Machine learning controlled laser wakefield acceleration simulations

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Introduction

One of the most promising technologies to form the next generation of compact particle accelerators is plasma acceleration. Plasmas have the ability to sustain waves with electric fields that can be three orders of magnitude higher than those in radio frequency (RF) cavities.

The ultimate goal of plasma-based acceleration is to produce relativistic, high quality electron and positron bunches for scientific and societal applications. The recent progress has been tremendous but improving beam quality still remains as a grand-challenge in the field.

The fundamental aspects and properties of these accelerators are accessible through simplified analytical models, but the self-consistent dynamics of the laser in the plasma can only be captured by numerical simulations. Search for optimised parameters to improve beam quality can be based on systematic parameter scans. However, because numerical calculations can be very computationally intensive, it is important to investigate more efficient techniques to scan over the entire parameter range currently available. In this work, we propose a machine learning approach to optimize this search based on genetic algorithms.

Recent experiments have employed genetic algorithms to control plasma based accelerators [1]. Here, instead, we will employ this technique to control the outputs and optimise plasma-based accelerators in particle-in-cell (PIC) simulations. We implemented a genetic algorithm in ZPIC, a fully relativistic PIC educational code[2]. The genetic algorithm is fully automated: it receives an initial set of input parameters, launches several simulations in parallel using MPI, and ends automatically once given convergence criteria are reached. The algorithm can thus take full advantage of large-scale super-computers. We present results from 1D simulations. We focus on plasmas with non-uniform density and lasers with variable longitudinal envelope profiles.

Setup

The optimizing function will be chosen from what is considered to be a good beam, which depends on the purpose for which the beam will be used. Some characteristics of the beam, like the mean energy of the particles, its energy spread and number of particles are likely to differ

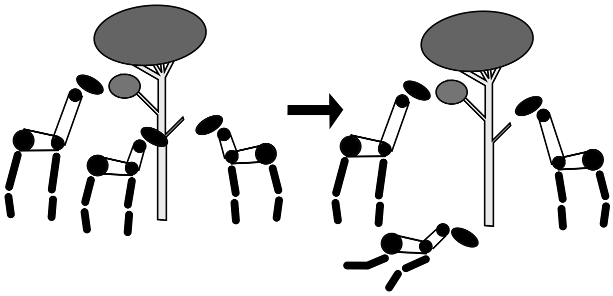

Figure 1: Depiction of the genetic algorithm. The fittest elements can produce offspring, something that is denied to the remaining individuals. This will produce a next generation which will be fitter.

between a beam used for medical purposes or one for particle collision.

The results that are presented throughout this paper come from a laser plasma interaction that is expected to be used for x-ray production [3]. A laser hits the plasma and then accelerates a short electron beam, that can be later used for ultrafast electron diffraction with a sub-10 fs resolution, which is smaller than all other technologies. The repetition rate for these cases (kHz) causes the energy of the laser to be of the order of mJ. For the 1D case, the energy of the laser is of that order if we consider the spot size to be similar to [3]. The laser frequency is also 2 times higher than the plasma frequency.

Genetic algorithms

Genetic algorithms consist on the evaluation of the function we want to optimize in a generation, which represents a set of individuals, each one being a different input. The individuals that get a better score are mutated, which means that the set of inputs is slightly modified. The next generation will consist only on individuals that are mutations from the best scoring individuals. The low scoring individuals are discarded (figure 1).

In this work, the optimization was made by changing both the laser envelope (figure 2 left) and the electron density profile in the plasma (figure 2 middle). We also explored the possibility to introduce a chirp in the laser(figure 2 right). Since it is unfeasible to have complete control on the density profile, the optimization was done on the size and slope of a ramp, whose objective was to promote self-injection in the beam. In the 2D runs that will follow, Zernike polynomials will be used to change the wavefront and the contributions of each polynomial will be optimized.

