution, s_c = Phase 1 solution;
Initial best solution, s_b = s_c;
Initialize tabu_short;
no_improvement_count = 0;
Do until no_improvement_count = max_count or iteration_count = max_rep
    Determine neighborhood of candidate moves;
    Zero out f_list;

    For each candidate move, σ
        Check maximum clearcut patch size for all periods for trial solution, s_σ;
        Check s_σ for existence of contiguous 200-acre block of MYG for period t* to 20;
        Check s_σ for existence of 500-acres total of MYG for period t* to 20;
        If s_σ is feasible then
                Evaluate f(s_σ);
                Add σ to f_list;
    Next candidate move

    Sort f_list by f(s_σ);
    Select 1st σ ∈ f_list;

    If f(s_σ) > f(s_b)
        s_c = s_σ;
        s_b = s_c;
        no_improvement_count = 0;
        Zero out tabu_short;
        Go to next_iteration_count;
    Else
        Do until σ ∈ f_list is not σ ∈ tabu_short
                Select next σ ∈ f_list;
        Loop
        s_c = s_σ;
        Add σ to tabu_short with tenure M;
        Update tabu tenure for remainder of tabu_short;
        no_improvement_count = no_improvement_count + 1;
    End If;

    next_iteration_count:
    iteration_count = iteration_count + 1;
Loop
Stop;
FINAL s_b is approximation to optimal solution
```

Figure 10. Pseudocode for tabu search processes (Phase 2 example).

$BLOB\_PEN_t$ = penalty for not achieving at least one 200 acre contiguous block of MYG during period t such that t >= t*
$ACRES\_PEN_t$ = penalty for not achieving at least 500 acres total of MYG during period t such that t >= t*
α , β , γ are dynamically varying penalty coefficients

CC_PEN_t is calculated by evaluating individual clear-cut patch sizes as described above. For each clear-cut patch exceeding 120 acres, the acreage in excess of 120 acres for that clear-cut is added to CC_PEN_t. $BLOB\_PEN_t$ is calculated by evaluating all contiguous blocks of MYG. The algorithm finds the largest block of MYG for the period, and if it does not meet or exceed 200 acres, $BLOB\_PEN_t$ is (200 acres – the largest contiguous block size in t). $ACRES\_PEN_t$ is simply the difference between the 500 acres of MYG goal and the actual amount for the period.

The parameters α , β , and γ are initially set to 1. If the last 10 iterations produce infeasible solutions with respect to one of the landscape constraints, the corresponding penalty coefficient is doubled. If the last 10 are feasible for a landscape constraint, then the coefficient is halved. The intent of this dynamic modification of parameters is to bias the search near the constraint boundaries. The self-regulating feedback is designed to coerce solutions back towards the border of the feasible region when they become either too slack or too infeasible with respect to individual constraints.

The TSSO implementation is identical to the TS procedure except that 1.) the neighborhood is not adjusted to exclude potential infeasible moves in TSSO and 2.) the value of the current solution's objective function includes possible penalty terms for violation of the landscape constraints. Aspiration criteria, intensification rules, and short-term tabu tenure remain the same (85 iterations). The entire neighborhood is searched each iteration, and the algorithm follows the same stopping rules as TS.

Heuristic evaluation

Comparison

For the TS algorithm, 20 runs were started from random initial solutions, and the Phase 1 results fed directly into Phase 2 without saving the Phase 1 solutions. Following this, three Phase 2 runs of the TS and SA algorithm were made from the same starting point. The SA values were 11398319, 11183674, and 11304768 while the corresponding TS values found were 11053168, 11221285, and 10946202. The *a priori* assumption that a well designed tabu search should outperform a simulated annealing algorithm spawned further investigation into improvements of TS leading to TSSO, and the “simple” TS approach was not further tested for performance. To compare performance of TSSO and SA heuristics from the same starting point, a series of 30 Phase 1 results, each starting from solution with randomly picked prescriptions assigned to the harvest units, was generated using TS. These initial random solutions were feasible for maximum clear-cut opening for all periods. Running Phase 1 produced solutions which were feasible for maximum clear cut opening, 500 acres of total MYG, and a contiguous 200-acre block of MYG from period 4 until the end of the planning horizon. These 30 feasible solutions were fed into TSSO and SA where Phase 2 was run, and results for solution time and objective function value compared.

Validation with extreme value theory

Using the methods of Sinha (1986) as implemented in Bettinger (1996), a three-parameter Weibull curve was fitted to the distribution of heuristic solutions for the SA and TSSO methods. Estimates of $\hat{a}, \hat{b},$ and $\hat{c}$ were obtained and interval estimates of $\hat{a}$ were calculated using the formulae presented earlier as suggested by Los and Lardinois (1981). The point and interval estimates of $\hat{a}$ are assumed to be the estimate and confidence interval of the globally optimal solution. Since this assumption is invalid if the data are not Weibull-distributed, BESTFIT software (Palisades Corporation 1997) was used to calculate Anderson-Darling statistics to test the hypotheses that the data could be distributed as Weibull distributions. The Anderson-Darling statistic was chosen because it does not depend on the number of intervals chosen (Palisades Corporation 1997), is more sensitive to differences in the tail of the distribution (Boston and Bettinger 1999) and produces a more powerful test than the Kolmogorov-Smirnov test (Law and Kelton 1991).

RESULTS

Wildlife goals

Using the two-phase heuristic, all runs of the algorithm were able to produce the upland landscape structure goals as specified by the planning team after period 4, or the years 2013-2017 in the projection. The large diameter goals of 500 total acres and at least 1 contiguous 200-acre block were maintained or exceeded from period 4 until the end of the planning horizon. The results from the best harvest schedule are shown below in Figure 11 as an example. Figure 12 and Figure 13 show the location of the stands meeting the large diameter goals for all periods for the entirety of this schedule. No attempt was made to control the shape of the contiguous block; i.e., area/ perimeter ratios were not used. This may explain some of the long, narrow "blobs" that occur later in the schedule. The location of activities necessary to achieve the forest structure and revenues associated with it are given in the appendix. All solutions did not violate the maximum clear cut opening size restriction (120 acres) for all of the periods.

