GAUSSIAN PROCESS REGRESSION AND BAYESIAN OPTIMIZATION FOR A 40-90 MeV LASER-PLASMA INJECTOR FOR THE dSTART STORAGE RING

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Abstract

Laser-plasma accelerators (LPAs) generate ultrashort high intensity electron bunches from a compact source size. At the Karlsruhe Institute of Technology (KIT), we will use an LPA as one of the injectors for the compact, high-momentum acceptance, non-equilibrium storage ring cSTART.

The LPA injector with a length of only a few millimeters will be optimized to match the cSTART operation beam energy of 40–90 MeV. It will be based on an ionization trapping scheme in combination with a tailored plasma density profile to produce an electron beam with small energy spread that maximizes the spectral charge density at our target energy, which is (for LPAs) comparably low. Moreover, the LPA injector must produce controlled electron beams with high shot-to-shot stability and avoid high-energy tails. These goals can be achieved largely by the detailed design of the plasma density profile and the laser pulse parameters.

In an LPA, small changes across the high-dimensional parameter space can have a disproportional influence on overall performance. To find parameters for stable high-quality LPA beams, we perform particle-in-cell (PIC) simulations and implement a machine-learning driven approach by using Bayesian Optimization (BO) based on Gaussian Process Regression (GPR). This procedure allows us to both optimize our gas target design and characterize the effects of the interaction parameters, giving us a functional LPA with a simple tuning mechanism.

INTRODUCTION

KIT is in the process of building a compact electron storage ring cSTART [1], which will be able to accept femtosecond bunches with large momentum spread for accelerator research into the storage of ultrashort bunches as well as non-equilibrium beam dynamics, beam stabilization, future compact light sources, and next-generation accelerator technologies. [2]

As part of the project, we plan to use LPAs (see Table 1) to inject femtosecond electron bunches into the compact storage ring [3]. LPAs have long been considered a promising technology for this purpose [4], and the high accelerating gradients produced in a plasma wakefield allow us to accelerate beams to our target energies over millimeter-scale acceleration distances, allowing the LPA injectors themselves to be orders of magnitude smaller than traditional RF-based approaches.

However, one persistent challenge associated with LPAs as stable electron sources is the shot-to-shot fluctuations of LPA generated electron beams [5]. This variability is currently substantially higher in LPAs than that of RF-based accelerators due to the nonlinearity of the laser plasma interaction coupled with a high accelerating gradient, which imply that small variations in the input parameters of an LPA system lead to disproportionately large changes in the properties of the generated beam.

Table 1: LPA Target Parameters

Parameter	Value
Energy Range	40 - 90 MeV
Momentum Spread	<4 %
Bunch Duration	femtosecond

We intend to mitigate this weakness through a careful choice of laser and plasma input parameters, selecting not just for suitable beam parameters, but for reproducible generation of such beams even when those carefully selected parameters vary from shot to shot.

PARAMETER SPACE

Our first strategy to mitigate LPA variability is our selection of an ionization trapping scheme, which adds a gas dopant with a higher atomic Z-number than the typical LPA background gas target in order to control when and where electrons begin to accelerate. [6] This scheme has been shown to substantially improve the stability of LPA beams [7].

In our simulations, this is implemented into the gas targets via a density up-ramp followed by a density plateau of a background atom species (hydrogen in our case), which forms the accelerating structure of the LPA. A small, localized dopant species (nitrogen in our case) is introduced close to the up-ramp. The simulated gas target ends with a gradual density downramp which increases energy stability by forcing the LPA to reach the dephasing length at the target energy (see Figure 1).

Similar density profiles can be generated experimentally, both with paired gas jets [8] and with gas capillaries at equilibrium [9]. We identified several relevant parameters which may randomly vary from shot to shot in an experimental LPA setup and affect beam stability. These parameters include the densities of both the background and dopant species, the laser focus position, as well as the overall gas density profile. Limiting ourselves to parameters that may affect beam stability, while also being simple to alter and simulate, left us with an 6-dimensional parameter space.

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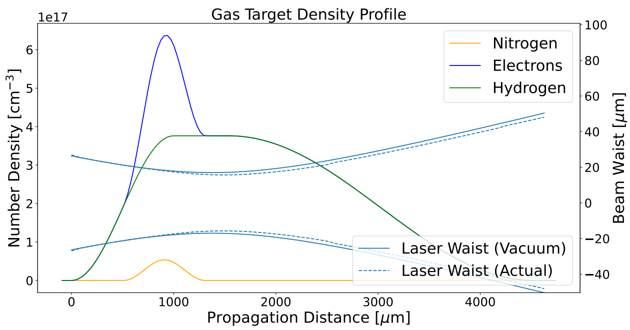

Figure 1: Typical longitudinal density profile of our gas target. The electron density corresponds to fully ionized atoms. The actual laser waist differs from the vacuum waist due to the laser-plasma interaction. The nitrogen, hydrogen and electron density correspond to the left axis, the laser beam waists to the right axis.

