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Tabu Search Experience in Forest Management and Planning

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1. Introduction

Tabu search was initially developed by Glover (1989, 1990), and has been applied to a number of forest management and planning problems (Murray & Church 1995; Bettinger et al. 1997, 1998, 2002; Boston & Bettinger 1999; Brumelle et al. 1998). In general, when using tabu search to address forest management and planning problems, a number of forest plans are deterministically developed and assessed, each subsequent plan being slightly different than its predecessor, and thus each is considered an iteration of the modeling process. A large number of iterations are usually required to ensure that the search process has explored the solution space sufficiently. In most cases in forest planning, tabu search is used as a 1-opt search process, where a feasible forest plan is modified by changing the status (harvest timing, prescription, etc.) of a single forest management unit, thus creating a new plan. However, as we will see, other intensification and diversification processes have been used to expand the capabilities of the search process.

A tabu search process begins with an initial, randomly defined, feasible solution (forest plan) (Figure 1). A simple Monte Carlo (i.e., random) process is generally used to select timber stands and management prescriptions, and constraints are assessed with programming logic to ensure that each choice results in a feasible solution. Feasibility is not difficult to obtain in the initial solution, as most choices are made by avoiding the violation of constraints. However, the initial solution is generally of low quality. This process is consistent with much of the work related to the use of heuristics in forestry (e.g., Bettinger et al. 1998). With each iteration (k) of the tabu search algorithm, a new feasible solution (x_k) is created from a transformation of the previous feasible solution (x_{k-1}) by a move (δ). A δ is a transition from one feasible solution to another feasible solution. The δ may represent the change that results in the best possible improvement in solution x_{k-1}, or that results in the least deterioration in the value of x_{k-1} (Voβ 1993).

With this search technique, a δ can consist of assigning a different prescription to a timber stand (1-opt δ) or swapping the prescriptions assigned to two different timber stands (2-opt δ). A candidate δ cannot consist of the assignment of more than one prescription to a timber stand. Each feasible δ requires that it does not result in a violation of the constraints. In all cases, a tabu tenure is assigned to each δ and aspiration criteria are employed. Most forest planning applications of tabu search involve the scheduling of harvests to timber stands. However, the allocation of timber stands and cutting patterns to logging systems has been

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explored with tabu search (Murphy 1998), as have optimal methods for bucking (cutting) logs from trees (Laroze & Greber 1997).

2. Intensification processes within tabu search

Recently, some have suggested that enhancements are necessary to tabu search to allow it to locate increasingly efficient solutions for complex forest planning problems, such as those facing forest landowners (Bettinger et al. 1999, Caro et al. 2003, Richards & Gunn 2000). One enhancement to tabu search that has shown promise in forest management applications is the addition of a 2-opt search strategy. A 1-opt search strategy in forest management planning is generally used to select the management prescription or harvest timing for a stand of trees. Simply stated, the best change to a forest plan is selected from the tabu search neighborhood, and if not tabu (or if tabu and if it passes the aspiration criteria test), the change is incorporated into the forest plan. A 2-opt search strategy is used to switch the prescription or timing of harvest of two separate stands of trees. This switching results in less of an impact on the objective function, and results in changes to forest plans that might not otherwise be acceptable in similar consecutive 1-opt choices. Several studies in the forest management literature have confirmed the notion that the addition of this process to a tabu search procedure will lead to significantly higher quality forest plans (Bettinger et al. 1999, Boston & Bettinger 2001a, Bettinger et al. 2002, Caro et al. 2003, Batten et al. 2005).

