

Prescriptive Treatment Optimization Using a Genetic Algorithm: A Tool for Forest Management

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Abstract: This paper describes research on the use of a multiobjective genetic algorithm (GA) to optimize prescriptive treatment plans for forest management. The algorithm is novel, in that (1) the plans generated by the algorithm are highly specific, stating precisely when and where treatments are to be applied; and (2) logical rules and inference engines developed for a decision support system are used to evaluate the fitness of each plan. Fitness is based upon satisfaction of varied and often incompatible goals. The current (generational) GA has been compared in experiments to hill-climbing and simulated annealing algorithms, as well as to a steady-state GA. In a separate experiment, a plan generated by the GA is compared to one produced by a human expert. In these experiments, the GA has fared well.

Keywords: Decision support system; Forest management; Genetic algorithm; NED-2; Silviculture Treatment scheduling; Forest Vegetation Simulator (FVS)

1 INTRODUCTION

This paper describes research on the use of a generational multiobjective genetic algorithm (GA) to optimize prescriptive treatment plans for forest management. The algorithm is novel, in that (1) the plans generated by the algorithm are highly specific, stating precisely when and where treatments are to be applied; and (2) logical rules and inference engines developed for a decision support system are used to evaluate the fitness of each plan. Fitness here is based upon satisfaction of varied and often incompatible goals—for example enhancing the environment for a particular species of wildlife or maximizing timber yield.

Treatment prescription is a complex multiple constraint problem with a search space that increases exponentially with the length of the plan (i.e. the number of years the plan covers divided by the treatment interval). Human experts cannot realistically consider every alternative plan and must instead fall back on general rules of thumb acquired from experience. Our goal is to take some of the guesswork and bias out of planning by providing the user with highly specific treatment recommendations at the level of individual stands. In the current study, treatment defi-

nitions are limited to end-of-rotation harvesting and various degrees of forest thinning. Future iterations of the GA may incorporate planting and other types of interventions.

A sizable literature exists studying machine learning techniques and their applications to multiple constraint problems in the forestry domain. ? developed a GA to categorize stands for different functions with the goal of finding the optimal balance of utility within a management unit. ? used a GA to categorize stands, optimizing management units along economic and visual dimensions. ? designed a GA that output the order in which stands should be harvested to optimize timber yields. In a similar project, ? used a GA to develop treatment schedules for harvesting. They made use of a simulation model for the endangered red-cockaded woodpecker to balance timber objectives with an ecological concern in an uncertain environment. ? employed dynamic programming techniques to optimize stand level management prescriptions for forests in the Blue Mountains of eastern Oregon.

The approach described in this paper differs from similar projects in part because a GA is used to develop plans with a high degree of specificity. A

framework has been developed that allows the GA to evolve highly specific treatment recommendations at the project-level for a variety of management goals, timber and non-timber (e.g., visual or ecological goals) alike. The approach does more than lay out a high-level strategy for forest management, it tells the forester when, where, and how to harvest each stand in the management unit to maximize the number of management goals that can be satisfied in the specified time period.

The approach is also novel in that the plans produced by the GA are evaluated using logic based components of the NED-2 decision support system (described below). Each plan is intended to satisfy multiple competing goals which are specified using knowledge bases of NED-2, and their satisfaction is determined using built-in inference engines. The fitness of each individual plan is based upon the results of these inferences.

The rest of the paper describes the genetic algorithm and its performance in more detail. Section 1.2 outlines the specification, simulation, and evaluation of plans in NED-2. Section 2 discusses the representation of treatment plans as individuals in the GA and introduces the function used to select individuals for survival. Section 3 presents the experiments used to evaluate the performance of the GA and the results obtained.

