MACHINE BASED OPTIMIZATION USING GENETIC ALGORITHMS IN A STORAGE RING *

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Abstract

In this paper, instead of applying GA in the conventional numerical calculations, we present a successful experimental demonstration of implementing GA in real machine based optimization. We conduct the optimization of the average vertical beam size of the SPEAR3 storage ring using GA. Beam loss rate is chosen as the sole objective function because it is inversely proportional to the vertical beam size and can be measured quickly in SPEAR3. The decision variables are the strengths of SPEAR3 skew quadrupoles, by varying which we can change both the betatron coupling and the vertical dispersion to search for the minimum beam size. The results in this paper can shed light on new applications of GAs in particle accelerator community, for example, optimizing the luminosity of the high energy collider in real time.

INTRODUCTION

GAs have been successfully applied in areas such as designing injector systems [1], diagnosing and designing accelerating cavities [2], and optimizing beam optics design in storage rings [3]. One core process of the GA is to evaluate objective functions from a given set of decision variables, i.e. knobs to be adjusted for optimum search. In spite of various approaches used in previous efforts, all of them evaluate the objective functions based on numerical simulations using particle tracking codes. In principle, when the optimization targets or their correlating parameters are measurable experimentally, it is possible to use the real machine as the function evaluator to directly measure the objective functions, rather than using a computer model. Compared to the simulation based optimization, the machine based optimization has the most accurate representation of the machine condition that includes all lattice errors. Moreover, when the physics quantities of interest can be measured quickly in experiment but cost long time to be calculated in simulations, the machine based optimization will excel in speed too. One example of such quantity is the luminosity of the high energy colliders. In SPEAR3, we have identified a similar parameter of interest that can be measured nearly instantaneously. In this paper, we report an innovative application of GA to minimize the average vertical beam size of the SPEAR3 storage ring in real time. To construct the GA, we use 13 skew quadrupoles in the storage ring as decision variables and the measured beam loss rates as the objective function. The results can serve as a proof of principle for using GA in machine based optimization.

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MINIMIZE THE VERTICAL BEAM SIZE

In a storage ring, circulating electrons are lost due to collisions with gas molecules and electron-electron scattering inside the bunch, where the latter is known as the Touschek effect [4]. As in most modern electron storage rings, the loss of stored beam current in SPEAR3 is mainly due to the Touschek scattering. Thus, one can derive the simple scaling law between beam loss rates *dI/dt* and vertical beam size as shown below:

$$\frac{\left|\frac{dI}{dt}\right|}{I^2} \propto \frac{1}{\bar{\sigma}_y}, \qquad (1)$$

where I is the stored current and $\bar{\sigma}_y$ is the average vertical beam size.

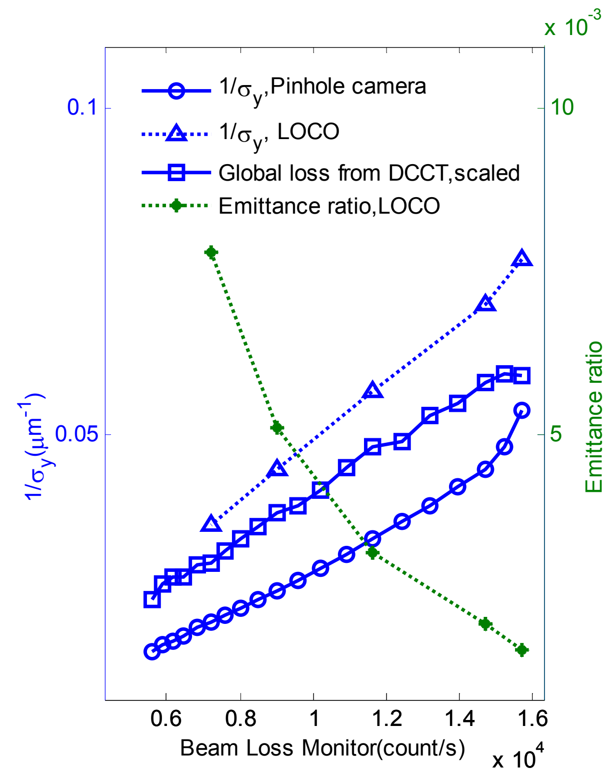

Figure 1: Experiment verification of Eq. (1).