Algorithm performance

Objective function value

Table 5 below summarizes how each of the algorithms performed in terms of objective function value and present net worth. There is not a one-to-one correspondence between objective function value and present net worth because of the flow penalty terms in the

Per	year	value mm$	cc mmbf	thin mmbf	total mmbf	cc acre	thin acre	ave age	end inv	big ac
0	1998	4.89	14.61	3.76	18.37	275	203	52.0	60	102
1	2003	4.24	13.19	2.38	15.57	269	102	47.3	52	99
2	2008	3.90	9.09	5.81	14.90	188	309	44.5	49	377
3	2013	2.94	7.25	2.83	10.08	137	214	42.2	43	502
4	2018	2.19	5.02	2.23	7.24	111	367	44.3	44	502
5	2023	1.71	3.44	2.57	6.01	58	495	45.9	48	544
6	2028	1.95	5.70	0.34	6.04	128	167	49.3	49	507
7	2033	1.69	5.08	0.68	5.76	93	180	49.5	54	581
8	2038	1.77	6.08	0.23	6.31	96	73	51.4	58	531
9	2043	1.91	4.05	2.77	6.82	72	337	52.6	65	502
10	2048	2.10	4.70	2.18	6.88	76	348	56.0	68	502
11	2053	1.77	3.83	1.74	5.57	57	251	58.8	72	501
12	2058	1.65	4.25	1.46	5.71	60	221	61.2	77	504
13	2063	1.82	5.63	0.70	6.33	79	122	64.5	76	501
14	2068	2.10	6.51	0.66	7.17	85	130	67.2	77	501
15	2073	2.12	5.33	1.24	6.57	61	176	69.3	79	536
16	2078	2.35	6.49	0.91	7.40	78	144	71.2	80	506
17	2083	2.95	8.38	0.95	9.33	152	163	72.7	80	500
18	2088	3.04	8.41	0.74	9.15	100	145	67.8	80	599
19	2093	3.34	9.39	0.84	10.23	136	137	66.4	79	727
20	2098	3.28	9.05	0.70	9.75	112	135	62.9	78	759

Figure 11. Results of the best harvest schedule found. mm= million; bf= board feet; cc = clear-cut; acre, ac = acres; end inv = ending inventory (MMBF) big ac = acres of forest satisfying mature young growth condition.

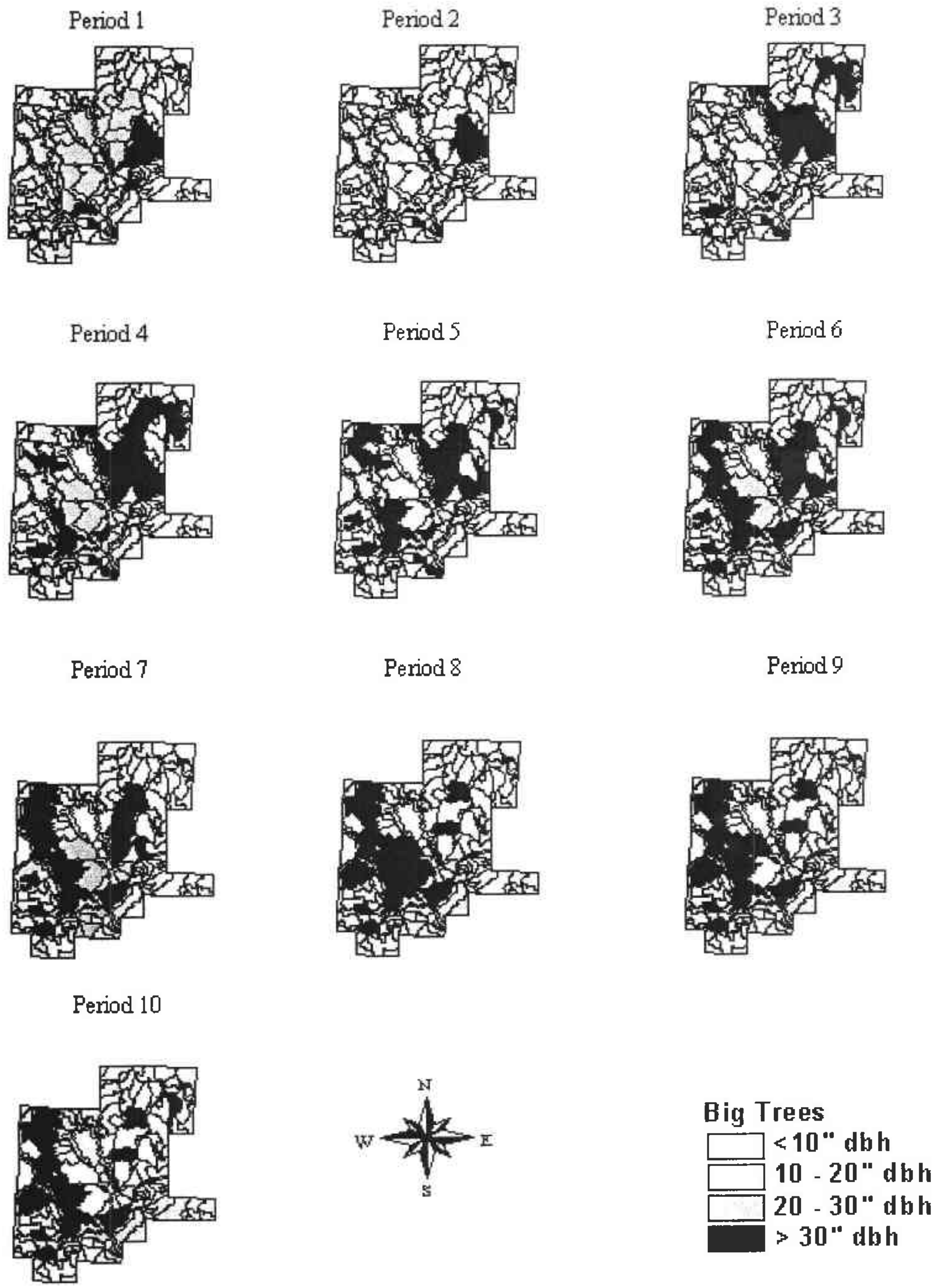

Figure 12. Location of harvest units meeting large diameter goals, periods 1-10

Figure 13. Location of harvest units meeting large diameter goals, periods 11-20.

Table 5. Objective function performance of heuristics. SA= simulated annealing; TS = tabu search; TSSO = tabu search with strategic oscillation. Present net worths, millions of dollars 4% discount rate, are in parentheses. Present net worths do not necessarily correspond directly with objective function values.

