

THE USE OF MULTI-OBJECTIVE GENETIC ALGORITHMS FOR ACCELERATOR AND LIGHT SOURCE OPTIMIZATION*

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Abstract

The nonlinear effects are very important in development of new accelerators and synchrotron light sources. Nowadays they are one of the main factors limiting the achievement of the required facility parameters. In many cases in development of new accelerators the analytical estimations give very rough results and in some cases they don't apply at all. Therefore, the best way to research and design accelerators is to use numerical simulation. Nevertheless, very often during complex physical process simulation (taking into account many nonlinear effects) the use of classical optimization methods is difficult and does not give the desired results.

The article deals with the application of multi-objective optimization using genetic algorithms for accelerators and light sources. These algorithms allow both simple linear and complex nonlinear accelerator structures to be optimized with the same effectiveness when obtaining the required facility parameters.

INTRODUCTION

There are many methods of optimization. All of them can be divided into three groups: determinate, random (stochastic) and combined.

Most accelerator and light source optimization problems can be attributed to combinatorial problems with many different quality solutions. An exhaustive search of all solutions or only subset of solutions is the main feature of combinatorial algorithms. To find the best solution directed, random and combined an exhaustive search of all possible problem variables is used. Therefore, the search of proper solutions often becomes the art. After all, very often if you want to optimize nonlinear multi-objective problem (for example – beam emittance minimization and dynamic aperture maximization) with many variable parameters and restrictions you will face serious difficulties (most rapid and effective optimization methods can't be used, there are many local minima solutions, solving time is directly related to the number of variable parameters, etc.).

One of the effective way to solve combinatorial problems within a reasonable time is the use of genetic algorithms. Genetic algorithms are heuristic search algorithms used to solve optimization problems by random selection, combining and modification of desired parameters using process like the biological evolution.

Genetic algorithms as any other optimization algorithms have their own advantages and disadvantages.

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Their most important advantages may be said to be:

- Any information about the fitness function behavior is not required.
- Discontinuities of the fitness function don't have a significant effect on optimization.
- Methods are relatively stable to fall into local minima.

Their most important disadvantages may be said to be:

- Methods are inefficient for optimizing fitness functions which have a long calculation time.
- A large number of parameters often turns «work with genetic algorithm» to «play with genetic algorithms».
- In the case of simple fitness functions, genetic algorithms are slower than specialized optimization algorithms.

Nowadays, genetic algorithms are powerful computing tool to solve different multidimensional multi-objective optimization problems. The use of genetic algorithms for accelerator and light source optimization allows to simplify and speed up the search of proper solutions.

The common block diagram for optimization process using genetic algorithms is shown in Fig. 1.

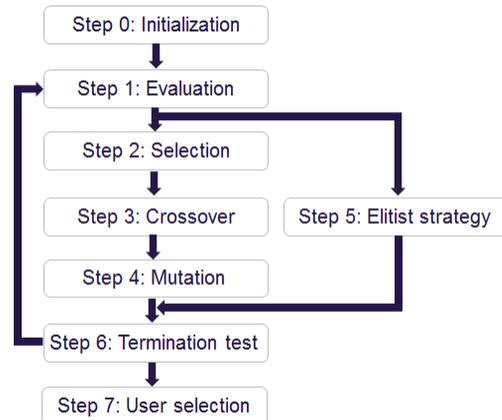


Figure 1: The block diagram of the optimization process using a genetic algorithm.

DESCRIPTION OF OPTIMIZATION METHOD

In general, all optimization problems can be divided into two groups. The first group contains only one fitness function optimization problems, the second one – at the same time two or more fitness function optimization problems. To solve the problems of each group it is advantageous to use a little different algorithms.

One fitness function optimization problem is the simplest situation with easy-to-analyse results. These kinds of problems can be efficiently solved with the help of the differential evolution method [1] is well suited.

Differential evolution is used for multidimensional real-valued functions but does not use the gradient of the problem being optimized, which means differential evolution does not require for the optimization problem to be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods. Differential evolution can therefore also be used on optimization problems that are noisy, not continuous, changing over time, etc.

To solve two or more fitness functions optimization problems it is well suited another methods – the so-called multi-objective genetic algorithms. The aim of our multi-objective optimization problem is to find all possible tradeoffs among multiple objective functions that are usually conflicting.

