

APPLICATION OF A HYBRID VERSION OF NSGA-II FOR MULTIOBJECTIVE DOSE OPTIMIZATION IN BRACHYTHERAPY

**M. Lahanas, N. Milickovic,
M. Papagiannopoulou,
D. Baltas and N. Zamboglou**

*Department of Medical Physics &
Engineering, Strahlenklinik, Klinikum
Offenbach, 63069 Offenbach, Germany
Email: mlahanas@gmx.net*

K. Karouzakis

*Department of Electrical and Computer
Engineering, National Technical
University of Athens, 15773 Zografou,
Athens, Greece
Email: kkkostas@SoftHome.net*

Abstract. We compare the efficiency of the NSGA-II algorithm for the brachytherapy dose optimization problem with and without supporting solutions. A local search method enhances the efficiency of the algorithm. In comparison to a fast simulated annealing algorithm the supported hybrid NSGA-II algorithm provides much faster many non-dominated solutions. An archiving of all non-dominated solutions is useful for the many objectives problem and the corresponding very large Pareto front.

Key words: NSGA-II, hybrid algorithm, brachytherapy, optimization.

1 INTRODUCTION

In high dose rate (HDR) brachytherapy that is a method of cancer treatment, up to 300 parameters must be optimized to satisfy often competing objectives.^{1,2} Aim of the optimization is to determine the time of a radioactive ^{192}Ir source at a given number of positions such that the resulting dose distribution fulfills various objectives. One such objective is the coverage of the planning target volume (PTV), which includes the tumor and an additional margin, with a sufficient high dose value. Simultaneously too high dose values in normal tissue and organs at risk (OAR) inside or in the vicinity of the PTV should be avoided. We use multiobjective evolutionary algorithms (MOEA) for the dose optimization problem with objectives expressed in terms of dose-volume histogram (DVH) derived quantities. The objectives can to some extent be also described by variances of dose distributions where deterministic local search based algorithms can

be applied but they are trapped sometimes in local minima if OARs have to be considered. DVH based objectives are used directly in the decision-making process and are therefore preferred. In this case deterministic algorithms cannot be applied. NSGA-II³ although found superior than other MOEAs such as SPEA, NPGA and PAES,⁴ requires a very large number of generations to converge near to the global Pareto front. The two main goals of the optimization are: (a) convergence to the global Pareto front and (b) accumulation of many non-dominated solutions. A deterministic algorithm is used in NSGA-II to drive a few members of the population very close to the global Pareto front. These members act as seeds and attract quickly the population towards the global Pareto front. These supported solutions are generated using objectives in terms of variances combined together using uniformly distributed random weights. The objective space is 3-6 dimensional depending on the number of organs at risk. A very large population size would be necessary to cover the entire Pareto surface, therefore a secondary population is used to accumulate all non-dominated solutions found. As the number of objectives increases methods to avoid clustering such as used in SPEA require a considerable time. We use the PAES archiving method for the accumulation of non-dominated solution. MOEAs are mainly Pareto ranking or local search based. We combine the Pareto based NSGA-II algorithm with a gradient based optimization routine. MOEAs produce good solutions for low-dimensional problems but the quality of the solutions deteriorates as the number of objectives and parameters increases. The population converges to only a local Pareto set. An analysis of the probability distributions of random solutions in objective space shows that for a large number of decision variables the probability of obtaining at random a solution close to the global Pareto set decreases significantly.

2 RESULTS

We compare the Pareto sets for a cervix implant with 272 source positions obtained by NSGA-II with and without supporting solutions. We use NSGA-II with a population size of 200.

2.1 Variance based objectives

The coverage of the PTV with the prescription dose can be expressed by a very small dose variance f_s of the sampling points (dose points) uniformly distributed on the PTV surface. In order to avoid excessive high dose values

inside the PTV we require a small as possible dose distribution variance f_V inside the PTV. Due to the source characteristics these two objectives are competing. We use normalized variances for the two objectives:

$$f_S = \frac{1}{m_S^2 N_S} \sum_{i=1}^{N_S} (D_i - m_S)^2, \quad f_V = \frac{1}{m_V^2 N_V} \sum_{j=1}^{N_V} (D_j - m_V)^2 \quad (1)$$

Where m_S and m_V is the average dose value on the PTV surface and in the PTV respectively and N_S , N_V the corresponding number of sampling points. For these objectives the Pareto trade-off surface is convex and gradient-based algorithms converge to the global Pareto front. These objectives are scale invariant and therefore the chromosome values of the genetic population can be limited in the range $[0,1]$. We compare the results with and without initialization by a gradient-based algorithm. For the initialization ten members of the NSGA-II population are initialized by solutions of a gradient-based algorithm. For each solution a different set of weights is used and the weighted sum of the objectives is combined to a single objective function to be optimized by the deterministic algorithm.