	TSSO	TS*	SA
Mean	11809456 (15.91)	11082181 (15.10)	11393817 (15.56)
Median	11831722 (15.89)	10977204 (15.01)	11398319 (15.59)
Best	11889591 (16.06)	11804004 (15.70)	11698238 (15.86)
Worst	11678555 (15.76)	10842147 (14.91)	10985987 (15.17)
Range	211035 (0.30)	961857 (0.79)	712251 (0.69)
Standard Deviation	58120 (0.077)	242654 (0.209)	159277 (0.183)
Number	30	20	30

*TS was not started from the same initial starting points as TS and SA

objective function. The TSSO algorithm outperforms the other algorithms in best, worst and average solutions, and provides a range of results over 3 times "tighter" than the other two algorithms. The straightforward TS approach produced the worst outcomes of all algorithms tested.

Figure 14 shows the solution trajectory of a typical TS process for this problem. Following an initial rapid rise in the value of the objective function, a local optima is reached first around the 100th iteration. The search continues intensively around this area of the solution space until short-term tabu restrictions force the algorithm to accept solution elements (different prescriptions for the harvest units) that deteriorate the value of the objective function. Eventually, this process pushes the search into a different region of the feasible solution space and a better local optimum is found. This pattern continues throughout the search until a termination criterion is reached (usually number of iterations without improvement). It is unclear whether a better solution would be found if the algorithm were allowed to proceed indefinitely.

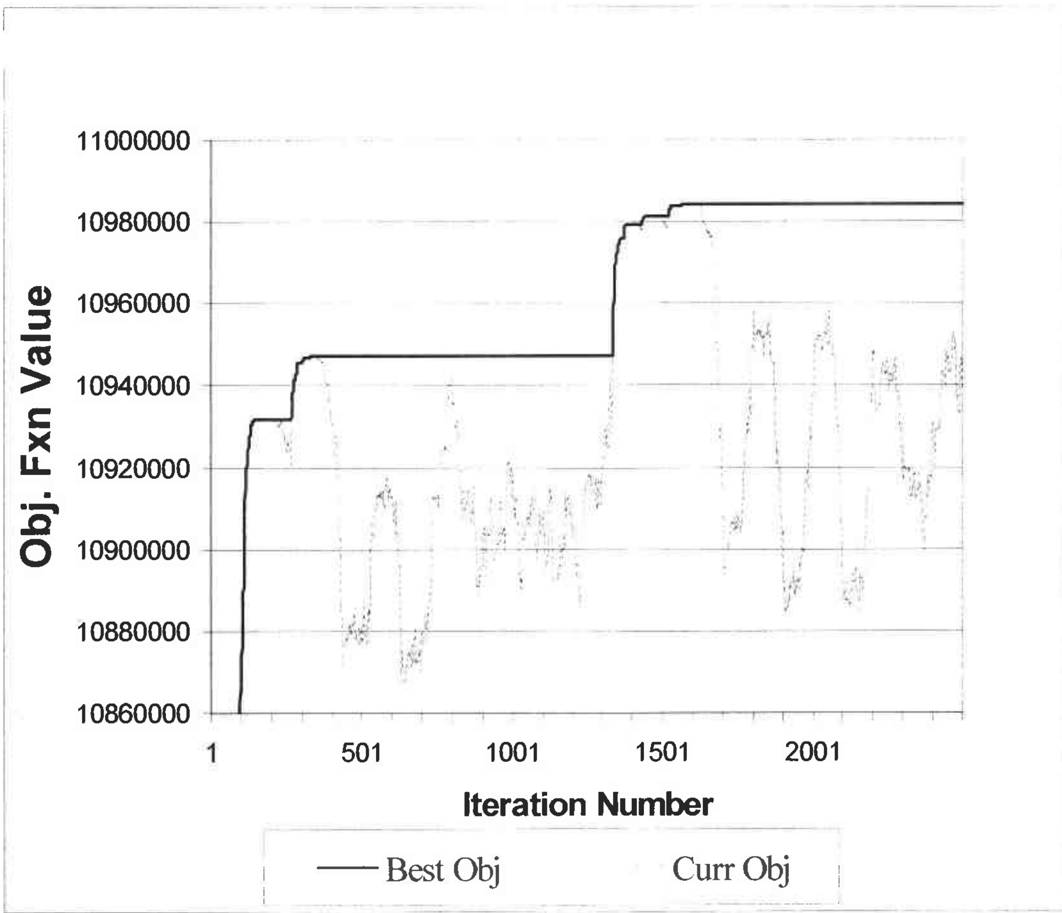

Figure 14. Solution trajectory of TS algorithm. Obj. = objective function value.

In comparison, Figure 15 shows a solution trajectory typical of a TSSO run. Again there is an initial period of steep early improvement to a local optimum. In the early part of the process, the algorithm is able to continually pick improving solutions in the feasible region. The longer the algorithm remains in the feasible region, the more the weights of the infeasibility coefficients in the objective function decrease. At the first local optimum, instead of cycling through tabu lists immediately, the algorithm finds the infeasible regions of the search space quite attractive, and spends a good number of iterations in this infeasible region. Eventually, the self-feedback mechanism increases the weight of the penalty coefficients and the search is "drawn" back into the feasible region. When it returns, around iteration 400 in this instance, it is able to find a local feasible solution

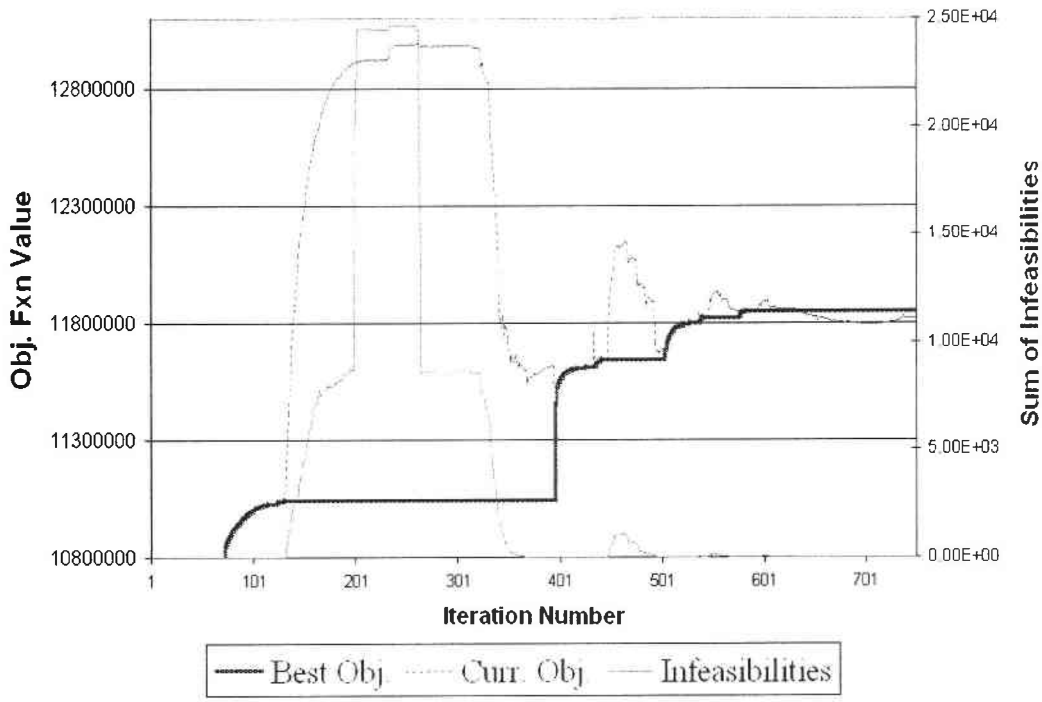

Figure 15. Solution trajectory of TSSO algorithm.

