# Bi-objective genetic algorithms for forest management: a comparative study

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## Abstract

Forest management today has become an arduous task. Many stakeholders, including the public, expect the forest to be managed in a sustainable way. This however imposes a considerable burden on the management planning process. As many – often conflicting – objectives have to be met, an intuitive approach is no longer sufficient. In this research, the possible use of genetic algorithms to design a forest management plan is investigated. Two genetic algorithms and a random strategy are applied to a real world forest planning problem. Their performance is then compared.

## 1 INTRODUCTION

Forest management, especially timber harvest planning, is usually characterized by the need to consider multiple non-commensurable and often conflicting objectives over a long time period. Forests can either be used for timber production or for non-timber production, such as recreation or scenic value. Because these many non-timber uses have no market-value, it is very hard to determine the monetary value without oversimplifying the problem. Hence it is difficult to apply the net present value criterion.

Another approach to solve this problem is to use an overall utility function. This requires that extensive knowledge and insight about the problem is available. This, however, is often not the case. Furthermore, in public forest resource management the ultimate goal is to maximize the social welfare, while on the other hand it is impossible to derive a utility function for society.

A third approach is to use multi-objective optimization techniques, that lead to a set of non-dominated solutions. These techniques require a lot of CPU-time and are difficult to implement.

## 2 RELATED WORK

Multi-objective GAs have been successfully applied in similar areas. In land-use planning, multi-objective GAs have been used by Matthews (1999 [6], 2000 [5]). He concludes that multi-objective GAs applied to rural land planning have significant potential for assisting land managers in tackling complex resource allocation problems with conflicting non-commensurable objectives. Also, their ability to search for populations of solutions defining the structure of the trade-off between the objectives not only allows them to be used directly as a decision support tool, but may also allow land managers to become better informed about the interactions between the components of their land management plans.

Urban planning is another area where multi-objective GAs have been used. Feng and Lin (1999 [2]) applied a GA to design several alternative urban plans for the city of Tanhai, north of Taipei. They conclude that the plans optimized using the GA are better than those previously designed by urban planning experts. Moreover they now have a choice of alternative plans, whereas before only one plan was devised.

As in these areas multi-objective GAs have shown their potential, it is assumed that in the complex matter of forest resource management the application of GAs is worth investigating.

## 3 STUDY AREA

Kirkhill forest lies 8 miles north west of the city of Aberdeen, Scotland. It was previously managed as a production conifer forest by the Forestry Commission and is now managed by the Aberdeen University. Kirkhill has a large area coming into production at present. These are areas of broad-leaves and long term retention of conifers giving good landscape and amenity values. Recreational use of Kirkhill forest is high because of the proximity to Aberdeen.

The main long term objectives of the forest owner are (1) sustained yield of timber, (2) to maximize timber production and to safeguard and enhance the conservation, (3) landscape and amenity value of the forest.

# 4 GENETIC ALGORITHM

## 4.1 REPRESENTATION

A binary representation is used for this problem. There is a total of 295 forest stands. Each stand can have one out of four possible main functions: economical function, habitat conservation, passive recreation and active recreation. These four functions are easily mapped using 2 bit-genes.

## 4.2 OBJECTIVE FUNCTIONS

Only two of the three aformentioned objective functions will be optimized. This is to allow for visualization of the trade-off front between the objectives. The first objective is to maximize harvest volume $V$. Since harvest volume is negatively correlated to the standing volume left in the forest, it is possible to write the first objective as in Eq. 1:

$$\begin{aligned} f_1 &= \max \sum_{i=0}^{i=N} v(i,a) \\ &\sim \frac{1}{v_{stand}} \end{aligned} \tag{1}$$

where

$$\begin{aligned} v(i,a) &= \text{harvest assoc. with stand } i \text{ and decision } a \\ v_{stand} &= \text{volume left standing} \\ N &= \text{number of stands} \end{aligned}$$

The second objective is to maximize the benefit that people obtain from the standing forest. This is measured by a utility function $U$. According to the law of diminishing returns, this function can be modeled using the square root of the volume standing (Gong, 1992 [4]). The more standing volume left in the forest, the more trees present for people to enjoy. However,the increase in benefit derived from the trees will decrease when the forested area is larger as the effect of leaving one more tree standing will decline. Therefore the second objective can be written as in Eq. 2:

$$\begin{aligned} f_2 &= \max \sum_{i=0}^{i=N} u_i \\ &\sim \sqrt{v_{stand}} \end{aligned} \tag{2}$$

where

$$\begin{aligned} u_i &= \text{utility assoc. with stand } i \\ v_{stand} &= \text{volume left standing} \\ N &= \text{number of forest stands} \end{aligned}$$

As follows from Eqs. 1 and 2, the two objectives are conflicting.