There are two drawbacks to the use of the 2-opt process in forest planning. First, it cannot be used in the absence of a 1-opt process. The 2-opt process can only switch management opportunities that are currently in a forest plan. For example, if all of the timber stands in a forest plan are scheduled for harvest in the first year of a ten-year plan, there is no opportunity with the 2-opt process to schedule stands in the other nine years. A 1-opt process provides these opportunities by changing the harvest timing of individual timber stands. Second, the 2-opt process is an intensive process from a computer processing standpoint, since the full neighborhood is about 0.5 (n x n) in size rather than (n x p), where n represents the number of stands, and p represents the number of prescriptions or harvest timing choices (generally a small number). This is important when developing a tactical plan that may cover 20 or more years and involve thousands of timber stands. Caro et al. (2003) investigated the use of 2-opt neighborhoods as well, yet in this case, the 2-opt process was only used to mitigate infeasibilities generated by 1-opt moves.

3. Diversification processes within tabu search

A number of diversification processes can be used to force a tabu search process to un-explored areas of the solution space. One involves the use of long-term memory. Here, the frequency with which choices are evaluated for each stand of trees is tracked, and at some point during the search, the least-selected choices can be forced into the solution. Boston & Bettinger (1999) illustrated the use of such a diversification process in a forest planning problem, however they found that simulated annealing was able to produce better solutions, even though tabu search produced solutions with less variability. Brumelle et al. (1998) tested frequency-based diversification within tabu search to force the process to test harvesting alternatives that were rarely selected during the development of a forest plan. In this work, a static diversification scheme was used to determine when to diversify the search. This consisted of initiating the process every *x* iterations, the size of which was explored through trial-and-error. In addition, a process for determining when to diversify was developed whereby the diversification process was initiated whenever the average improvement in objective function value fell below some pre-defined threshold. Neither of these diversification schemes, once optimal parameters were identified, outperformed the other.

Pukkala & Heinonen (2006) suggest that when applying tabu search to forest management problems, one way to prevent the increase in computational time as a problem gets larger is to decrease the size of the neighborhood. In a large forest planning problem, Bettinger et al (2007) described how a region-limited neighborhood could be used in conjunction with tabu search to effectively allow the development of a forest plan. The management problem involved scheduling stand-density management prescriptions to over 17,000 timber stands contained within a 178,000 ha watershed in eastern Oregon (USA). Two types of tabu search were utilized: 1-opt moves only (changing the prescription of a single timber stand), and 1-opt and 2-opt moves (switching the prescriptions of two timber stands). The objective of the problem was to locate a plan that provided the highest, and most even timber harvest volume over a 100-year time horizon. The attainment of the objective was complex in that the prescriptions available to each timber stand involved partial cutting activities that produced timber volume at various points in time through the 100-year time period. Given the size of the problem and the observation that developing a full neighborhood for 1-opt moves was computationally slow, the search was adjusted to examine 1-opt moves only within a 2,000 timber stand window. This window shifted 1 stand upward with each iteration of the tabu search process. When used, the 2-opt neighborhood was even smaller (1,000 stands), and shifted by 20 stands with each iteration of the search process. While using the full neighborhood produced harvest levels that were, on average, consistent with the region-limited process, the region-limited process produced harvest levels that contained less variation across the 100-year time horizon, thus these solutions were noted as being superior to those derived when using the full neighborhood. However, some of this improvement is attributable to the use of the 2-opt neighborhood of choices. Caro et al. (2003) also used sub-region tabu neighborhoods to limit the amount of computations necessary for each iteration of tabu search. And Heinonen & Pukkala (2004) diversified their tabu search process by developing neighborhoods of randomly-chosen 1-opt and 2-opt moves. In this sense, a full neighborhood was not developed due to the size of the problem, but a smaller neighborhood composed of randomly chosen moves was employed.

Penalty functions have also been incorporated into tabu search processes to allow the search to more freely explore the solution space. Caro et al. (2003) allowed infeasible 1-opt moves to be accepted during a search, yet these infeasibilities were either mitigated using 2-opt moves, or a penalty was added to the objective function value to force (hopefully) the infeasibility to eventually go away. Richards & Gunn (2003) describe a strategic oscillation process where infeasible 1-opt moves are acceptable, yet they were penalized in the objective function using a biased penalty weighting procedure. Here, solutions (forest plans) that were "near" the boundary of the feasible region were penalized less than solutions that had moved further away from the boundary. The conclusion from these efforts is that for some problems, allowing solutions to temporarily deviate from feasibility could result in higher quality solutions.