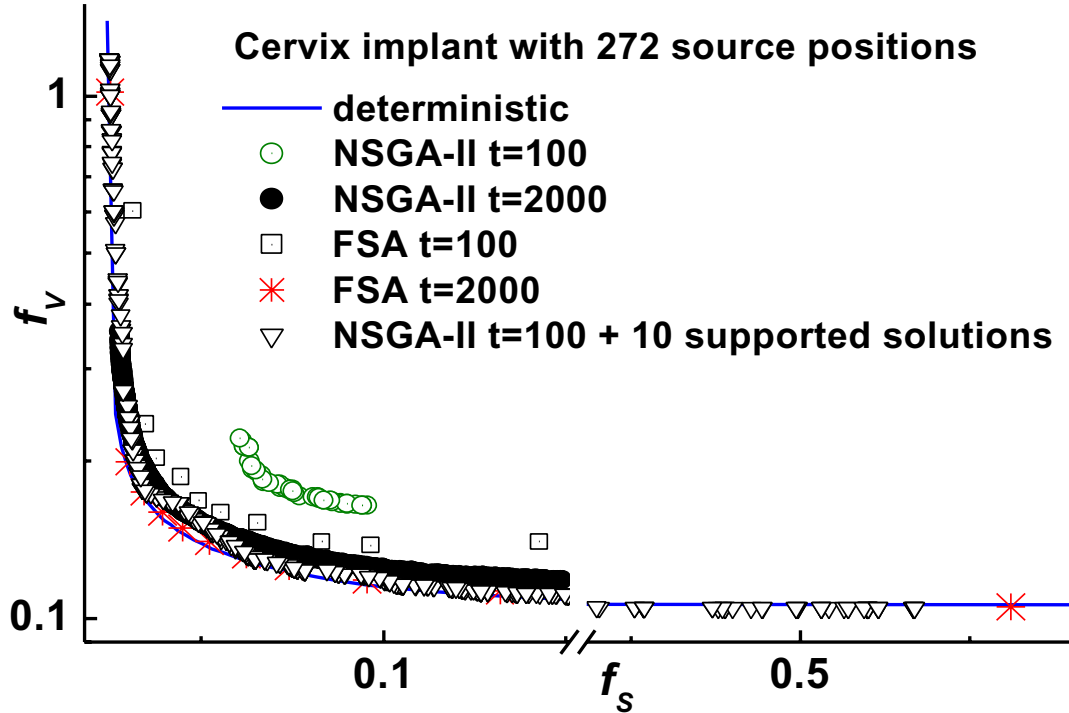


Figure 1 – Example of a two-dimensional archived Pareto set obtained by NSGA-II after 100 generations with and without supported solutions. The results without supporting solutions for $t=2000$ generations is also shown. The global Pareto obtained by a deterministic gradient-based optimization algorithm is included. The result is also shown using a fast simulated annealing method with 100 and 2000 iterations.

The initialized population approaches the global Pareto front after 100 generations, see Figure 1. Without initialization, even after 2000 generations,

the population converges only to a local Pareto set. The results of a fast simulated annealing optimization algorithm FSA⁵ with 100 and 2000 iterations are included. The convex Pareto set is obtained by repeating the FSA optimization algorithm several times each time with a different set of weights for each objective.

2.2 DVH based Objectives

One advantage of the so-called DVH based objectives is that the results in terms of objective values are more intuitive to understand. We use the following set of objectives:

- 1) Fraction of PTV with dose values smaller than the prescription dose.
- 2) Fraction of PTV with dose values larger than a critical dose value.
- 3) Average squared dose in the surrounding normal tissue.
- 4) Fraction of OARs with dose larger than a critical dose value.

All objectives values except for objective 3) are in the range $[0,1]$. We have an ideal dose distribution if all objective values are close to 0. For these objectives deterministic algorithms cannot be applied. We use a deterministic algorithm to initialize a small part (5-10%) of the population of the NSGA-II algorithm using the variance-based objectives. The result for an implant with two organs at risk is shown in Figure 2. The initialization of the population improves the results. It is therefore not necessary to use exactly the same objectives to initialize the population. Our analysis of the distribution of solutions in objective space has shown that the majority of solutions obtained by a random initialization are distributed far away from the global Pareto front. As the probability of generating random solutions close to the Pareto front is very small only after a very large number of generations the global Pareto can be reached. The gradient-based algorithm uses information from derivatives and approaches the global Pareto front after only a few iterations. The initialization moves a part of the population very close to the global Pareto front. These solutions attract into their neighborhood other members of the population. If we include objectives for the organs at risk then the deterministic algorithm gets trapped into local minima. Combining the deterministic algorithm with NSGA-II improves the performance of the later very significantly and helps also to escape from the local minima. Finally the deterministic algorithm helps NSGA-II to find better solutions for DVH based objectives where deterministic algorithms cannot be used. It is important to include in the supported solutions the

extreme single objectives solutions that define the extent of the Pareto front.