In SPEAR3, Eq. (1) can be directly validated by experimentally measured data. During the experiment, 100 mA beam is filled in SPEAR3. We achieve 20 conditions in the ring by varying all skew quads in a fixed step size. For each condition, we measure the vertical beam size at 1Hz with an x-ray pinhole camera [5]. The beam loss rate is recorded instantaneously at 1Hz by a beam loss monitor (BLM) [6], installed next to the SPEAR3 beam horizontal scraper. The scraper is inserted close to the beam in order to capture nearly all of the beam loss at one point. The global beam loss is also

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acquired by recording the current decay during 2-minute period using a dc current transformer (DCCT). The current droop during the entire period of the experiment is less than 4%, thus, the stored current can be considered as a constant for the analysis in Eq. (1). Sampling 5 out of the 20 different cases, we measured the response matrix of the ring for each, and then fit the model to the measured data using LOCO. Emittance ratio and average vertical beam size then can be calculated from the fitted model. All results are shown in Figure 1, where the monotonic relationship of the measured beam loss monitor data, the vertical beam size, and the emittance prove the simple scaling law in Eq. (1).

ALGORITHM DESCRIPTION

In this section, we will detail the formation of a GA based technique in maximizing the beam loss rate of SPEAR3 in real time. The algorithm is based on NSGA – II [7].

Objective Functions and Decision Variables

The normalized beam loss rate measured by the BLM next to the scraper is the single objective function in our GA formation. The currents, which represent the strengths of the skew quadrupoles in SPEAR3, are the independent decision variables. After varying the currents of the 13 skew quadrupoles, the objective function is evaluated from the direct measurement of the BLM. Distinct from most other applications of GA, the accelerator serves as the function evaluator, instead of a numerical or analytical model. The SPEAR3 skew quadrupoles are powered by high precision MCOR power supplies featured with fast switching. The data acquisition from the BLM is also nearly instantaneous.

Genetic Operations

Except the first generation, all sequential generations are generated via the process of genetic operations. We use two of the most popular genetic operators: real-coded Simulated Binary Crossover (SBX) [8] and polynomial mutation [8]. In each genetic operation, one of the two operators is chosen randomly but conforms to a predefined ratio. During a crossover, two parents are picked to create two children, while one child is generated from one parent in the case of mutation. Once a child is created, its corresponding objective function is evaluated. Eventually, an offspring population is generated. Crossover and mutation are governed by the user-configurable nonnegative tuning parameters η_c and η_m respectively. A more detailed discussion of these two parameters can be found in the literature such as reference [8]. In short, these tuning parameters control the probability density function of the likeness between parents and children. For mutation, a smaller η_m represents less probability to have a similar child, which in turn provides a global search to the optimum regardless the parent solution. On the other hand, with a bigger η_m, it is very likely that the child only varies slightly from the parent and the operation is conducting a local search of optimum around the parent. The behavior of η_c is quite similar to η_m: the children tend to be close to one of the parents with large η_c or be randomly generated with small η_c.

The performance and speed of genetic algorithms highly depends on specific problems and can be adjusted with mutation and crossover tuning parameters. We have programmed the code to dynamically adjust these factors according to the diversity of the population in the new generation. It appears that the optimization progresses faster by promoting more global search with relatively small mutation tuning parameters in early generations. When the population starts to cluster toward the optimum region, it helps to save time by using large mutation tuning parameter or shrink the search space.

Replacement, Re-evaluation, and Stopping

To ensure an elitist approach, the current population is replaced by the best solutions chosen from both the offspring and the older generation. To maintain a fixed population size, the remaining solutions are discarded. As the objective functions are measured directly from the SPEAR3 machine, the results may change over time due to variation of machine condition. Therefore, we re-evaluate the surviving solutions from all previous generations every 10 generations. Limited by the machine time available for the experiment, we run the algorithm as long as possible, so normally we stop the program manually after a certain amount of time.