PARAMETER OPTIMIZATION

We used Bayesian Optimization (BO) [10] to automate the exploration of the high dimensional parameter space of the LPA and to select input parameters for an optimized beam. Our approach to BO forms a surrogate model of the parameter space using Gaussian Process (GP) regression with a Radial Basis Function (RBF) kernel [11]. This surrogate model allows an acquisition function to intelligently select a new set of candidate parameters to iteratively explore the parameter space and approach the global maximum of a black-box objective function as illustrated in Figure 2. The acquisition function used for this study is a Monte-Carlo based batch logarithmic expected improvement function implemented in BoTorch [12].

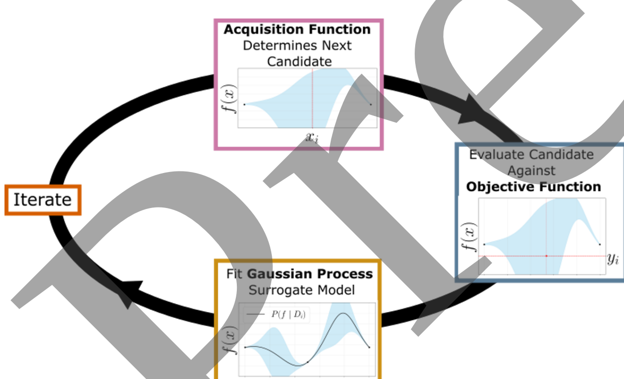

Figure 2: Diagram of a typical Bayesian Optimization loop.

We use the particle-in-cell (PIC) simulator FBPIC for our optimization loop [13]. FBPIC decomposes 3D cartesian coordinates into azimuthal modes, making bulk simulations of nearly cylindrically symmetric LPA systems both simple and computationally cheap.

The correct choice of objective function is important for BO. A poorly selected objective function that incentivizes [14] unwanted features can lead the BO algorithm to "reward hack" [15], meaning it converges on a "perverse optimum" which technically maximizes the objective function, but leads to beams with undesirable parameters.

Our goal for the beam is to maximize the spectral charge density at the target energy range while minimizing dark current and beam segments outside the accepted energy range. Thus, we used an objective function that serves as a charge-suppressed spectral density [16] for these scans: $f(x) = \sqrt{q\,[\mathrm{pC}]}/\left(\Delta E/\tilde{E}\right)[\%]$, where q is the charge, $\tilde{E}$ is the median energy and ΔE is the energy spread given in median absolute deviation (MAD). Maximizing this objective function within reasonable bounds results in a beam that delivers high charge within a narrow energy spread and is thus suitable for injection into cSTART.

RESULTS

We performed BO loops across four pairs of laser and plasma parameters and found several solutions that produce suitable beams, meaning they meet the cSTART beam energy and momentum spread requirements. The simulated longitudinal phase space of one such electron beam is shown in Figure 3.

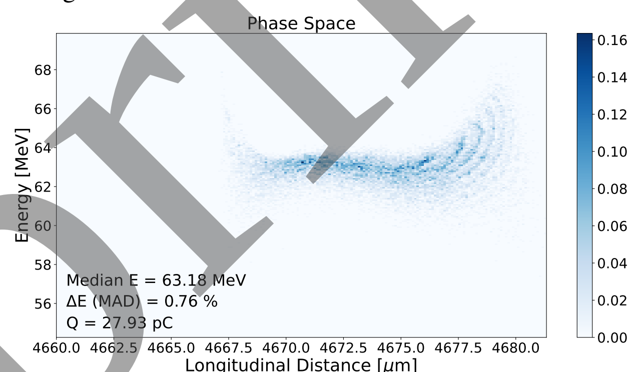

Figure 3: Longitudinal phase space density of an optimized electron bunch with beam parameters shown in the figure, generated by a 1.6 J, 25 fs FWHM laser with a spot size near 20 µm FWHM, focused 1.38 mm from the start of the gas target. The gas target profile is of the shape shown in Figure 1 with a peak hydrogen density of 3.8×10^{17} cm^{-3} and a peak nitrogen density of 4.5×10^{16} cm^{-3}.

The GP surrogate models generated by our scans provide an effective approximation of our entire parameter space, highlighting regions of stability where we expect suitable electron beams from laser and plasma parameters that jitter from shot to shot. Several surrogate models depicting our parameter space are shown in the gray color maps of Figures 4 to 6. The markers in those figures indicate simulations that were used to fit the surrogate models. Darker values in the gray-scale map for the surrogate model correspond to higher values in the objective function (i.e., more suitable beams). The color of each marker represents the median beam energy of the corresponding simulation.