Since it is difficult to choose a single solution for a multi-objective optimization problem without iterative interaction with the decision maker, one general approach is to show the set of Pareto optimal solutions to the decision maker. Then one of the Pareto optimal solutions can be chosen depending on the preference.

Pareto frontier and Pareto optimal solutions for example emittance and dynamic aperture optimization is shown in Fig 2. Blue dots – Pareto optimal (nondominated) solutions, red dots – other (dominated or not Pareto optimal) solutions.

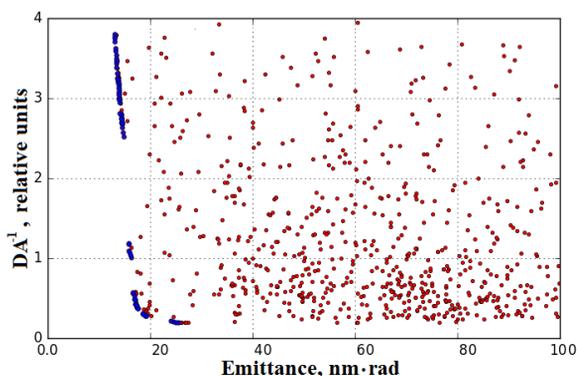


Figure 2: Pareto frontier. Blue dots – Pareto optimal solutions, red dots – other solutions.

A multi-objective optimization is an evolution of conventional numerical or combinatorial optimization, therefore many existing methods could be applied to this general case which makes defining of fitness function the main issue needs to be resolved. In recent decades, a number of approaches was developed to do it.

For solving accelerator lattice optimization problems only Step 2 (selection) and Step 5 (elitist strategy) in optimization process (see Fig. 1) are of particular interest.

For selection we chose the Nondominated Sorting Genetic Algorithm [2] as one of the most powerful and faster algorithm up to date. As an alternative, we also tried to use simpler and faster Random Weights Genetic Algorithm [3], but results were not as good as with the previous one.

In scenario when optimization is being done with smooth and continuous fitness function the genetic algorithms prove to be effective and everything works

well. However, this is not the case when optimization needs to be performed for circular accelerators since its fitness function is not smooth, nor continuous, for which reason using of the genetic algorithms becomes quite problematic. Mostly because of a large amount of not periodic or incorrect solutions which means that no optimization is really accomplished.

This problem can be successfully addressed through the use of elitist strategy. During every new generation after fitness functions evaluation a certain number of best solutions are selected as elite individuals. When mutation is done N solutions are randomly removed from the current population and replaced by solutions from elite individuals. This elite preserve strategy has an effect in keeping the variety of each population.

SIMULATION RESULTS

To research genetic algorithms capabilities we used Siberia-2 storage ring lattice of Kurchatov synchrotron radiation source.

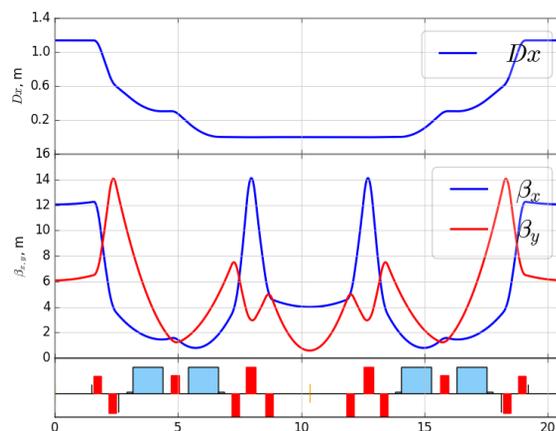


Figure 3: Optical functions for one of 6 ring cells in regular operation mode.

Optical functions of one of Siberia-2 superperiods being used in synchrotron radiation experiments are shown in Fig. 3 and the main parameters of the storage ring are presented in Table 1.

Table 1: Siberia-2 Storage Ring Main Parameters into Regular User Operation Mode

Parameter	Value
Circumference	124 m
Beam energy	2.5 GeV
Beam current	up to 150 mA
Horizontal emittance	98 nm-rad
Horizontal/vertical tune	7.775 / 6.695
Horizontal/vertical chromaticity	-16.9 / -12.9

Siberia-2 magnetic lattice consists of 6 mirror symmetric cells with 4 bending magnets and 6 quadrupole lenses. Each cell contains one nondispersive straight

section (3 m) for installing RF cavities and insertion devices and one dispersive straight section (3 m). The chromaticity is being corrected by 2 families of sextupole lenses.