4. Tabu tenure adjustment

In general, when applied to forest planning problems, the tabu tenure is generally fixed. To locate the best fixed tabu tenure, this requires an extensive examination of a range of tabu tenures to locate those that produce high quality solutions. Not only is this parameterization process time-consuming, but also it must be performed for *each forest planning problem*. The size (number of timber stands and number of management actions that can be applied to each timber stand) and the complexity of each forest planning problem are so diverse that this situation precludes the attainment of a single tabu tenure rule for all problems. However, Heinonen & Pukkala (2004) suggested that the use of a tabu tenure which was one-fifth of the potential size of the tabu list might be appropriate in some instances. Modifications to a fixed tabu tenure have been explored in several forest planning efforts. For example, a randomly determined tabu tenure was described in Caro et al. (2003), Brumelle et al. (1998), and Pukkala & Kurttila (2005). This process randomly determines the length of the tabu tenure for each choice that was made, the length of which is usually confined to a suitable range of tabu tenures.

Richards & Gunn (2003) suggested the use of a reactive tabu tenure, where when cycling of solutions is recognized, the tabu tenure is increased, and when cycling of solutions is not apparent, the tabu tenure is decreased. However, through partial experimentation of this method, they concluded that a fixed tabu tenure would be more appropriate, and that the extensive trial-and-error experimentation of tabu search to determine a tabu tenure could not be avoided. Pukkala & Kurtilla (2005) went further to assess the optimal range of the tabu tenure, and their work provides us with some guidance for certain types of forest planning problems.

5. Meta-models involving tabu search

A number of forest planning meta-models involving tabu search have been described in the literature. For example, tabu search has been used in conjunction with linear programming to illustrate how strategic and tactical goals could be met within a hierarchical system. In Boston & Bettinger (2001b), linear programming was used to solve a long-term forest planning problem, which was considered "relaxed" since spatial constraints were not incorporated into the planning system. Tabu search then used the outcomes of the optimal plan (harvest levels) to develop a tactical plan where spatial considerations were recognized and controlled. In this system the objective was to minimize the deviations between the harvest levels suggested by linear programming, and the harvest levels that could be accommodated in a tactical plan.

Within forest management planning, tabu search has also been used in conjunction with several other heuristics in an effort to capitalize on the search behavior of each. For example, Boston & Bettinger (2001a) combine forest plans developed with tabu search with a genetic algorithm process where the better tabu search plans are periodically split and recombined at a randomly defined crossover point to diversify the search. In another area of work, Boston & Bettinger (2002) compared two meta heuristics that involved tabu search: (1) a 1-opt tabu search process and a genetic algorithm process, and (2) a 1-opt and a 2-opt tabu search process and a genetic algorithm process. Here, the latter of the two provided the better solutions for the planning problems because, as we noted earlier, the addition of a 2-opt process generally improves the quality of the outcomes. Li (2007) recently explored numerous combinations of tabu search, simulated annealing, threshold accepting, and the raindrop method (Bettinger & Zhu 2006) to determine whether a meta-model could be developed that would capitalize on the search behavior of each. The transition between search processes in Li (2007) was determined by continuously assessing the quality of solutions, thus acquiring knowledge of the behavior, then switching heuristic processes when further improvements in solution quality were seemingly lacking. Nalle et al. (2004) embedded the tabu search neighborhood structure within a simulated annealing search process. Here, a neighborhood was defined as a forested stand and its adjacent neighbors, and when stand was selected for a 1-opt move, after the move was incorporated into the solution, its neighbors were then randomly selected for 1-opt moves using a simulated annealing process for a small number of iterations. Afterwards, another forested stand was selected, and its neighbors subjected to a simulated annealing process, and so on. This integration of techniques allowed small areas of the solution space to be more thoroughly analyzed than larger areas, and interestingly, the combination of techniques was computationally faster than the two methods working alone on the same problem.