## 4.3 SELECTED ALGORITHMS

In this research three algorithms were selected.

The first algorithm is based on the work of Fonseca and Fleming (1995) (FF) [3]. This algorithm was selected because it was applied successfully by Matthews (1999, 2000) ([6], [5]). This algorithm was adapted to allow an elitism strategy. Both parent population and child population were merged, and ranked according to their fitness. The $N$ best solutions were copied into the next generation.

The second algorithm was based on the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) (Deb *et al.* 2000 [1]). This algorithm was chosen because it was a new algorithm claiming to reduce the complexity of finding the non-dominated fronts.

A random search algorithm (RAND) was also implemented, as additional point of reference.

In all the algorithms linear fitness scaling was used.

## 4.4 OPERATORS

Uniform crossover was chosen as crossover operator. Deb *et al.* (2000)([1]) have determined the mutation probability $1/N$ where $N$=number of variables. This value was divided by two as each time mutation was allowed, the bit value was changed.

# 5 RESULTS AND DISCUSSION

After application of both the genetic algorithms and the random strategy, the following non-dominated fronts were obtained (Fig. 1). These fronts are the result of a single trial. From Fig. 1, it can be concluded that the FF-algorithm and NSGA-II-algorithm perform better than the random simulation. The NSGA-II-algorithm finds higher solutions than the FF-algorithm. The non-dominated front of the latter, however, is spread out more evenly. In order to compare these algorithms more objectively, scaling-independent measures were calculated.

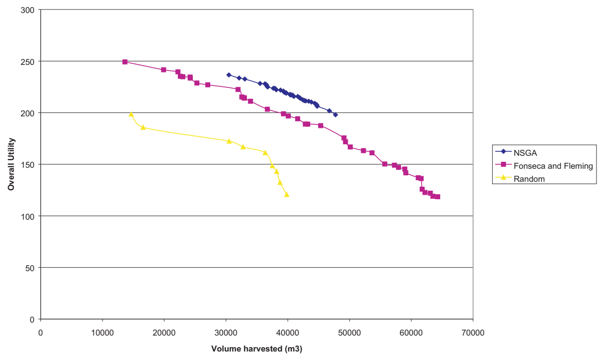


Figure 1: Comparison of the non-dominated front between RAND, FF and NSGA-II

Zitzler (1999, [7]) developed both scaling-independent as well as scaling-dependent measures. In this research the scaling-independent measures were implemented.

The function $\mathcal{S}$ (Zitzler, 1999 [7]) is a measure of how much of the objective space is weakly dominated by a given non-dominated set $A$.

**Definition 5.1 (Size of the dominated space)** *Let* $A = \{x_1, x_2, \ldots, x_l\} \subseteq X$ *be a set of* $l$ *decision vectors. The function* $\mathcal{S}(A)$ *gives the volume enclosed by the union of the polytopes* $p_1, p_2, \ldots, p_l$*, where each* $p_i$ *is formed by the intersections of the following hyperplanes arising out of* $x_i$*, along with the axes: for each axis in the objective space, there exists a hyperplane perpendicular to the axis and passing through the point* $(f_1(x_i), f_2(x_i), \ldots, f_k(x_i))$*. In the two-dimensional case, each* $p_i$ *represents a rectangle defined by the points* $(0, 0)$ *and* $(f_1(x_i), f_2(x_i))$*.*

The function $\mathcal{D}(A, B)$ defines the coverage difference of two sets $A$ and $B$ (Zitzler, 1999 [7]).

**Definition 5.2 (Coverage difference of two sets)** *Let* $A$*,* $B \subseteq X$ *be two sets of decision vectors. The function* $\mathcal{D}$ *is defined by*

$$\mathcal{D}(A, B) := \mathcal{S}(A + B) - \mathcal{S}(B)$$

*and gives the size of the space weakly dominated by* $A$ *but not weakly dominated by* $B$ *(regarding the objective space).*

When $\mathcal{D}(A, B) > \mathcal{D}(B, A)$ it can be concluded that the size of the objective space weakly dominated by $A$ is bigger than the size of the part of the objective space weakly dominated by $B$. When $\mathcal{D}(A, B) = 0$ and $\mathcal{D}(B, A) > 0$ it means that $A$ is completely dominated by $B$.