1.1 The NED-2 Decision Support System

Our research on the GA began as an offshoot of the NED Decision Support System project, a collaboration between the University of Georgia and the USDA Forest Service. NED-2 is a decision support system (DSS) that provides users with a planning environment for forest management and expert system components for evaluating and comparing plans within a management unit (?). In this context, a management unit is simply the area of forest under consideration. Management units are divided into stands, which are sections of forest with some uniform characteristics. A plan in NED-2 is a schedule of treatments, such as planting or row thinning, applied to individual stands over predetermined intervals.

Treatment plans in NED-2 are divided into cycles, which are separated by regular intervals. Each plan is simulated using the Forest Vegetation Simulator (FVS), a growth and yield simulator produced by the USDA Forest Service (www.fs.fed.us/fmcs/fvs/). A typical plan might, for example, span fifty years with a treatment period every ten years, for a total of five cycles (managers may also opt to select no treatment for a cycle and just let the forest grow). The

plan in this example would consist of five treatments, chronologically ordered.

The NED-2 knowledge base contains rules that define desired future conditions (DFCs) for satisfying management goals across different forest types. For example, if the user selects the goal "Focus on cubic foot production" (a timber goal), a stand classified as an aspen-birch forest type meets the goal if its total basal area and acceptable growing stock for timber pass certain thresholds. The thresholds have different values for different forest types, depending on how productive one would expect them to be. ? provides an extensive discussion of the hierarchy of DFCs and goals in NED-2. These rules, while not definitive, have a sound theoretical basis in expert opinion.

The DFCs are used to evaluate the success or failure of user-defined treatment plans in achieving a set of objectives. The point is to give the user some feedback on how likely his or her plan is to succeed in meeting their management objectives after they have designed and simulated a plan. Goals are assigned a fuzzy "confidence factor" (CF) indicating the degree to which the DFC requirements for a goal are satisfied. A CF of 1.0 is assigned to goals that are completely satisfied, 0.6 to marginally satisfied goals, and 0.4 to nearly satisfied goals. A CF of 0.0 indicates that the goal completely failed the associated DFCs.

2 DESIGN OF THE GA

2.1 Representation

A genetic algorithm in general attempts to solve a given problem by evolving populations of candidate solutions. New candidates are created by crossing (recombining) or mutating material from existing solutions. In this way the space of possible solutions is explored. The candidates are evaluated according to some fitness function, and relatively fit individuals are more often selected to create new individuals. Over time, the population as a whole converges, hopefully to some optimal solution. The choice of fitness function and mutation, recombination (crossover), and selection operators has a dramatic effect on the performance of the algorithm.

In our GA, an individual in the population consists of numerical representations of treatments to be applied at given cycles. Currently the GA is limited to representing only forest thinning treatments.¹ Each thinning treatment is represented by three floating point values between 0 and 1; these specify the minimum and maximum DBH (diameter at breast height) of a

¹it is also possible to specify that no treatment be performed during a given cycle

tree to be cut as well as a cutting efficiency. The latter defines the percentage of trees within the given range that will actually be cut. By manipulating these three values, a great variety of thinning treatments can be implemented.

Relative values are used to specify the minimum and maximum diameters; this ensures that a treatment is meaningful regardless of the data set used. Similarly, each value occupies a single gene of the individual, and all values are of the same type. This guarantees that manipulating the individual using genetic operators will yield a meaningful candidate solution.

2.2 Fitness Function

Five DFC-based goals from the NED-2 knowledge base have been adapted into a fitness function for the GA. Four of these goals involve timber production, while the fifth relates to the visual quality of the forest. Treatment prescription becomes a more complex and interesting problem when economic needs must be balanced by aesthetic or ecological goals. Any combination of these goals may be selected for optimization. To determine the fitness of a treatment plan, the GA simulates the plan with FVS and checks whether the output satisfies the DFCs for the selected goals.

The goals used in the GA are: (1) focus on cubic foot production, (2) focus on board foot production, (3) periodic income, (4) focus on net present value, and (5) enhance big tree appearance. The first places emphasis on production of pulpwood and fiber products, while the second attempts to maximize production of sawtimber, veneer, and other high value products. The third maximizes annual income, and the fourth treats the management unit as an investment whose value is to be maximized. The fifth goal, an aesthetic goal, encourages the development of old growth forest.