Before starting an optimization process, we set following requirements and restrictions. In order for an injection into the Siberia-2 storage to stay efficient new optics must have a large dynamic aperture. Switching from the regular operation mode to the new mode should be performed only by adjusting the quadrupole and sextupole lenses strengths. As previously stated the six-fold symmetry optics is required for the new modes.

To accelerate optimization process we used initial approximation for variable parameters – the polarity of quadrupoles lenses is the same as used in Siberia-2 regular operation mode. As well, we set quadrupole lenses strengths of Siberia-2 regular operation mode as initial approximation for used optimization algorithms. Here we present the results obtained through the use of two different optimization genetic algorithms.

The first genetic algorithm applied was the differential evolution. This algorithm was used to minimize electron beam emittance in the presence of one additional condition – dispersion function should be zero in one of the two straight sections. After optimization we have that minimum emittance with the above-mentioned condition is approximately 65 nm·rad. It may be a little bit higher or lower depending on size of dynamic aperture, the precision of zeroing dispersion function and betatron tunes. Optical functions of one of the possible lattice tuning (emittance is 67 nm·rad) are shown on Fig. 4.

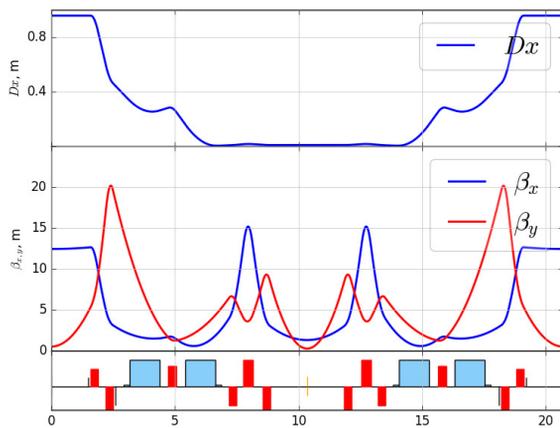


Figure 4: Optical functions for minimum emittance with zero dispersion function operation mode.

The second used genetic algorithm was multi-objective genetic algorithm with NSGA-II selection algorithm and elitist strategy. Now we will simultaneously minimize electron beam emittance and maximize dynamic aperture without any additional restrictions. Pareto frontier for emittance and dynamic aperture optimization is shown in Fig 2 and optical functions of one of the possible lattice tuning (emittance is 17 nm·rad) are shown on Fig. 5. As you can see on Fig. 2 achievable emittances are close to theoretical minimum emittance for Siberia-2 storage ring lattice. But in practice operation with such small

emittance is not be possible with existing injection system due to very small dynamic aperture.

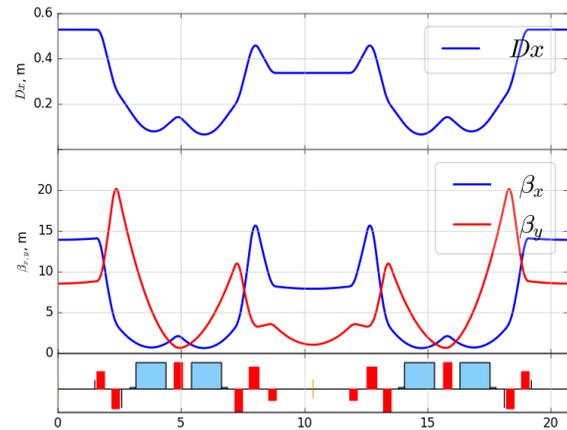


Figure 5: Optical functions for minimum operation mode.

It is also worth noting that reducing emittance to the minimum attainable level makes it impossible to keep zero dispersion function into one straight section. For that reason operating superconductive wiggler in this low-emittance mode is not advisable.

The obtained lattices look quite achievable. But before changing to the new optics tuning it is necessary to carry out more detailed research on the subject in order to obtain the optimal lattice parameters. As well, it is necessary to perform a lot of additional work at accelerating facility.

CONCLUSION

Genetic algorithms provide to be an effective optimization tool. Using these methods for solving complex accelerator lattices optimization problems yields good results. The carried out research demonstrates that when no initial approximation is made or only minimum prior information about behavior variable parameters is available using of genetic algorithms allows to provide desired results within a reasonable time.

In addition, we would like to note that it is not always possible to obtain exact optimal solution using genetic algorithm. Nevertheless, this problem can be solved by using solution obtained with the help of genetic algorithms as initial approximation for specialized optimization algorithms.

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