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A comparison of a neighborhood search technique for forest spatial harvest scheduling problems: A case study of the simulated annealing algorithm

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ABSTRACT

In this research application paper, the usefulness of the *s*-metaheuristic neighborhood search technique of simulated annealing algorithm when applied to forest management planning problems was explored. We concentrated on tactical forest spatial harvest scheduling problems where the net present value of management activities over thirty 1-yr periods was to be maximized. Constraints mainly included those related to the need for an even-flow of scheduled wood products and the need for spatial constraint types, i.e., unit restriction model and area restriction model, respectively. Four hypothetical grid datasets with different age class distributions (i.e., young, normal, older and spatially organized) and one real dataset from northeastern China were used to illustrate how a 2-opt moves can intensify a search within high-quality areas of a solution space and thus produce higher-valued solutions as compared to the sole use of 1-opt moves. Finally, extreme value theory was employed to estimate the global optimum solution and to evaluate the quality of the heuristic solutions. We found that the 2-opt technique not only produced consistently better solutions than the 1-opt technique in terms of the mean and maximum solutions values, but also significantly decreased the standard deviations associated with the sets of solutions. The maximum solution values were usually more than 98% of the estimated optimal values. The motivation for using a 2-opt technique is found in the generation of more efficient solutions that will allow a forestry organization to produce higher returns to its owners.

1. Introduction

Forest management plans are often developed to help process conflicts that arise between a desired number of goods and services in human society and to more specifically arrange the timing and placement of forest management activities (Bettinger et al., 2015). Societal values have changed recently, but for a long time forest management plans only focused on timber production and economic concerns in many countries around the world. Today there is an increased awareness of the importance of landscape pattern on the ecological functions of forests (e.g., wildlife habitat, biodiversity, recreation, water conservation). These concerns require new developments in forest planning, the problems of which now usually involve spatial information. A few of the more typical spatial restriction problems include controlling the maximum or mean sizes of contiguous final harvest (clearcutting) areas (McDill et al., 2002; Öhman and Lämås, 2003; Heinonen and Pukkala, 2004; Martins et al., 2014), decreasing fragmentation of forests (Borges and Hoganson, 2000; Öhman and Lämås, 2005), or developing and maintaining habitat of concern for endangered species (Tóth et al., 2008; Pukkala et al., 2012). Depending on the methods used to describe these problems, the processes may exceed the capability of traditional mathematical programming techniques (e.g., mixed integer programming), because they may need to be formulated as 0–1 mixed integer programming problems. Since solving these types of problems with traditional methods may be a formidable task, no one particular solution approach has become universally acceptable (Murray and Church, 1995), and research into traditional and metaheuristic methods continue to progress forward.

Within the field of forestry, harvest adjacency and green-up constraints have become the most commonly used constraint types for spatial harvest scheduling (Shan et al., 2009). As

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Murray (1999) described, harvest adjacency constraints can be described as two basic types: the unit restriction model (URM) and area restriction model (ARM). In general, the URM prohibits strictly the neighboring management units to be scheduled for a final harvest during the same time period. However, the ARM allows some limited neighboring units to be scheduled for a final harvest during in the same time period, as long as the total final harvest area does not exceed a user defined maximum size. Also, the concept of green-up constraints was introduced in order to guarantee a time buffer between the locations of two final harvest areas. Temporal constraint can be used along with the URM and ARM approaches (Boston and Bettinger, 2006; Zhu and Bettinger, 2008), yet can further complicate the development of the constraint set. Within the United States, the rules for adjacency and green-up constraints vary between different states and regions. The reasons for using adjacency and green-up constraints not only include the need to adhere to regulations, but also to comply with the guidelines of voluntary certification programs. For example, the Sustainable Forestry Initiative requires the maximum average clearcut areas must be less than 48 ha and the trees in adjacency final harvest units cannot be cut for 3 yr or until the regenerated trees reach an average height of 1.2 m (Sustainable Forestry Initiative, 2015). However, at one point in time for the subalpine region in Sweden, clearcut areas needed to be less than 20 ha and adjacent units could not be scheduled for a final harvest for 15 yr (Dahlin and Sallnas, 1993). In assessing the impact of adjacency and green-up rules, Zhu and Bettinger (2008) suggested that landowners with small-sized forests and young initial age class distribution would be significantly more affected by potential adjacency and green-up constraints. Boston and Bettinger (2006) also showed how certain rules can affect forest plan values. In summary, shortening the green-up period or increasing the assumed maximum clearcut size may be beneficial economically, but may also intensify the process of the fragmentation of landscapes or habitat patches.