A deceptively simple method of tuning the electron energy of an LPA generated beam would be either to change the background plasma density, thereby changing the magnitude of the accelerating field, or to change the length of the gas target, thereby changing the acceleration distance. However, Figure 4 indicates that for our parameters, both approaches

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lower beam quality. Additionally, the parameters co-vary in such a way that the stable interaction between them is precisely the one that leaves electron energy constant.

Background Density versus Plateau Width

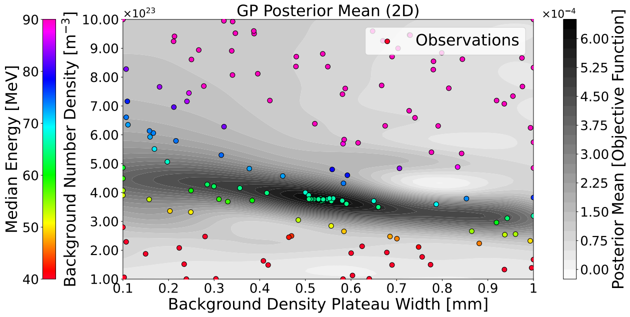

Figure 4: 2D GP Surrogate Model of Background Density vs. Plateau Width. The latter is an effective stand-in for the length of the gas target.

Instead, we find a simple energy tuning mechanism that preserves beam suitability by following the color gradient of simulated beam energies across stable regions of the surrogate models in Figures 5 and 6. In the case of Figure 5, energy tuning is performed by changing the position of the dopant gas, thus changing the electron trapping position and the effective acceleration distance. However, doing so lowers beam quality unless the laser focal plane is also changed approximately in lock-step so that the laser focus plane remains downstream of the dopant position.

Dopant Position versus Longitudinal Laser Focus

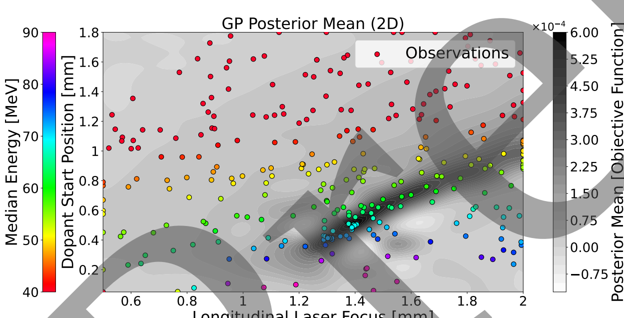

Figure 5: 2D GP Surrogate Model of Dopant Position vs. Longitudinal Laser Focus.

Another method for energy tuning can be achieved by changing the dopant density. This changes the total charge of the beam, which in turn changes the magnitude of the accelerating field through beam loading. This effect for the cSTART LPA injector was discussed in a previous paper [17]. The surrogate model in Figure 6 indicates that the density downramp can be adjusted to achieve a similar effect, but that the stable range of both is low, meaning that tuning the beam to substantially different energies also results in a beam that is unsuitable for cSTART. However, because the covariance of the two parameters is nearly zero, both can be adjusted independently, or in combination with each other to magnify their effect on electron beam energy.

Dopant Density versus Driver Downramp

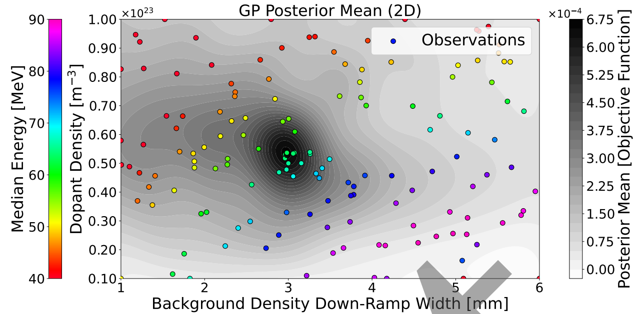

Figure 6: 2D GP Surrogate Model of Dopant Density vs Density Downramp.

CONCLUSION

In this study, we used the GP surrogate models generated from a Bayesian Optimized parameter scan of a simulated ionization injection scheme for an LPA in preparation for designing and building an LPA injector for cSTART. The optima are well within the acceptance window of our future storage ring, and a simple tuning mechanism for adjusting beam energy was identified. Future work will experimentally test gas targets with similar parameters in order to provide experimental feedback. We also intend to explore beyond the bounds set in this study in simulation with improved objective functions to expand the region of stability described by the surrogate models, leading to fewer wasted shots and simple energy tuning parameters across cSTART's entire range, from 40 to 90 MeV.

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