The fitness of a stand is calculated by adding the confidence factors of all the goals that were at least marginally satisfied over the course of the plan. This involves checking the CFs assigned to goals during each treatment interval, or cycle, of the plan, then summing those values. Checking the status of management goals during each cycle, as opposed to evaluating the goal status at the end of a plan, enables the GA to show a preference for plans that satisfy management goals early and often. If two plans satisfy the same goal set but one satisfies those goals through more cycles than the other, the latter plan will be assigned a higher fitness.

The maximum CF that can be assigned to a goal is

1.0. If two goals are selected for a management unit comprising 10 stands over 10 treatment cycles, the maximum possible fitness assigned to the plan would be 10 (# of stands) $\times 10$ (# of cycles) $\times 2$ (# of goals) = 200.

2.3 Selection

One of the fundamental problems encountered when trying to optimize the design of a GA is balancing the needs for population diversity and strong selection pressure. Ideally the GA should find optimal or near-optimal solutions, but the final population should be diverse enough that the program can offer alternative recommendations. The difficulty is that the strength of selection pressure is often inversely related to the amount of diversity in the population.

Wright (1989) advocates a rank-based selection scheme as the best way to fine tune this balance. Rank-based selection has the advantage of providing consistent selective pressure throughout the run of a GA and prevents premature convergence due to dominant super individuals. For these reasons rank-based selection is currently our selection method of choice, although we have also implemented roulette-wheel and tournament selection schemes for the sake of comparison.

2.4 Crossover and Mutation

The order of the treatments in our representation is significant (as it is in the real world), and so the GA uses order-preserving crossover operations. A two-point crossover and uniform crossover have been implemented. Three alternative crossovers for systems with continuous values—linear cross, BLX-a (Wright, 1989), and SBX (Deb, 2000)—were also tested, but produced results inferior to a standard uniform crossover.

Mutations should facilitate systematic convergence on good solutions instead of randomly jumping around the search space. To this end, an incremental mutation strategy is used in our GA. Since the values for thinning treatments are all percentages, an incrementally mutated gene changes to plus or minus .05 its previous value.

When management goals are timber-related, plans incorporating clearcutting or simply growing a stand will be relatively easier and less costly to execute, and so are preferable to plans which satisfy the same goal set but are otherwise more complex. For this reason the GA occasionally mutates treatments into grow or clearcutting treatments. In the current configuration, 20% of all mutations result in a grow treatment, 20% create clearcuts, and the remaining 60% evaluate each gene independently and modify values

incrementally. The 20/20/60 breakdown is not theoretically grounded but produced reasonable results in testing. All test runs were performed with a fairly standard baseline mutation rate of 5%.

Gene values are usually mutated individually, save when a treatment is being converted into a grow or clearcut treatment. Here, all three genes representing the treatment are used. Mutation into a grow treatment sets the cutting efficiency to 0 and ignores the diameter values. Mutation into a clearcut sets the cutting efficiency to 100% and the entire range of tree diameters is affected.

3 EXPERIMENTS

To gauge the performance of our generational GA (GGA), it was compared to three other search algorithms: hill-climbing (HC), simulated annealing (SA), and a steady state GA (SSGA). Also, the plans evolved with the GA were compared with a treatment schedule recommended by a forestry expert. The forester is involved with the NED project and familiar with the goals and underlying DFCs used in the fitness function (This helped to control for the possibility that he might develop a plan based on different values or criteria than the computer generated plans).

It should be noted that in the following experiments, the choice of population size and number of generations to run the GA was constrained by the long time needed to simulate each plan. To optimize a single stand (simulating 50 plans for 40 generations) took roughly an hour on a contemporary desktop computer. The simulations needed to compare the GAs performance to the forester took roughly 600 computer hours to execute. Larger populations and higher generation caps simply could not be feasibly tested. This gives some indication of the computational difficulty of the problem.