6. Incorporation of non-linear goal assessment processes

One of the most common non-linear goal assessments in contemporary tactical forest planning processes involves the timing and placement of clearcut harvesting activities. The maximum size of clearcut harvests has been noted in several laws and policies related to the management of forests in North America. For example, in the United States, some state laws, such as those in place in Oregon, California, and Washington, recognize clearcut size limitations (Boston and Bettinger 2006). Some U.S. National Forests have limits on the sizes of clearcuts, such as the 16 ha maximum on the Chattahoochee-Oconee National Forest (U.S. Department of Agriculture, Forest Service 2004). Many industrial forestry organizations in the southeastern United States have also adopted the Sustainable Forestry Initiative (Sustainable Forestry Initiative, Inc. 2005) to show a commitment to social responsibility, and to demonstrate that their forests are managed in a sustainable manner. Like the Forest Stewardship Council (Forest Stewardship Council - U.S. 1996), participation in the Sustainable Forestry Initiative program is voluntary, and each program contains a number of principles and objectives that need to be implemented and achieved. One of the performance measures in the Sustainable Forestry Initiative program relates to the size, shape, and placement of clearcut harvests, which restricts the average size of clearcuts 48 ha or less. In addition, many companies have developed internal policies to voluntarily limit the maximum clearcut sizes to 96 ha or less (Boston and Bettinger 2001a). Some private landowners have also expressed an interest in adhering to these principles and objectives without the formality of becoming a member of a certification program (Batten et al. 2005).

Controlling where and when harvests are placed on a landscape requires an additional, perhaps extensive, set of non-linear constraints to a forest planning problem formulation. There are two conceptual models of adjacency and green-up commonly used in forest planning, the unit restriction model (URM) and the area restriction model (ARM), both of which are described in detail by Murray (1999). The URM controls the placement of activities by precluding the scheduling of one harvest that might touch (or be near) another harvest that has already been scheduled. The ARM controls the size of activities being scheduled by allowing adjacent activities to be scheduled concurrently (within the green-up period) as long as the total size does not exceed some pre-defined maximum. If timber stands are small relative to the maximum harvest area, URM constraints may significantly mis-represent the problem (Barrett and Gilless 2000), a concern that must be kept in mind, since changing the maximum harvest area in a planning problem is relatively easy, while changing the average size of stands of trees maintained in a geographic information system is relatively difficult. The ARM is not constrained in this manner, and can rely on the most disaggregate data available (Murray and Weintraub 2002). In our assessment of the recent literature, the URM and ARM are equally addressed, suggesting that each method has value even though they have their limitations. Inherent in each conceptual model is the green-up period, or exclusion, period. This is the length of time that must pass before activities are allowed in adjacent management units or stands. The green-up period is usually expressed in terms of years (2-4 years in the southern United States, for example, and 5-20 years in the western United States). Conceptually, it represents the amount of time a regenerated stand needs to "green-up," or grow to a certain height, before an adjacent stand is allowed to be harvested.