All the algorithms were repeated 30 times. Independent of the algorithms, the number of generations $T$, crossover rate $p_c$ and mutation rate $p_m$ were fixed: $T = 50$, $p_c = 0.8$ and $p_m = 0.125$. Both the $\mathcal{S}$-measure (Table 1) and $\mathcal{D}$-measure were calculated for each of the algorithms.

Table 1: $\mathcal{S}$-means for FF, NSGA-II and RAND

| **Algorithm** | $\mathcal{S}$ |
|---|---|
| FF | 13491904.43 |
| NSGA-II | 10471003.95 |
| RAND | 7339239.14 |

After statistical analysis it can be concluded that FF is significantly better than NSGA-II ($p$=0.95), and that both genetic algorithms are significantly better than the random strategy. For all 30 repetitions, it holds that $\mathcal{D}$(FF, NSGA-II) $>$ $\mathcal{D}$(NSGA-II, FF). Therefore it can be concluded that the algorithm of Fonseca and Fleming gives the best results. When the $\mathcal{D}$-measure was calculated between each genetic algorithm and the random strategy it was found that the RAND-non dominated front was entirely dominated by the genetic algorithms ($\mathcal{D}$(RAND, FF) $= 0$ and $\mathcal{D}$(RAND, NSGA-II) $= 0$). The two most extreme solutions of the algorithm of Fonseca and Fleming are visualized in Figs. 2 and 3.

## 6 Conclusions

It is concluded that the use of GAs can be helpful in the forest planning process. The solutions provided by the NSGA-II algorithm are better solutions than those provided by the FF-algorithm. When taking into account the global measures for the size of the dominated space and the difference between these sizes, the FF-algorithm gives better results. It must be noted that the optimal solutions for the decision-maker will finally determine the best algorithm. If the decision-maker is looking for a compromise solution then the NSGA-algorithm will indeed be the better.

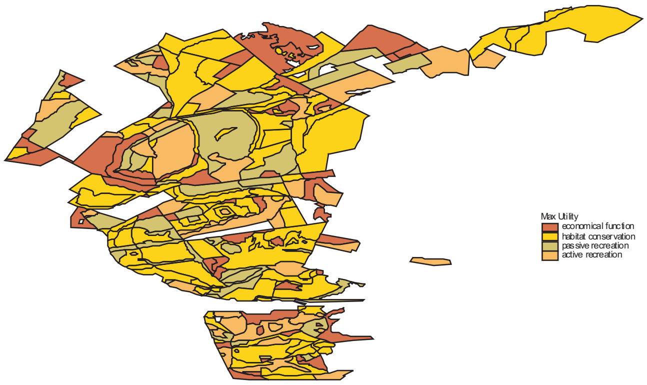


Figure 2: Example of configuration of the functions in the forest for maximum utility


Figure 3: Example of configuration of the functions in the forest for maximum harvest volume

## 7 Future work

In future work it will be investigated what the decision-maker thinks is the optimal solution to the problem at hand. This will be investigated by presenting the results of both algorithms to the forest managers and asking them to evaluate the different alternatives.

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### References

[1] K. Deb, S. Agrawal, A. Pratab, and T. Meyarivan. A Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II. KanGAL report 200001, Indian Institute of Technology, Kanpur, India, 2000.

[2] C. Feng and J. Lin. Using a genetic algorithm to generate alternative sketch maps for urban planning. *Computers Environment and Urban Systems*, 23:91–108, 1999.

[3] C. M. Fonseca and P. J. Fleming. Multiobjective Optimization and Multiple Constraint Handling with Evolutionary Algorithms I: A Unified Formulation. Technical Report 564, University of Sheffield, Sheffield, UK, January 1995.

[4] P. Gong. Multiobjective dynamic programming for forest resource management. *Forest Ecology and Management*, 48:43–54, 1992.

[5] K. B. Matthews, S. Craw, S. Elder, A. R. Sibbald, and I. MacKenzie. Applying genetic algorithms to multi-objective land use planning. In D. Whitley, D. Goldberg, E. Cantu-Paz, L. Spector, I. Parmee, and H. Beyer, editors, *Proceedings of the Genetic and Evolutionary Computation Conference*, pages 613–620, Las Vegas, Nevada, July 10-12, 2000. Morgan Kaufmann.

[6] K. B. Matthews, A. R. Sibbald, and S. Craw. Implementation of a spatial decision support system for rural land use planning: Integrating geographic information system and environmental models with search and optimisation models. *Computer and Electronics in Agriculture*, 23:9–26, 1999.

[7] E. Zitzler. *Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications.* PhD thesis, Institut für Technische Informatik und Kommunikatinsnetze, 1999.