much better than previously encountered. Further forays into the infeasible region as the search progresses continue to result in gains in the best feasible solution found. The pattern of large increases in objective function value of the best feasible solution found early on in the search (<500 neighborhood searches) following the current solution becoming extremely infeasible was commonly observed in most TSSO runs. However, the best solution was not always found early in the process. The average number of iterations to find the best solution for all runs of TSSO is 1379.6, with a standard deviation of 1163.07. Most (67 %) runs produced their best result in less than 1000 iterations; however, the total range was 482 to 4991. Obviously these solution trajectories were very dependent on their initial starting points.

Figure 16 shows how well TSSO compares to the SA with the best "cooling schedule" and starting and ending temperatures found. The diagonal line represents the line y=x, where any point along the line would represent an initial Monte Carlo solution that had the same final objective function value for each heuristic. Points on the TSSO side of the diagonal indicate initial solutions for which the TSSO process outperformed SA and vice versa. As the graph shows, TSSO found better solutions than SA for all initial random starting points. Actually, SA produced only one solution that was superior to the lowest valued solution TSSO found, although each were from different starting points.

Solution times

While TSSO was consistently able to produce better objective function values than the other algorithms tested, SA was vastly superior in terms of solution cost. All processes were run on a personal computer with a Pentium II 450 MHz processor and 256 MB RAM to yield the following average solution times in user-time minutes (standard deviations in parentheses): TSSO: 358.2 (109.2); TS: 303.2 (82.6); SA 12.4 (2.2). The reasons for the variations in both tabu search procedures had to do with the stopping criteria; depending on the original random solution start, the search trajectory could find its best feasible solutions, which would reset no_improvement_count (see Figure 10) sooner or later in the

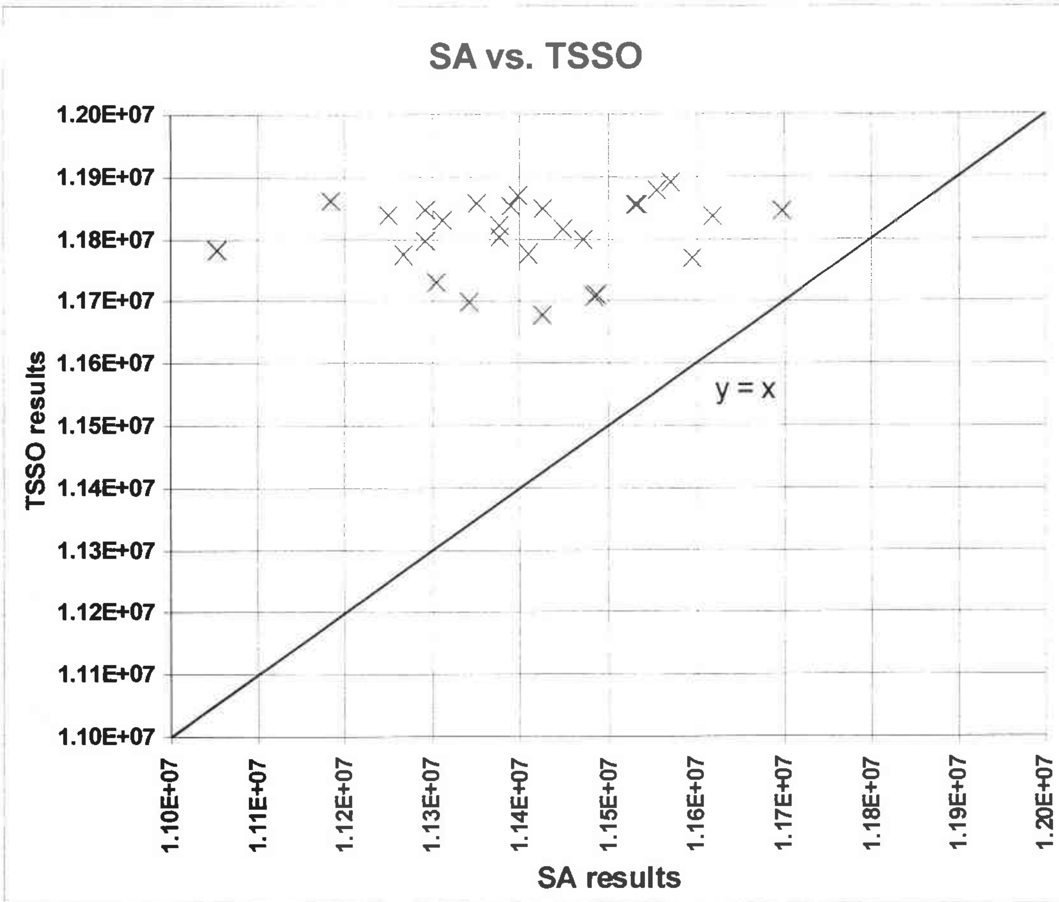

Figure 16. Results of 30 heuristics started from the same initial random solutions.

process, leading to shorter or longer total solution times. In TSSO, evaluating feasibility while the existing solution was infeasible took slightly longer per iteration. For all runs of TSSO, the algorithm spent only 26.7% of all iterations with the existing solution being feasible, based on log files of the solution processes. 52.7% of the time existing solutions were infeasible for meeting the 500 acres total large diameter goal; these figures were 51.0% and 44.8% respectively, for violations of the contiguous block and maximum clear cut size constraints. For SA, each time a solution is proposed that violates the maximum clear cut size constraint, the solution is rejected and a new one evaluated before an iteration is registered. Stochastic selection of infeasible solutions during the process thus likely caused the variance in SA solution times.

