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BEAM DIAGNOSTICS FOR MULTI-OBJECTIVE BAYESIAN OPTIMIZATION AT THE ARGONNE WAKEFIELD ACCELERATOR FACILITY

J. P. Gonzalez-Aguilera*, R. Roussel, Y.-K. Kim, University of Chicago, Chicago, IL 60637, USA
W. Liu, P. Piot, J. G. Power, E. E. Wisniewski
Argonne National Laboratory, Argonne, IL 60439, USA

Abstract

Particle accelerators must achieve certain beam quality objectives for use in different experiments. Usually, optimizing certain beam objectives comes at the expense of others. Additionally, there are many input parameters and a limited number of diagnostics. Therefore, accelerator tuning becomes a multi-objective optimization problem with a limited number of observations. Multi-objective Bayesian optimization was recently proposed as an efficient method to find the Pareto front for an online accelerator tuning problem with reduced number of observations. In order to experimentally test the multi-objective Bayesian optimization method, a novel accelerator diagnostic is being designed to measure multiple beam quality metrics of an electron beam at the Argonne Wakefield Accelerator Facility. Here, we present a design consisting in a pepper-pot mask, a dipole magnet and a scintillation screen, which allows a simultaneous measurement of the electron beam energy spread and vertical emittance. Additionally, a surrogate model for the vertical emittance was constructed with only 60 observations and without prior knowledge of the objective function nor diagnostics constraints.

INTRODUCTION

Particle accelerators need to be tuned to achieve beam quality objectives. This tuning must be done continuously during operation due to variable external factors and the large number of components present in the accelerator. Generally, optimizing certain beam parameters comes at the expense of others. Additionally, there is usually a limited number of diagnostics. Thus, the online tuning becomes a multi-objective optimization problem which must be solved in real time and with few observations.

Various attempts to implement optimization algorithms have been made in order to solve this problem, such as Bayesian optimization with a Gaussian process surrogate model [1]. In this algorithm, the surrogate model predicts the objective function and the model is updated iteratively, guiding the optimization search. This implementation has been shown to efficiently solve the optimization problem in accelerators with a high-dimensional input space and reduced number of observations [2, 3]. Nevertheless, this method has only been implemented for single-objective optimization problems.

Multi-objective optimization algorithms attempt to find the Pareto front, which is the set of non-dominated objectives. One example is the genetic optimization algorithm, which has been successfully used to optimize multiple beamline parameters [4]. These algorithms use parallel computing to evaluate multiple input-space combinations simultaneously, so they are useful for offline optimization problems where it is possible to run multiple beamline simulations at the same time. However, this methodology would take too much time for online tuning. The reason is that, when the accelerator is in operation, the measurement of the objectives can only be made one at a time for each single set of input parameters.

Multi-Objective Bayesian Optimization (MOBO) [5] extends the single-objective Bayesian optimization to multi-objective optimization by using a surrogate model for each objective function. MOBO has been used for online optimization in simulations, and it has been shown to reduce the number of observations needed to converge to a Pareto front by at least an order of magnitude when compared to genetic algorithms such as NSGA-II [6].

In order to test MOBO for accelerator tuning experimentally, we propose a beam diagnostics design at the Argonne Wakefield Accelerator Facility which allows the simultaneous measurement of vertical emittance and energy spread. We also show the surrogate model obtained for the vertical emittance, as well as the use of Bayesian statistics to overcome diagnostics constraints challenges when exploring the parameter space.

METHODS

The Argonne Wakefield Accelerator Facility (AWA) can produce electron beams with a wide range of charges and energies [7]. We used the RF photocathode gun and RF accelerating cavities section for our experiment, and fixed the charge to −5 nC, the initial bunch length to 6 ps and the beam energy after the last linac cavity to roughly 42 MeV. Figure 1 shows a cartoon of the photoinjector and linac cavities section of the AWA facility, as well as the free parameters we use: gun phase (ϕ_1), first linac cavity phase (ϕ_2), focusing solenoid current (I_1), and matching solenoid current (I_2). The objective functions are the geometrical vertical emittance (ε_y) and the energy spread (dE).