In recent research designed to examine methods for solving spatial planning problems, two general methodologies are explored: mathematical programming techniques and heuristic algorithms (Shan et al., 2009). Mathematical programming techniques include linear programming (e.g., Charles et al., 2007), mixed integer programming (e.g., Tóth et al., 2012), goal programming (e.g., Diaz-Balteiro and Romero, 2004), non-linear programming (e.g., Miina et al., 2010) and dynamic programming (e.g., Borges et al., 1999; Yousefpour and Hanewinkel, 2009). Although some mathematical programming approaches have been developed to address spatial problems encompassing a large number of stands (e.g., Constantino et al., 2008; Goycoolea et al., 2009; Tóth et al., 2013), there still may be insurmountable difficulties in solving complex planning problems, such as the speed of optimization time. Advances have been made recently to help improve the computing time necessary to solve large forest planning problems through, for example, the strategic use of lazy constraints (Tóth et al., 2013) the reduction in variables and use of cluster variables (Constantino et al., 2008), or the tightening of adjacency constraints through the use of clusters or cliques (Goycoolea et al., 2009). However, these enhancements do not universally obviate the notion that when the size of a problem increases, and the properties of the formulations can affect computing performance (Goycoolea et al., 2009). Thus the process employed and the resulting high combinatorial nature may require a significant amount of computing time. Therefore, large problems, problems with non-linear relationships, or problems containing integer decision variables may require the use of a heuristic technique.

Although well-developed heuristics can provide acceptable solutions to complex problems within a reasonable amount of time, rather than provide the optimal solution (Borges et al., 2014), heuristics have been widely used in forest management planning problems over the last two decades. The heuristics that have been described for use in forest management and planning include Monte Carlo integer programming (e.g., Boston and Bettinger, 1999; Nelson and Brodie, 1990), simulated annealing (e.g., Lockwood and Moore, 1993; Crowe and Nelson, 2005; Gonzláez-Olabarria and Pukkala, 2011), tabu search (e.g., Richards and Gunn, 2003; Zeng et al., 2007), threshold accepting (e.g., Calkin et al., 2002; Heinonen and Kurttila, 2007) and genetic algorithms (e.g., Lu and Eriksson, 2000; Falcão and Borges, 2001). Simulated annealing and threshold accepting are considered *s*-metaheuristics (improvement of one solution), while genetic algorithms are considered *p*-metaheuristics (use of a population of solutions). These methods differ in their mechanisms employed to prevent the search process from becoming trapped in local optima. Comparisons of the quality of results generated by heuristic methods have been described previously. For example, Boston and Bettinger (1999) compared the performance of three methods for addressing spatial harvest scheduling problems, while Bettinger et al. (2002) compared the performance of eight methods for addressing increasingly difficult wildlife planning problems. Pukkala and Kurttila (2005) compared the performance of six methods applied to five different forest planning problems.

As was suggested, two of the heuristics mentioned above belong to a set of local improvement methods (*s*-metaheuristics). A typical process employed during each iteration of these models involves an attempt to improve a solution by changing the harvest period or management prescription for one unit. This process is usually considered a 1-opt move. If changes in harvest periods or management regimes are made simultaneously to n units, then we consider this an n-opt move process. For forest management problems, n-opt moves, especially 2-opt moves, have recently been explored, and typically a higher value of n may lead to better objective function values (e.g., Heinonen and Pukkala, 2004). The reason is that if the planning problem contains strict constraints or tight achievement targets for non-spatial goals, the tendency of getting trapped in local optima may severely hinder the attainment of better objective function values. It may also be the case that once the solution process has reached the border of the feasible region of a non-spatial goal, most 1-opt moves may be either non-feasible or clearly poorer in value than the current solution. Comparison the effects of different moves of heuristic have been described previously as well. For example, Bettinger et al. (2002) and Heinonen and Pukkala (2004) reported that 2-opt moves can significantly improve the quality of solutions for smaller problem instances when compared to 1-opt moves, however Bachmatiuk et al. (2015) reported that when the combinatorial problem is very large, changing simultaneously the treatment schedule in more than one stand does not improve the performance of simulated annealing. However, the employment of 2-opt moves in Bachmatiuk et al. (2015) is different than what was reported in Bettinger et al. (2002), where instead of exchanging the treatment scheduled to two stands (as in Bettinger et al. (2002)), the treatment schedules for two stands are simply simultaneously and randomly changed (i.e., not exchanged). We are therefore expanding on the work of Bachmatiuk et al. (2015) to further explore this alternative approach to the use of 2-opt moves.

The objective and contribution of this paper is to systematically assess the performance of different neighborhood search techniques (1-opt and 2-opt) of a simulated annealing algorithm in solving forest spatial harvest scheduling problems. The objective function was to maximize the net present value of activities over thirty 1-yr periods less a penalty for not achieving the volume goals. The planning problem is also subject to non-spatial, URM and ARM constraints respectively. Four hypothetical grid datasets and one real dataset were used to illustrate how a 2-opt move