RESULTS

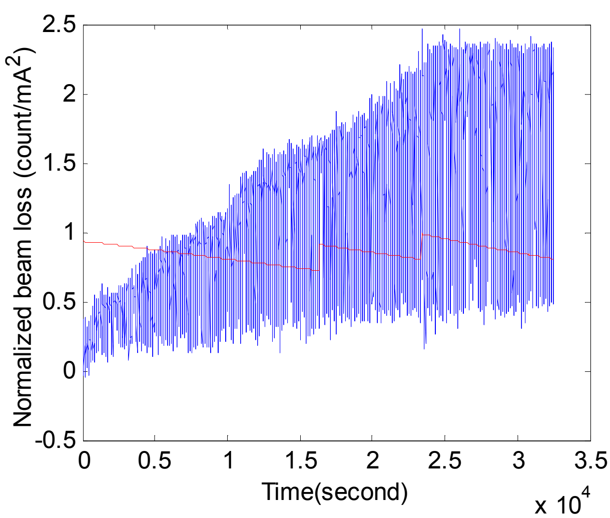

Figure 2: Normalized beam loss rates at the scraper during the experiment at 1Hz update rate.

We choose the population size of 120 in each generation for reasonably big sample size and relatively short time for generating the whole population during the experiment. As a result, it takes less than 3 minutes to generate one generation.

Figure 2 shows the results with 211 generations of GA optimization. To reduce the effect of stored beam current decay, we refilled SPEAR3 twice during this experiment

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as shown by the normalized stored beam current (scaled stored current shown as red curve). The optimization was paused during the refill and restarted by loading the dumped data after the fill. Overall, the algorithm behaved well. The normalized beam loss rates grow steadily for the first 150 generations, and then start to converge. In Figure 3, we compare the skew quadrupoles currents of the GA solution and the LOCO solution. The beam loss rates for the best solution found using GA are compared with the solution found using LOCO in Table 1. Average vertical beam size and emittance ratio of the ring with these two solutions are also calculated from the fitted model using LOCO.

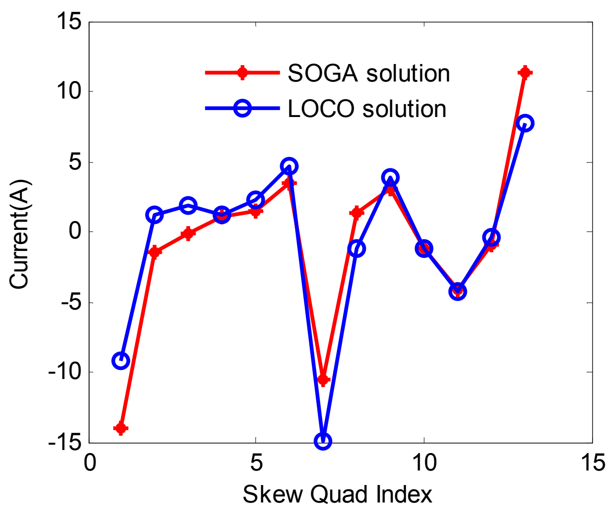

Figure 3: Comparison of the GA solutions and LOCO solution.

The normalized beam loss rate measured with the GA solution is increased by 17.9% from that with the LOCO solution. According to the scaling law in Eq. (1), this is translated to the reduction of vertical beam size by 15.18%. The calculated values using LOCO fitting show a 10.99% reduction of vertical beam size for the GA solution. The discrepancy comes from the accuracy of the fitting in LOCO, loss rates measurement, and the assumption of solely Touschek effect when deriving the scaling law in Eq. (1).

Table 1: Comparison of Solutions

	LOCO	GA
$\bar{\sigma}_y$ (μm)	7.9617	7.087
Emittance Ratio	0.0605%	0.0461%
Normalized Beam Loss rate	2.07	2.44

SUMMARY

Genetic algorithms are believed to be especially suitable for problems with high complexity where traditional gradient-based search methods normally fail to optimize. As the storage ring lattice is well designed, the coupling optimization of the ring tends to be a well behaved problem. This is evident from the final solution: out of 13 skew quadrupoles, only 3 are required to be set above 5A, while most of others are near zero. This fact weakens the advantage of using GA based optimization. Nevertheless, with machine based GA, we are able to find good solution regardless the time spent. Also, we have more confidence in its global validation. In addition, one should note that machine based GA may show advantage in speed over the traditional gradient based techniques when optimizing problems involved with more decision variables. As long as the corresponding hardware can be set roughly simultaneously, the time cost by machine based GA is independent of the number of decision variables. However, most traditional algorithms are scaled with the number of decision variables in high order. Thus, machine based GA can be more valuable for large machines.

The GA techniques we used are far from being refined. In future study, we will focus on improving speed and robustness. One possible approach is to create a hybrid algorithm that combines both GA and one of the traditional techniques for fast local search. When blending the two algorithms, it is challenging to maintain their original advantage, which requires thorough study.

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