Area-based (ARM) clearcut size restrictions can require a large number of constraints to enable the control of adjacent harvests. As the potential maximum clearcut size increases relative to the average size of a management unit or stand, the number of constraints and potential constraint redundancies increases (Yoshimoto and Brodie 1994, Crowe et al. 2003). A number of methods have been assessed for generating sets of constraints that will increase the efficiency of integer programming problem solving methods, since a reduction in constraints plays an important role in the amount of time needed to solve a problem. Yoshimoto & Brodie (1994) and Murray & Church (1995) describe several constraint constructs that can be used to represent adjacency relationships in forest planning problems. The formulation of adjacency constraints has taken on considerable debate over the last 20 years, with the early work by Jones et al. (1991), who suggested that different formulations of constraints needed to be tested to determine their efficiency in assisting with the solving of a problem. Later work by Yoshimoto & Brodie (1994), Murray & Church (1995), McDill et al. (2002), and Goycoolea et al. (2005), to name a few, proceeded to do just that - examine how adjacency constraints might be arranged to solve a problem exactly, and quickly. Along these lines, constraints are either simply combined to reduce redundancy, or developed for cliques of stands, or developed for sets of mutually adjacent units (Murray & Church 1996). While the rather simplistic pair-wise adjacency constraints can be used for URM problems, they may not provide the most efficient formulation for integer programming problems (Murray & Church 1995). However, these types of constraints are commonly used in heuristic methods because they can quickly be assessed (Bettinger et al. 2002). Pair-wise adjacency constraints typically take the form of:

$$S1P1 + S2P1 \leq 1$$

Where S1P1 is a binary integer that represents the potential harvest of timber stand 1 during time period 1, and S2P1 is a binary integer that represents the potential harvest of timber stand 2 during time period 1. If these timber stands are considered adjacent, the constraint prevents them from being harvested in the same time period.

URM adjacency constraints are evaluated by assessing the status of all adjacent timber stands to each timber stand that is being considered for clearcut harvest. ARM constraints are evaluated, as previously noted, using logic to check all neighbors of clearcut timber stand *n*, and if they are clearcut within the green-up window, their neighbors, and so on

until the sprawling cluster has been fully identified. The two conceptual models of adjacency are not mutually exclusive, and there are times when a planning effort may require both ARM and URM methods. For example, the ARM constraints could be used to control the size of a harvested area (forming a harvest block), while the URM constraints could be used to prevent two harvest blocks from merging together (Bettinger & Johnson 2003, Bettinger et al. 2005). In addition, the ARM method need not be simply used to control the maximum harvest area. There may be management instances where the average harvest opening size is more important than the maximum opening size (Boston & Bettinger 2001b).
There are two generally methods for acknowledging these constraints within tabu search: (1) assess the constraints during the development of the tabu search neighborhood, and (2) assess the constraints after a choice has been selected from the tabu search neighborhood. The former approach can be computationally expensive, particularly when a full neighborhood is being used, and when ARM constraints are being assessed. However, the latter approach may also be computationally wasteful, since the choices made from the neighborhood are not necessarily feasible until the constraints have been assessed.
One of the first tabu search papers in forest management that involved non-linear wildlife habitat goals was presented by Bettinger et al. (1997). Here, a standard 1-opt tabu search process was used to maximize an even-flow timber harvest objective while also meeting constraint levels for the development and maintenance of Rocky Mountain elk (*Cervus elaphus nelsoni*) habitat. In this work, 80% of the elk forage area, which included land that was recently cleared or contained timber stands less than 10 years old had to be within 200 m of elk hiding cover, which was composed of timber stands containing trees at least 40 years old. The hiding cover areas also had to be at least 3 ha in size. In addition, 80% of the elk forage area had to be within 300 m of elk hiding cover, which was composed of timber stands at least 40 years old, and when aggregated, were at least 17 ha in size. The data describing the landscape was in grid form, and a moving window assessment was performed subsequent to the choice selected from the neighborhood. If after performing the moving window analysis the constraints were violated, then the potential choice was unscheduled. This work illustrated the search behavior of tabu search in the development of a forest plan, and suggested that three phases of the search were evident: (a) a hill-climbing phase where improvements to the objective were found, (b) an adjustment phase composed of both improvements and declines in objective function quality, and (c) a steady-state phase where no more improvements were recognizable. When further constrained, the steady-state phase was no longer evident, and was replaced by a heavily constrained phase, where general declines in objective function quality were noted after the best solution was located in the adjustment phase. More than likely, this was due to the fixed tabu tenure that was assumed.
Bettinger et al. (1998) later developed a tabu search process for scheduling timber harvests subject to stream sediment and stream temperature constraints. Here, after the scheduling of each timber harvest an assessment of sediment and temperature levels in the stream system was made. These assessments used procedures that involved logic and rules of thumb to assess aquatic habitat quality, which were distinctly non-linear in nature. Further, when sediment levels exceeded maximum threshold levels, three options were available to the scheduling model: (1) unschedule the timber harvest, (2) change the status of a road, perhaps decommissioning one, or (3) assign to a road the use of central tire inflation in all logging trucks (reduced air pressure levels in the tires). Each of these in effect can reduce