Validation using extreme value theory

Based on the Anderson-Darling test statistics, we failed to reject the null hypothesis that the distribution of solution values generated by the heuristics fit a Weibull distribution for the TSSO and SA algorithms. When solution results were combined, the Weibull distribution hypothesis was rejected (Table 6).

This may be seen more clearly in Figures 17 - 19, which show the distribution of solution values and their estimated Weibull probability density functions for each algorithm and the combined solution values. The distribution of the combined values appears bimodal, reflecting the superior solutions found by TSSO versus the inferior ones obtained with SA. Since the SA algorithm produces a wider range of solution values, the

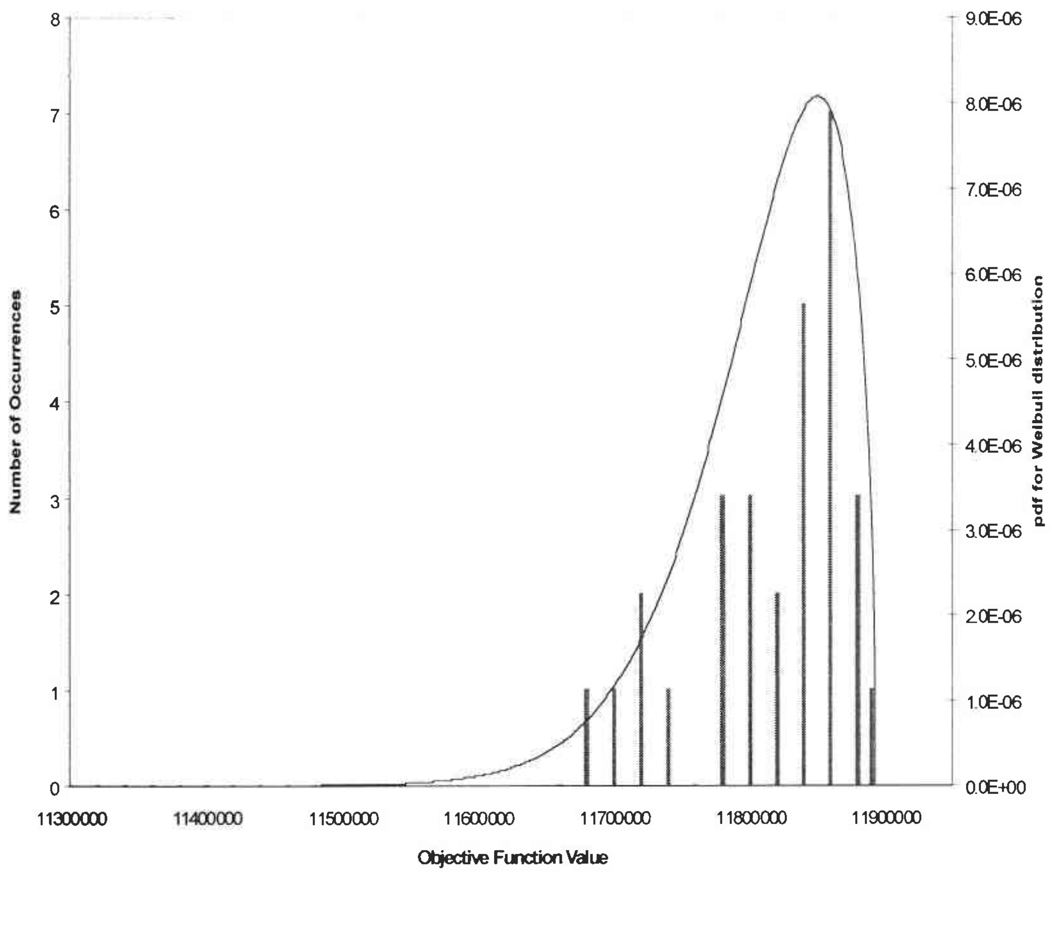

Figure 17. Weibull distribution and solutions for TSSO

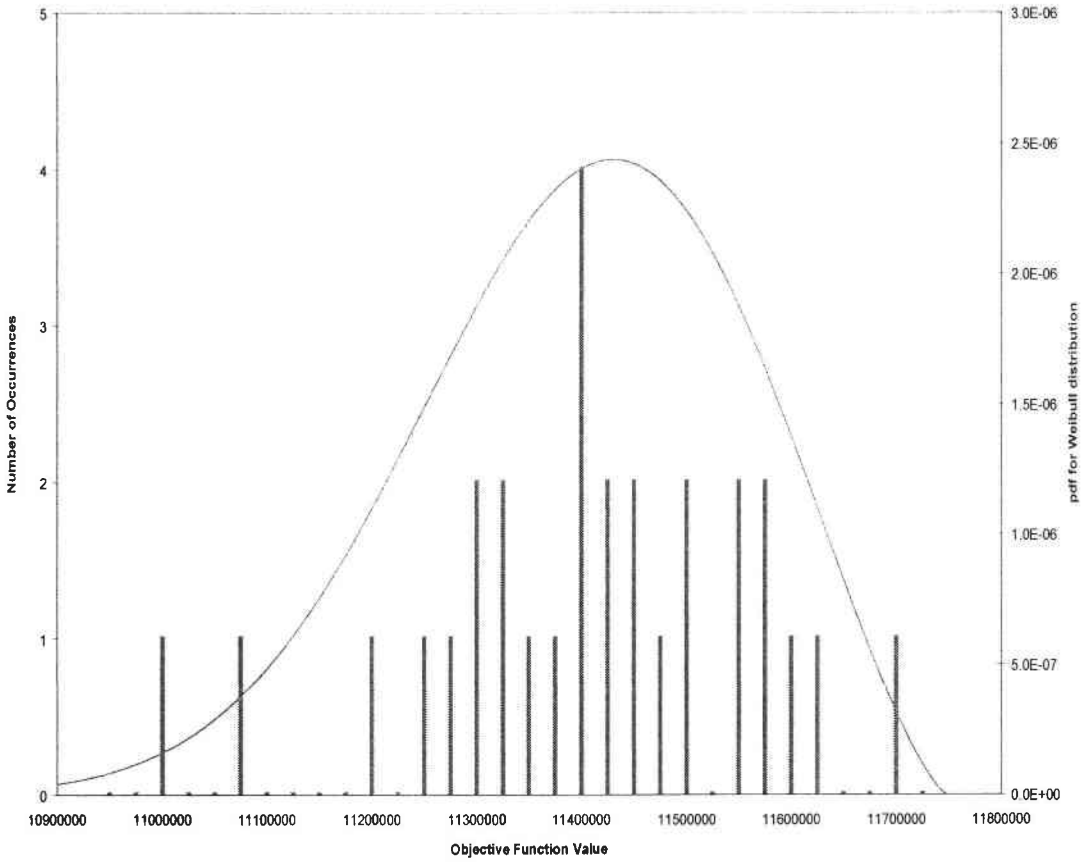

Figure 18.Weibull distribution and solutions for SA.