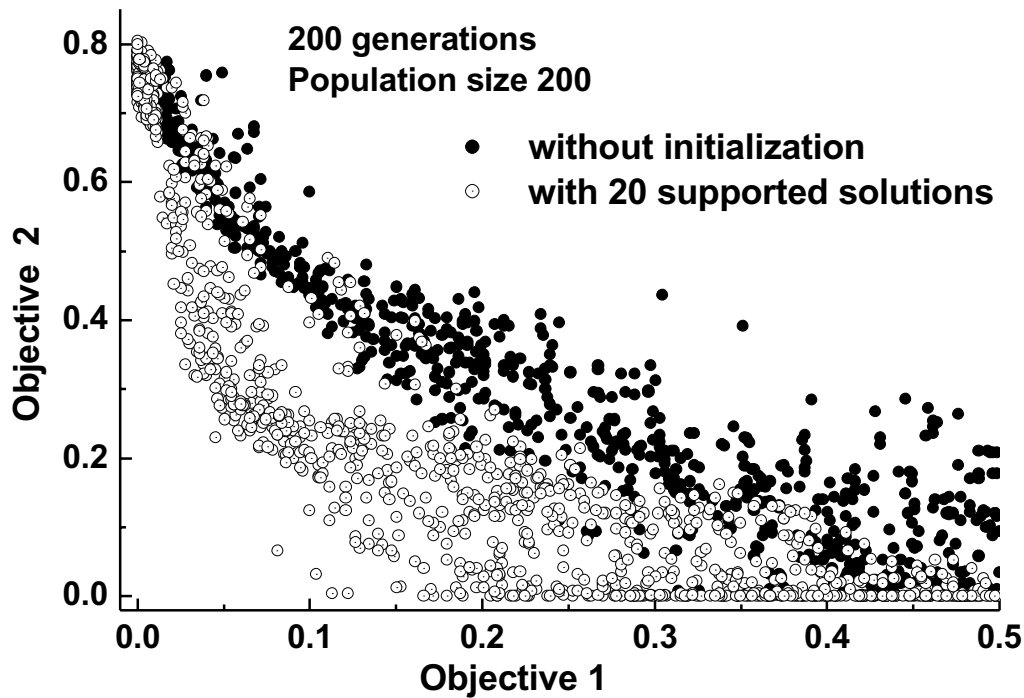


Figure 2 – Example of a two-dimensional projection of a five-dimensional archived Pareto set obtained by NSGA-II with and without supported solutions.

As the number of objectives increases a large population would be required to cover uniformly the multidimensional Pareto front. We use the PAES archiving method to accumulate non-dominated solutions. Continuously this set increases and can reach a size of 5-10 times the population size used by NSGA-II. Some clustering of the population is observed. We expect that modifications of the population fitness using density estimation techniques such as used in the SPEA2 algorithm⁶ could improve the distribution of the solutions. The performance of the algorithm is improved using an adaptive crossover.⁷ The hybrid NSGA-II algorithm that is initialized by deterministic algorithms or FSA provides a representation of the trade-off surface with up to 1000 solutions in a few minutes. A sequential FSA algorithm requires a few hours for the same statistics. An additional benefit of using NSGA-II is the possibility to include constraints on the objective values. This allows the solutions to populate a smaller part of the entire Pareto front where more likely a final solution will be selected. The large set of solutions can be processed and allows physicians to select a solution that satisfies at best their objectives and provides by the analysis of the trade-offs an insight into the possibilities of which criteria and to what extent can be satisfied.

3 REFERENCES

- [1] M. Lahanas, D. Baltas, N. Zamboglou, “Anatomy-based three-dimensional dose optimization in brachytherapy using multiobjective genetic algorithms”, *Med. Phys*, **26**, 1904-1918 (1999).
- [2] M. Lahanas, N. Milickovic, D. Baltas and N. Zamboglou, “Application of Multiobjective Evolutionary Algorithms for Dose Optimization Problems in Brachytherapy” in Proceedings of the first international conference, EMO 2001, Zurich, Switzerland, edited by E. Zitzler, K. Deb, L. Thiele, C. A. Coello Coello, D. Corne, Lecture Notes in Computer Science Vol. 1993, Springer, 574-587 (2001).
- [3] K. Deb, S. Agrawal, A. Pratap and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II”. Technical Report 20001, Indian Institute of Technology, Kanpur, Kanpur Genetic Algorithms Laboratory (KanGAL) (2000).
- [4] N. Milickovic, M. Lahanas, D. Baltas and N. Zamboglou, “Comparison of Evolutionary and Deterministic Multiobjective Algorithms for Dose Optimization in Brachytherapy” in reference [2]Proceedings of the first international conference, EMO 2001, Zurich, Switzerland, edited by E. Zitzler, K. Deb, L. Thiele, C. A. Coello Coello, D. Corne, Lecture Notes in Computer Science Vol. 1993, Springer, 167-180 (2001).
- [5] H. Szu and R. Hartley, “Fast simulated annealing”, *Phys. Lett. A*, 122, 157-162 (1987).
- [6] E. Zitzler, M. Laumanns and L. Thiele, “SPEA2: Improving the Strength Pareto Evolutionary Algorithm”, TIK-Report 103, May 2001, Computer Engineering and Networks Laboratory, ETH Zurich.
- [7] Deb, K. and Agrawal. R. B. “Simulated binary crossover for continuous search space”, *Complex Systems*, 9 115-148 (1995).