Figure 2 shows the beam diagnostics proposed to measure ε_y and dE simultaneously. It consists in a pepper-pot mask with holes on the y-axis, a dipole magnet and two YAG screens. The first YAG screen is used to measure the reference beam size on the x-axis (σ_β) when the dipole is

* jpga@uchicago.edu

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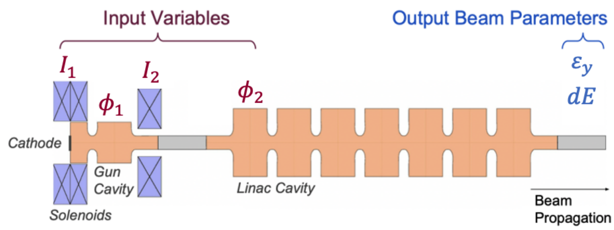

Figure 1: Scheme of the AWA photoinjector and linac cavities section. Reproduced with modifications from [8].

off. The second YAG screen is used to measure both the vertical emittance and the energy spread when the dipole is on. The lower energy particles will be deflected more than the higher energy ones, so the x beam size in the second YAG screen is correlated with the energy spread:

$$\sigma_x = \sigma_\beta + \eta\, dE. \tag{1}$$

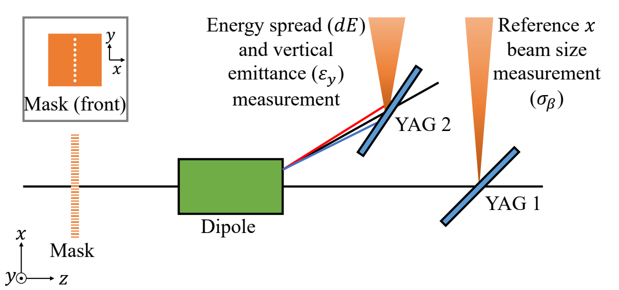

Figure 2: Proposed beam diagnostics design. The dipole is turned off when using the first YAG screen to measure the reference beam size on the x direction (σ_β). Consequently, the dipole is turned on to perform the vertical emittance (ε_y) and energy spread (dE) measurements on the second YAG screen.

The geometrical vertical emittance at the position of the mask is calculated by:

$$\varepsilon_y = \sqrt{\langle y^2\rangle\langle y'^2\rangle - \langle yy'\rangle^2}, \tag{2}$$

whose parameters can be estimated with a YAG screen located a distance L away from the mask and by capturing the image with a CCD camera. Figure 3 (a) shows a cartoon of the $y' - y$ phase space at the mask location, and Fig. 3 (c) shows the beamlets projections to the screen. Let y_i be the position of the ith hole in the mask, and let a_i, b_i, and c_i be the beamlets' intesities, peak positions on the y-axis, and standard deviation on the y-axis respectively. Let $y'_i = (b_i - y_i)/L$ and $\sigma'_i = c_i/L$. Then we can estimate the following $y' - y$ phase space values [9, 10]:

$$\langle y\rangle = \frac{\sum_i a_i y_i}{\sum_i a_i}, \tag{3}$$

$$\langle y^2\rangle = \frac{\sum_i a_i (y_i - \langle y\rangle)^2}{\sum_i a_i}, \tag{4}$$

$$\langle y'\rangle = \frac{\sum_i a_i y'_i}{\sum_i a_i}, \tag{5}$$

$$\langle y'^2\rangle = \frac{\sum_i a_i \sigma'_i}{\sum_i a_i}, \tag{6}$$

$$\langle yy'\rangle = \frac{\sum_i a_i y_i y'}{\sum_i a_i} - \langle y\rangle\langle y'\rangle. \tag{7}$$

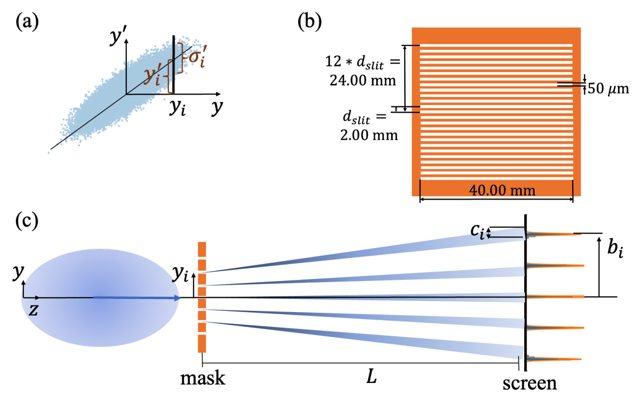

Figure 3: Emittance diagnostics used for the emittance surrogate model. (a) $y' - y$ phase space cartoon. (b) Multi-slit mask design for emittance-only measurement (not to scale). There are 25 slits with width of 50 µm separated 2.00 mm. (c) beamlets on screen: for the slit located at the mask at y_i, the corresponding beamlet has a peak position at b_i and a standard deviation of c_i on the y-axis.