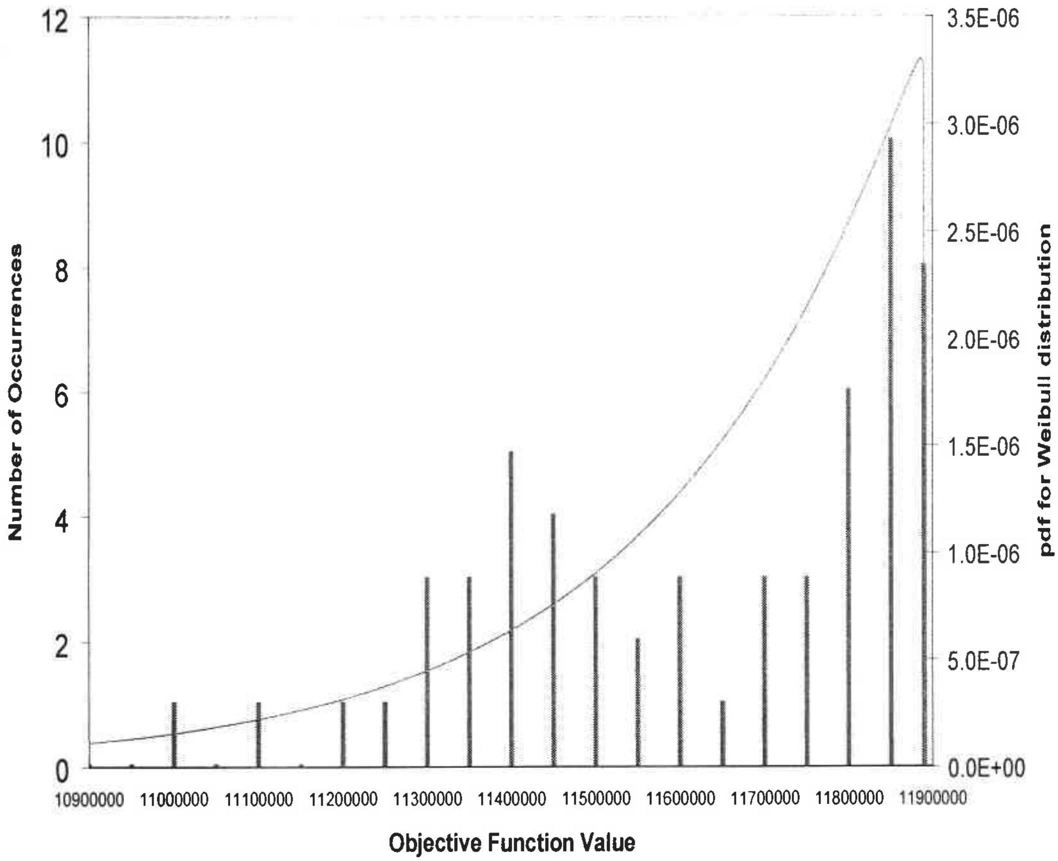

Figure 19. Weibull distribution and solution values for combined TSSO and SA. Using the Anderson-Darling test statistic, the goodness-of-fit hypothesis for a Weibull distribution was rejected

estimated shape and scale parameters are naturally larger than TSSO, which also affects the 95% confidence interval estimate for the location parameter, $\hat{a}$.

Table 6. Estimated Weibull parameters, intervals, and test statistics

	TSSO	SA	COMBINED
Anderson-Darling test statistic	0.32697	0.207	1.255095
Reject H_0 @ critical value .05 (0.757)?	NO	NO	YES
Number of Observations, R	30	30	60
Weibull location estimate, $\hat{a}$	11892600	11748500	11889700(N/A)
Weibull scale estimate, $\hat{b}$	91835.27	399574.4	289118.8(N/A)
Weibull shape parameter, $\hat{c}$	1.470016	2.389972	1.009997(N/A)
$S = \left(- \dfrac{R}{\ln \alpha} \right)^{1/\hat{c}}$	4.684568	2.585313	N/A
$\hat{b} / S$	19603.79	154555.5	N/A
95% confidence interval	11889591, 11909195	11698238, 11852793	N/A

The estimated location parameter using the SA distribution is only 11748500, which would only be greater than five of the TSSO solutions. The upper confidence interval limit is 11852793, which represents a slightly better than median TSSO result. Since the combined data are rejected for fitting a Weibull distribution, the best estimate of the global optimum is the estimated location parameter for TSSO, 11892600.

Using the location parameter estimate from the TSSO distribution, all SA results were within 7.6% of the estimated global optimum; 22 were within 5%, and one was within 1.7%. All TSSO results were within 1.8% of the estimated optimum; 23 were within 1%, and one was within .03%.

DISCUSSION AND CONCLUSIONS

Wildlife goal achievement

Using the heuristic methods presented in this research, the complex spatial wildlife goals as elaborated by the Blodgett Planning team were modeled to produce very good schedules which maximized net value subject to specific revenue flow constraints. The spatial specifications, and the planning units they affected through time, were determined in advance by the planning team and research forests staff. It is possible that the arrangement of acres through time in various seral stages as produced by the model results may not provide optimal wildlife habitat. The scheduling model, operating only on information available to it regarding adjacency of units and the spatial requirements of the plan, may produce spatial arrangements of the mature young growth contiguous block that are too irregular, or move about the forest too rapidly. The heuristic framework is flexible enough to allow reformulation of the problem to incorporate additional goals measuring the suitability of habitat throughout the landscape if the appropriate measures and data exist. One way to influence the arrangement of the mature young growth patches through time would be to include in the objective function shape goals with area and perimeter of mature young growth patches as inputs (e.g. Boston 1996), or weighted landscape metrics such as those from FRAGSTATS (McGarigal and Marks 1995). In practice, while working with the diverse group of stakeholders represented by the planning team and the Dean of the College of Forestry, it was found that visual representation of results and feedback from the planning team members revealed preferences for both landscape arrangement and revenue flow. Consequently, earlier formulations which emphasized larger or smaller amounts of wildlife habitat were dropped when stakeholders were able to see how the schedules would play out on the ground. Since landscape ecology's implications for forest management planning are still in an evolving phase, expert opinion on habitat suitability at this point in time is dependent on examining and judging the results of forest plans in relation to other goals (e.g. Hayes 1998). The advantages of heuristic techniques- fast solution times and flexible constraint formulation- were apparent in these early stages when goals were not firmly established and the results of different scenarios needed visitation.

