Forest Planning Optimization

Qiang Hao
Learning, Design and Technology & Computer Science
University of Georgia

Introduction

The goal of most forest planning problems is to obtain an optimal timber harvest schedule for a multiple-stand forests under certain constraints, so the difference between the actual and the target volume can be minimized. In this particular experiment, the problem settings from Bettinger and Zhu (2006) were used. The objective of this experiment was to find a harvest schedule for a management unit of 73 stands in 3 harvest periods, so the difference between the target harvest volume and actual harvest volume is minimized. The constraints and specifications of this experiment were:

- 1. Each stand could be harvested in at most one of 3 harvest periods
- 2. No two geographically adjacent stands could harvest in the same period.
- 3. The target harvest volume of each harvest period is 34,467 thousand board feet.

Optimality is measured according to the function:

Fitness Value =
$$1/[(H_1 - T)^2 + (H_2 - T)^2 + (H_3 - T)^2]$$

(H₁, H₂, H₃ represent harvest volume of each harvest period. T refers to the target harvest volume)

Application of the Genetic Algorithm

The genetic algorithm (GA) was firstly applied to solving this problem. The solution representation was chosen as integer vectors with the length of 73. Each integer in the vector stands for a field. For each integer in the vector, random value among 0, 1, 2, 3 was used when a population was generated. 1, 2, 3 stand for harvest in 1st, 2nd, and 3rd harvest time period separately, while 0 stands for "do not harvest in any of the three time periods".

To resolve the adjacency issues of a generated individual, a fix scheme was applied after mutation in every generation. The aim of the fix scheme was to eliminate violators of the constraints and minimize the loss of fitness value. The fix scheme included two options. The first option converted encountered violators to 0 starting from the beginning of the individual till no violators could be found. In contrast, the second option converted encountered violators to 0

starting from the end of the individual. Both options were tried on every individuals, and the option that yielded smallest fitness value loss would be finally adopted.

The GA experiment settings were:

• Population size: 20,000

• Crossover rate: 0.8

• Crossover type: Two-point crossover

• Mutation rate: 0.03

• Selection Method: Tournament selection

• Elitism: {No Elitism, Elitism, Selective Elitism}

• Stopping criteria: 60 generations

150 trials were conducted in total. 50 trials were conducted using each elitism scheme specified above.

Results

The best result GA using No Elitism successfully found was as the following:

- Individual: [1, 2, 1, 2, 2, 3, 2, 0, 3, 3, 1, 1, 2, 2, 1, 3, 0, 3, 0, 2, 2, 3, 1, 3, 2, 2, 3, 2, 1, 3, 3, 3, 2, 3, 3, 1, 1, 1, 1, 0, 0, 3, 2, 1, 1, 1, 2, 2, 2, 2, 3, 3, 2, 3, 2, 3, 1, 2, 3, 2, 2, 1, 1, 3, 3, 3, 2, 3, 2, 1, 2]
- Fitness Value: 1.7630494849339107e-07
- Error: 5671990.539944974

The best result GA using Elitism successfully found was as the following:

• Individual: [1, 2, 1, 2, 2, 3, 2, 0, 3, 3, 1, 1, 2, 2, 3, 1, 1, 0, 0, 2, 2, 3, 3, 3, 2, 2, 3, 1, 1, 3, 1, 3, 2, 3, 3, 2, 1, 2, 1, 2, 0, 3, 3, 1, 1, 1, 2, 2, 2, 2, 3, 2, 3, 2, 3, 1, 1, 3, 2, 2, 1, 3, 3, 3, 3, 2, 3, 0, 1, 1, 1]

Fitness Value: 1.513870831473284e-07

Error: 6605583.377459027

The best result GA using Selective Elitism successfully found was as the following:

- Individual: [1, 2, 1, 2, 2, 3, 2, 1, 3, 3, 1, 1, 2, 2, 1, 3, 0, 3, 0, 2, 0, 3, 1, 3, 2, 2, 3, 2, 1, 3, 3, 3, 2, 3, 3, 0, 1, 1, 1, 0, 0, 3, 2, 1, 1, 1, 2, 2, 2, 2, 3, 3, 2, 3, 2, 3, 1, 2, 3, 2, 2, 1, 1, 3, 3, 3, 2, 3, 0, 2, 1, 1]
- Fitness Value: 1.5590469294722372e-07
- Error: 6414175.103365979

T-test was applied to compare whether including elitism influenced the performance of GA. To avoid inflating type I error, Bonferroni correction was applied to the threshold of significance level (.05 / 3 = .016). Two t-tests showed significant results, indicating that GA using No Elitism performed significantly better than both GA using Elitism and using Selective Elitism. The following table shows the detailed information of the three t-tests.

Table 1. T-tests on different Elitism Schemes.

	Variable 1	Variable 2	t value	p value
Test 1	GA-NE (Mean = 596377)	GA-E (Mean = 663045)	-5.776***	1.301e-07
Test 2	GA-NE (Mean = 596377)	GA-SE (Mean = 669765)	-6.457***	2.652e-07
Test 3	GA-E (Mean = 663045)	GA-SE (Mean = 669765)	-1.021	0.043

GA-NE: GA without elitism scheme; GA-E: GA with elitism; GA-SE: GA with selective elitism p < .016; **p < .003; ***p < .003

Relationships between Mutation Rate and Performance

In the first stage of this experiment, the relationship between mutation rate and performance of GA was noticed as different from most other GA applications. The decrease of mutation rate was observed as positively related to performance of GA on forest planning problems. Therefore, more systematic testing has been done in the second stage to confirm the observation.

The GA experiment settings were:

• Population size: 200,000

• Crossover rate: 0.8

• Crossover type: Two-point crossover

• Mutation rate: 0.03, 0.06, 0.1, 0.13, 0.17, 0.2, 0.23

• Selection Method: Tournament selection

• Elitism: {No Elitism}

• Stopping criteria: 200 generations

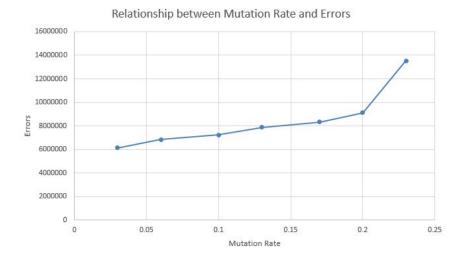


Figure 1. Relationship between Mutation Rate and Errors.

7 trials were run using the same mutation rate. 49 trials were run in total. Keeping all other parameters constant, the performance of GA decreased from 6124583 to 13535423 as the mutation rate increased from 0.03 to 0.23. Based on the observation, we conclude that the decrease of mutation rate is positively related to the performance of GA application on this forest planning problem. The possible explanations could be that fix scheme is not well aligned with the natural evolution process, and higher mutation rate leads to more frequent constraint violation, and fix in a chain effect, which makes it more difficult to evolve better individuals.