sediment levels in the stream system. In developing this scheduling process, two networks were necessary. The first involved the stream system. All of the sediment and temperature effects within the watershed were routed down the stream system to the exit point of the watershed. It was at this exit point that sediment and temperature levels were constrained. This process was consistent with the acquisition of real data from field gauging stations, and provided a validation of the aquatic assessments. The second network involved the road system. Here, access to all scheduled timber harvests needed to be maintained. If a road was scheduled for decommissioning, alternative access routes needed to be available. A shortest path algorithm was used to ensure that the schedule harvests could be transported out of the watershed at all times during the development of the forest plan. This work by Bettinger et al. (1998) was also the first in the forest sciences to utilize extreme value theory in estimating the global optimum solution to a forest planning problem. Since the aquatic assessments were distinctly non-linear in nature, and given the size of the problem, an exact solution was unobtainable.

7. Conclusions

In our experiences with tabu search in forest planning efforts, we have learned that the basic 1-opt scheduling process produces relatively good results to difficult problems. However, the incorporation of intensification processes, such as a 2-opt neighborhood of choices, always leads to higher quality solutions. However, using a 2-opt search neighborhood is computationally expensive, and therefore increases the time required to obtain a solution. Diversification processes, such as the use of strategic oscillation, can also force the search to un-explored areas of the solution space, and can result in higher quality solutions as well. A region-limited approach for the development of tabu search neighborhoods can also be of value in both diversifying the search as well as reducing the time required to generate a high-quality solution. Determining the appropriate tabu tenure to use in forest planning problems is an area of work that needs further exploration. Almost every forest planning problem requires a different tabu tenure assumption, given differences in problem size and complexity. Some approaches for varying the tabu tenure, and for assuming that the appropriate tenure is a function of the size of the problem, have both been explored, however no firm assumption has been proposed. Tabu search is a process that is adaptable to the various non-linear functional relationships that are becoming common in forest plans. As with other heuristics, the advantage of this search process over traditional mathematical programming methods (e.g., mixed integer programming) is that it allows forest planners to more fully capture the essence of a planning situation, and allows us to thereby develop forest plans that may not require further assessment prior to implementation.

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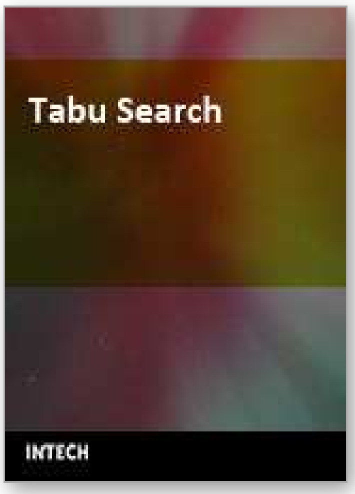

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The goal of this book is to report original researches on algorithms and applications of Tabu Search to real-world problems as well as recent improvements and extensions on its concepts and algorithms. The book' Chapters identify useful new implementations and ways to integrate and apply the principles of Tabu Search, to hybrid it with others optimization methods, to prove new theoretical results, and to describe the successful application of optimization methods to real world problems. Chapters were selected after a careful review process by reviewers, based on the originality, relevance and their contribution to local search techniques and more precisely to Tabu Search.