Forest planning implications

While there is no claim here as to the efficacy of the landscape plans produced by this method for producing favorable wildlife habitat over a long time period, these methods do represent an advance in demonstrating how complex spatial landscape details can be met over a long planning period in concert with other management objectives. In this instance, heuristic programming techniques combined strategic and tactical planning for a complex set of spatial and temporal landscape goals that could not be recognized by more traditional methods such as LP. Even for relatively straightforward requirements of harvest unit integrality and simple adjacency restrictions, IP and MIP formulation continue to be practically limited by problem size (Bettinger 1996; Boston and Bettinger 1999). When maximum patch size- whether of clear-cut units or units in a later seral stage- of contiguous stands is considered, additional complexities of formulation are introduced which make problems unworkable (Richards 1997). In the face of large, realistic problems with complex spatial restrictions, heuristics at this point may offer the only viable means for longer-term tactical planning. While planners cannot have certainty that the solutions to complex problems are globally optimal using heuristics, spatial and temporal feasibility are easily determined. This explicitness, and the ability to combine strategic with tactical plans in the same problem formulation, could be useful in forming and documenting habitat conservation plans for endangered species, or as support for seeking third-party, performance-based forest certification.

Algorithm relative performance

Recently, forest planning researchers have chosen tabu search over other "general purpose" heuristics such as simulated annealing or Monte Carlo integer programming to solve tactical planning problems and problems with complex spatial relationships, citing its superior performance on hard optimization problems in other fields and intelligent use of memory in guiding the search process (e.g. Boston 1996; Bettinger 1996; Bettinger et al. 1997; Richards 1997; Brumelle et al. 1998). Until Boston and Bettinger (1999), the only research in forest planning directly comparing heuristic methods (Monte Carlo integer programming, interchange, simulated annealing, and tabu search) had found tabu search to produce the best and narrowest range of solutions for two different tactical planning problems (Murray and Church 1995).

Richards (1997), however, warns against the straightforward application of tabu search for hard optimization problems in forest planning, noting that modelers can spend considerable time in designing methods to choose tabu tenure yet never actually achieve good results. Paulli (1993) and others (e.g. Kincaid 1991) exploring different fields share a similar view that finding the correct list size is the most difficult aspect of tabu search, and that, at least in Paulli's (1993) view, a quick simulated annealing approach is better than a thorough and slow tabu search process. Boston and Bettinger (1999) found that simulated annealing outperformed tabu search for three out of four similarly sized data sets. In this research, considerable effort was spent early on experimenting with different list lengths, simple aspiration, and frequency-based long term memory strategies, all to little result as it became obvious that simulated annealing usually outperformed straightforward tabu search for this problem. Boston and Bettinger (1999) have suggested that tabu search is able to outperform simulated annealing in more constrained solution spaces because of its inherent design to search intensively. In instances where the solution space is less concentrated, simulated annealing may produce an overall better solution because of its ability to jump to different regions of the solution space more freely in a stochastic manner. The disadvantage is that the range of solutions found under these circumstances is likely to be wider than tabu search (Boston and Bettinger 1999). If the solution space is very disjoint, such as the case with complex adjacency constraints, a tabu search may be more likely than simulated annealing to become entrapped in a local optimum and remain around that "attraction basin" for the duration of a solution process due to its aggressive searching nature (Battiti and Tecchiolli 1994). In this research and in larger, more complex forestry planning, problems are characterized by very disjoint solution spaces due to adjacency relationships of harvest units through time.

Without extensive experimentation involving short-term tenure length, different long-term memory strategies, intensification and diversification procedures and so forth, or the results of another solution procedure to compare results with, it is very difficult to judge how well a tabu search procedure is performing. Often, the performance of straightforward tabu search leaves something to be desired (Richards 1997). This research confirms that conclusion. Of all the strategies to improve tabu search performance, Richards (1997) found strategic oscillation to be indispensable. Without it, diversification strategies and self-regulating tenure strategies were ineffective. Similarly, strategic oscillation produced in our case a markedly superior set of results as well. During algorithm execution, strategic oscillation is able to admit spatially infeasible solutions temporarily into the solution path, driving the search towards different, more promising regions of the solution space. Thus it served as an extremely effective diversification strategy (Glover and Laguna 1998), and with the self-regulating penalty coefficients, biased the search towards the boundaries of the feasible region. Intuitively, for a constrained optimization problem such as the tactical planning problem, this sort of approach makes sense; the well-known simplex algorithm for LP arrives at optimality by traversing the most promising linear boundaries of the feasible solution space and examining corner point solutions. A heuristic algorithm that can search systematically around feasible boundaries would be expected to find better solutions than one which did not seek these boundaries out.

The discussion of relative algorithm performance, however, is not complete without considering solution times. Simulated annealing produced very good solutions in a fraction of the time the tabu search approaches took. Relative to TS, further efficiency was gained by the straightforward manipulation necessary to fine-tune the SA algorithm and the resulting quick feedback. The results of changing the few "standard' model parameters involved in the simulated annealing procedure were available within 15 minutes. Unlike tabu search, there is not as much guesswork involved in choosing correct tenure lengths or diversification strategies that best fit the presumed solution space, since SA is fundamentally a guided random sample, mimicking a natural process. Therefore, improving the algorithm mostly involved manipulating cooling schedules and beginning and ending temperatures. Although the spread of results were wider, the average simulated annealing result was within 4% of the average result found with the best tabu search approach-TSSO and the best result was within 1.7% of the estimated global optimal value. One might argue that the additional modeling and run time necessary to design efficient tabu search procedures in future applications of similar or larger magnitude is not worth the effort, and simply that a greater sample of SA runs should be taken in order to get the best solution possible.