As a first step to construct a surrogate model for one of the objective functions, we used a multi-slit mask which allows vertical emittance measurements only. Figure 3 (b) shows the mask design that has been used to construct the vertical emittance surrogate model.

RESULTS

Parameter Space Exploration

Exploring the parameter space usually costs time since the diagnostics introduces technical constraints for having valid measurements. The constraints for a valid emittance measurements are: the number of blobs at the screen should be more than three, the blobs cannot touch, and there should not be blobs on the edges or outside the screen. Using Bayesian exploration and a quadrupole magnet as an auxiliary parameter which doesn't change the emittance, the algorithm was able to find a region in the parameter space which led to valid measurements. Figure 4 shows both random and Bayesian exploration sampling in the parameter space defined by the two solenoid currents and the auxiliary parameter given by

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the quadrupole strength. Bayesian exploration allowed to find the region inside parameter space which lead to valid measurements and thus, it samples the valid region with higher density. Additionally, the validity of the measurements was not affected by the quadrupole magnet strength.

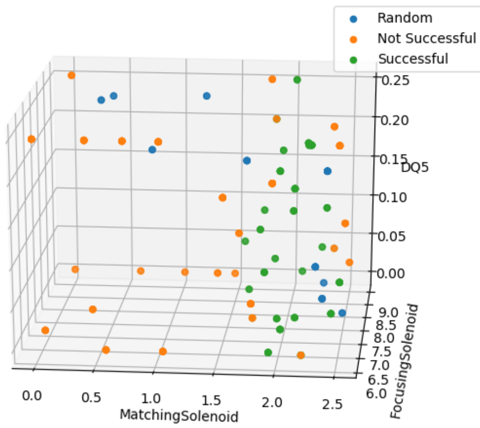

Figure 4: Observations in the solenoids parameter subspace with a quadrupole magnet strength as an auxiliary parameter (DQ5). Blue points are random samples. Green and orange points are samples obtained with Bayesian exploration which led to successful and unsuccessful measurements respectively. All three parameters are normalized in a zero to ten scale.

Emittance Surrogate Model

A Gaussian process surrogate model [6] was generated for the vertical emittance after 60 observations (see Fig. 5). The model predicts the mean and uncertainty at quadrupole strength of zero. Note that the algorithm was able to find a length-scale in both axes of the parameter subspace. Also, the model was constructed without prior knowledge of the objective function.

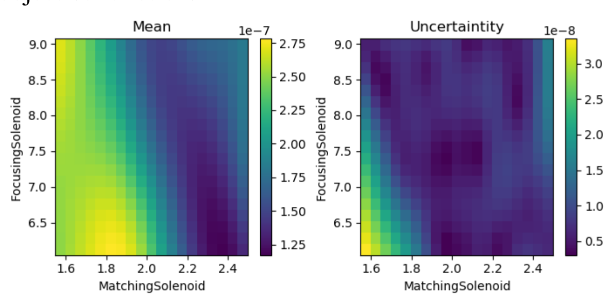

Figure 5: Gaussian process surrogate model for vertical emittance mean (left) and uncertainty (right) as a function of the solenoid currents parameter subspace. Parameters are normalized in a zero to ten scale, and the geometrical emittance mean and uncertainty are in m rad.

CONCLUSION

In this paper, we proposed a beam diagnostics design to measure vertical emittance and energy spread simultaneously at the AWA facility. A multi-slit mask has been installed in the beamline and a Gaussian process surrogate model for the emittance was constructed with only 60 observations and without prior knowledge of the emittance behaviour. Furthermore, Bayesian exploration was shown to be useful in exploring the parameter space, which was constrained by technical requirements of the diagnostics.

We are currently planing the next stage of the experiment, which consists in constructing a surrogate model for the energy spread and run the MOBO algorithm at the AWA Facility.

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