3.1 Comparison of Search Algorithms

Methods. Experiments comparing the search heuristics were performed using data from 10 stands in the Deer Hill management unit located in Williamsburg County, South Carolina. Two management goals were selected for simultaneous optimization: (1) “enhance big tree appearance”, and (2) “focus on periodic income”.

The GA was run with a population size of 50 and halted after 40 generations. The planning horizon included 20 treatment cycles, with 10 years between cycles. The uniform crossover rate was 0.6 and the mutation rate 0.05.

The other search methods were implemented in a similar fashion to the GA (and so all are computationally similar). For the hill climbing and SA algorithms, an individual is created and chosen as a starting point. A population of individuals is then generated by mutation from this one point. For hill climbing, the fittest individual from the current point and the new population is chosen as as the new starting point. With the SA algorithm, moving to a new point is probabilistic and governed by a cooling schedule.

Each search method was simulated 10 times on each of the 10 stands. The fitness of the best solution from each trial was saved, and the results from all the trials were averaged to obtain a representative score for each search method on each stand. The total score for each search method was assigned by summing its scores on each stand. Statistical analysis of the results was performed using two-factor ANOVA with replication, $\alpha = 0.05$. The two-factor test was selected to account for the possibility of an interactive effect between the composition of the different stands and the search method.

Results. The choice of search technique was significant with $p < 0.001$. Results on the GGA condition were not significantly different from the SSGA condition ($p = 0.066$; $p > 0.05$). However, the GGA performed significantly better than the HC ($p < 0.001$) and SA ($p = 0.002$; $p < 0.05$) conditions.

Averaging the results from all 10 trials shows that the hill-climbing procedure performed the worst while the GGA turned in the best performance. Table 1 shows the best fitness on each condition by stand number. The values in the first ten rows are out of a maximum value of 20. Values in the last row (All Stands) are out of a maximum value of 200.

Stand	GGA	SSGA	HC	SA
1	15.22	14.36	12.72	13.02
2	13.78	13.4	12.98	13.26
3	11.1	12.06	10.32	9.7
4	15.04	14.86	14.32	15.08
5	15.18	14.7	14.14	14.92
6	15.2	15.04	14.72	15.2
7	15.12	14.72	14.14	14.7
8	14.6	14.1	13.04	14.52
9	13.5	12.36	10.84	11.04
10	13.32	12.86	10.94	12.46
All Stands	142.06	138.46	128.16	133.9

Table 1: Comparison of search heuristics

3.2 Comparison to the Forestry Expert

Methods. The forestry expert developed a treatment schedule for the Bent Creek experimental forest management unit located near Asheville, North Carolina. A planning period of 40 years beginning in the year 2005 was agreed on, with 5 year intervals between treatments. Because of the difficulty of designing a long term plan with multiple and possibly incompatible objectives, the expert designed a plan for one goal only—periodic income—which emphasizes long-term and sustainable timber production.

The expert devised a treatment schedule with a focus on creating a more favourable size-class distribution in the management unit. Bent Creek is a very even-aged and even-sized forest, which is undesirable for a periodic income treatment regime. The expert noted that much of the management unit comprises yellow poplar and oak stands, and devised a treatment schedule to balance size structures with a secondary concern of getting high value species back in the regenerated stands (Rauscher, personal communication, June 11, 2005). Mature yellow poplar stands were harvested using the clearcut method once during the 40 year planning horizon. Mature oak stands were thinned to a basal area of 60 square feet per acre followed by a final harvest to remove the remaining large overstory trees 15 years later. The different final harvesting strategies for yellow poplar and oak forests reflect different biological requirements to establish the next generation of trees. The timing of these treatments was distributed so that, for example, not all the yellow poplar stands were clearcut in the same year.