Another approach to constructing a heuristic that produces very good results in a reasonable amount of time may be to use a self-tuning tabu search such as Battiti and Tecchioli (1994a 1995) developed combined with a reduced neighborhood search. Comparing simulated annealing algorithms and a tabu search strategy with tabu tenure that is determined reactively during algorithm execution, Battiti and Tecchioli (1994b) argue that fast evaluations of neighborhoods can be executed in the tabu search framework and that in the long run, the memory aspect of tabu search implementations gives it a competitive advantage over simulated annealing. Because of the randomness of the search, simulated annealing is unable to "recognize" when it is in a suboptimal region of the solution space. Their tabu search procedure, reactive tabu search (RTS), in which tabu tenure is changed "reactively" depending on the reoccurrence of previously visited solution configurations, is able to make additional gains at later points during the search where simulated annealing cannot by utilizing information gained from the search history. The self-tuning of tabu tenure could reduce the design time necessary to experiment with different tabu list lengths (Battiti and Tecchioli 1994b).

Meanwhile, partial evaluation of neighborhoods could reduce CPU time. Glover and Laguna (1998) and Glover (1990) suggest the use of candidate list strategies to decrease the portion of the neighborhood searched each iteration of tabu search, or simply to use a random sampling scheme. In fact, introducing stochastic elements through a random sampling scheme may add robustness to the search (Glover and Laguna 1998). In this research, no attempt was made to employ partial neighborhood search techniques.

While a scheme utilizing reactive tabu tenure *and* a reduced neighborhood search would seemingly have potential, relative to simulated annealing, to offer superior performance with similar CPU time but *less* investment of design time picking the correct parameters, Richards (1997) found that RTS by itself was inadequate in improving results reached from different fixed tenure approaches. For the tactical planning problem, strategic oscillation was the necessary ingredient to produce vigorous solutions. It is probable that the most important factor in the strategic oscillation is the systematic guidance of solutions near the constraint boundaries, rather than exhaustive neighborhood search each iteration. Therefore, a plausible approach to future forest planning problems with complex spatial and temporal constraints may be to use a tabu search procedure with partial neighborhood evaluation and strategic oscillation. Additionally, using an RTS approach could minimize modeler time spent experimenting with different fixed tabu tenures. Richards (1997) found the best results with a combination of strategic oscillation and RTS.

Forestry so far has seen little of the experimentation with tabu search procedures and extensions that has occurred in other industries and in academia. Simulated annealing, on the other hand, is relatively easy to understand, implement, and manipulate, is as effective as tabu search in many instances, and can produce good results in a short amount of time (Battiti and Tecchioli 1994b). To present and assess alternatives quickly in the face of complexity and uncertain stakeholder objectives, it is important to have a solution procedure which can produce a series of feasible solutions rapidly under different scenarios and constraints. Furthermore, in the absence of shadow price information generated from an LP solution, tradeoffs have to be assessed by varying the weights of different penalties in the objective function (e.g. Richards 1997; Brumelle et al. 1998). This tradeoff analysis allows the modeler insight into the nature of the solution space, and helps the modeler and stakeholders understand what can and cannot be produced. During this early part of the analysis, random start hill climbing, simulated annealing, or another random search technique may be a more appropriate choice as alternatives are presented, the solution space is explored, and the preferences of stakeholders become more defined. These techniques would offer ease of implementation and relatively fast solution time for evaluation of alternatives. Later, once goals and constraints are firmly established, a more involved, directed process such as TSSO, or, if the problem is small enough, IP, may be formulated to find even better answers for the problem at hand.

Validation using extreme value theory

Validation of heuristics through extreme value theory continues to be an unresolved topic. This research found that although Weibull distributions for both SA and TSSO results could not be disproved, parameter estimates of extreme values were significantly different. Using interval estimation techniques of Los and Lardinois (1982), the 95% confidence intervals of the estimates of the Weibull location parameter failed to intersect, leading again to the conclusion found by Boston and Bettinger (1999) that although the distribution of results from randomly started heuristics may indeed fail to be rejected as fitting a Weibull distribution, the location parameter estimate, representing the theoretical global optimum, depends on the quality of the solutions produced. In other words, without *a priori* knowledge of the global optimum, it is not possible to determine how close heuristic solutions approach it. Comparing the results of the two heuristic algorithms evaluated for Weibull distributions in this case, an intuitive argument could be made that because TSSO produces a distribution of results which have significantly better objective function values than SA and have less dispersion as measured by the estimated shape and scale parameters, that fitting the TSSO results produces a "more reliable" estimate of the global optimum than a more dispersed distribution like SA. The Weibull distribution can exhibit a large range of shapes depending on the shape and scale parameters; the question is: are some parameter ranges more acceptable than others for estimating global optima reliably? Future research might concentrate on this question. Meanwhile, researchers need to be wary of applying these estimation techniques to results gathered from only one heuristic approach, even if the results do fit a Weibull distribution.

Summary

Using heuristic solution techniques, a long-term, "real-world" forest planning problem involving explicitly articulated spatial wildlife habitat goals in a context of active commercial management for timber revenue was solved. By showing how strategic goals could be met exactly at the tactical level, the methodologies presented here represent an advance over traditional forest planning techniques which are often not able to tie together strategically determined outputs with tactical plans through time, especially as the complexity and size of spatial and temporal constraints increase. Increased spatial and temporal complexity characterize attempts to include wildlife habitat considerations in forest planning, so methodologies such as those presented in this research may be beneficial to forest managers as pressures to address wildlife habitat in forest planning grow.

Numerous heuristic solution approaches have been proposed to address the tactical planning problem in forestry. This research confirms the results of Richards (1997), who suggested researchers must be wary of straightforward tabu search applications and that a strategic oscillation approach in conjunction with tabu search is extremely well-suited to the tactical planning problem. Furthermore, this research suggests that any heuristic technique evaluated only by itself may be inadequate for judging how "good" its results are. From a forest planing perspective, a full appraisal must consider the use of the plans produced by the heuristic, the cost both in modeler and solution time to implement the technique versus the potential benefit, the heuristic's performance in relation to other solution techniques, and the relative consistency and range of its results. There do not appear to be clear guidelines at present for validating results of heuristic procedures using extreme value theory when the globally optimal solution is not known. Developing better-defined, standard approaches for validation would provide future users better understanding of the worthiness of these approaches and confidence in the decision to use them or not.

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APPENDIX

Figure A- 1. Location of silvicultural activities for best schedule found, period 1-10.

Figure A- 2. Location of silvicultural activities for best schedule found, period 11-20.