At the request of the forestry expert, in addition to evaluating his plan with the GA's fitness function, the plans were also compared by evaluating total removals in terms of merchantable cubic foot volume, sawlog cubic foot volume, and sawlog board foot volume, as well as the amount of harvestable timber left in reserve at the end of the plans.

The expert also requested that the GA be penalized for treatments resulting in harvests of less than 3000 board feet per acre. Volumes smaller than this were judged as unlikely to be economical in practice. For each harvest > 0 and < 3000 bd ft/acre, one point was subtracted from the fitness of the plan.

The GA was run with a population size of 40, with the program halting after 40 generations. We again employed uniform crossover with a 0.6 crossover rate, and a mutation rate of 0.05.

Results. As expected, neither the plans created by

Year	Product				
	merch cu ft	sawlg cu ft	sawlg bd ft		
2005	128 647	122 478	662	2539	
2010	179 243	173 168	963	895	
2015	176 281	165 210	906	1107	
2020	184 264	166 219	880	1159	
2025	347 293	333 246	1833	1303	
2030	173 213	146 189	765	1041	
2035	231 236	216 214	1169	1196	
2040	143 309	141 283	768	1547	
2045	292 389	267 359	1452	2019	
All	206 319	192 263	1044	1423	

Table 2: Mean merchantable cubic feet, sawlog cubic feet, and sawlog board feet harvested under the forester's and GA's (italicized) plans. The GA results are the average of 10 runs.

the GA nor the expert's plan resulted in balanced size classes by 2045. As a result the periodic income goal was never satisfied at the level of the management unit. This can be attributed to the very even-aged and even-sized starting conditions of the Bent Creek forest and the long time to maturity of yellow poplar and oak dominated forests. However, the plans can still be compared by evaluating performance on a stand-by-stand basis. In terms of stand-level DFCs, the GA scored an average of 487.28 (out of a maximum possible score of 585) over 10 runs, while the expert's plan scored 279.8. These numbers roughly indicate the number of times that the goal "periodic income" as defined by the DFC was satisfied for each plan in simulation, minus any penalties for harvests of less than 3000 board feet per acre.

In terms of timber removals produced, the plan recommended by the GA resulted in higher amounts than the experts plan in merchantable cubic-foot volume, sawlog cubic-foot volume, and sawlog board-foot volume. The experts plan left more harvestable timber in reserve at the end of the plan.

Table 2 shows the average per acre harvest volumes for each year of the plans. Table 3 shows the volume of harvestable timber in each product category remaining at the end of the last treatment cycle. Note that these averages are for the entire management unit, including unharvested stands. Individual treatments typically yielded greater than 3000 board feet per acre.

4 CONCLUSIONS AND BENEFITS TO FOREST MANAGERS

A genetic algorithm is a promising approach to the problem of treatment prescription for two reasons. First, the space of possible solutions for even a mod-

	Unharvested Product (2045)		
	merch cu ft	sawlg cu ft	sawlg bd ft
Expert	3819	3329	17956
GA	2401	2268	12,663

Table 3: Mean volume per acre of unharvested timber products at end of planning horizon (2045).

estly sized management unit is too big to exhaustively search. There may be general heuristics that could be helpful in making plans, but these would likely be of limited use because of geographic differences in forest types around the country. Although GAs are not guaranteed to find optimal solutions, when the search space is sampled effectively they often find very good and sometimes optimal solutions.

Another advantage to GAs is that they operate blindly, without preconceived notions about which characteristics of a forest stand might be relevant to the satisfaction of a management goal. This equal-opportunity approach may enable the GA to find novel solutions to management problems that might not occur to human experts.

Although GAs have been applied to prescriptive management problems in forestry before, we are not aware of any applications that evolve highly specific treatment recommendations at the stand level. Our research has shown that the GA is an effective search tool for prescriptive silvicultural applications. By combining the search power of the GA with the substantial (and growing) compilation of expert forestry knowledge in NED-2, we are optimistic that the GA can work as a practical prescriptive tool for forest managers.

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