Example of a complete result - 1D optimization with chirp

In this case the function used to optimize was $l = \langle E \rangle / (\sigma_E - \alpha) n^{1/2}$, where <E> is the mean energy of the beam, σ_E is the energy spread of the beam and n is the number of particles in the beam. This variable was taken during the simulation at the time <E> was the largest. The simulation was stopped as soon as the laser energy dropped to a certain fraction of the initial

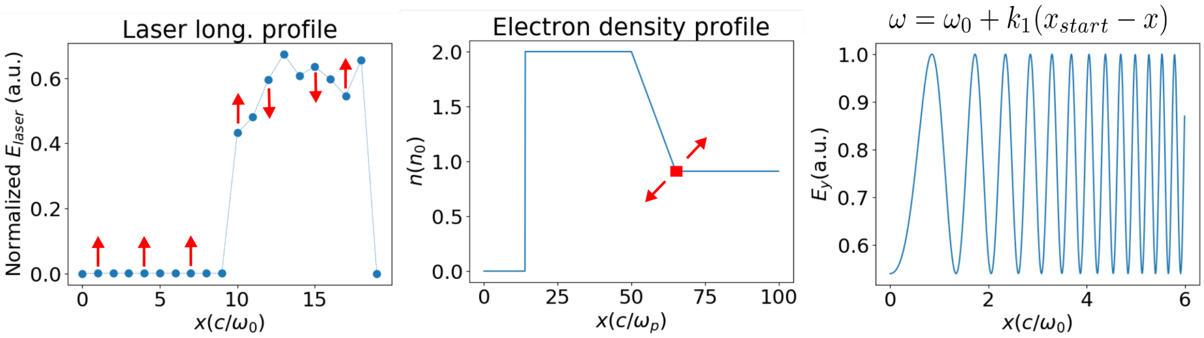

Figure 2: Input variables considered: Left - Envelope of the laser (before multiplication by cos(kx)). The envelope is normalized to its maximum value. Cubic spline interpolation is made between points. The mutation includes variations (examples in red) in the relative height of each point except for those at the beginning and at end of the laser, which are kept to 0. Middle - density profile for the 1D case. The optimization of the profile is done via changing length and slope of the ramp (changing coordinates $(x, n(x))$ of red point). The quantity n_0 was taken from [3] as the maximum density attainable by the experiment. Right - Example of a chirp in an electric field (start is where the laser begins and ω the local frequency at x (k_1 is the variable to be optimized)

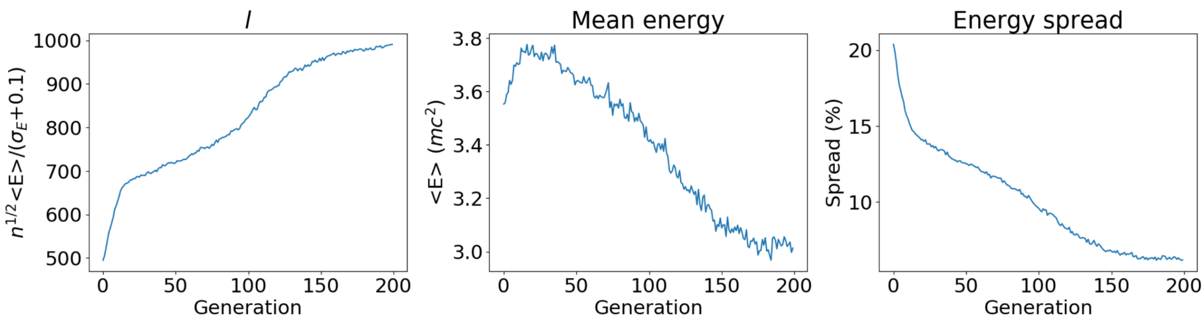

Figure 3: Example of the evolution of three main parameters of the beam, from left to right: mean energy, energy spread (%), l.

laser energy. The laser energy was kept constant throughout the optimization. A particle was selected as part of the beam if its energy was above a certain threshold, defined by the user.

We found that having $\alpha = 0$ would produce an optimized beam that would get really high scores just for having a small σ_E compared to the remaining individuals, even if its mean energy and number of particles were subpar. The factor α was then introduced to control the relative importance of the energy spread in our simulations.

The code was run for 200 generations with 200 individuals each. For each generation, the best individual (the one with the largest luminosity) was taken and the evolution of some final quantities and of the envelope was plotted (figures 3 and 5, respectively).

The algorithm did improve the optimizaiton quantity l. In fact, the energy spread is smaller than the one obtained in [3]. However, the mean energy decreased, even though relativistic electrons were still produced. The envelope (figure 5) is fairly similar to what is shown in [3], being split into 2. However, 2D runs are necessary in order to further compare these results.

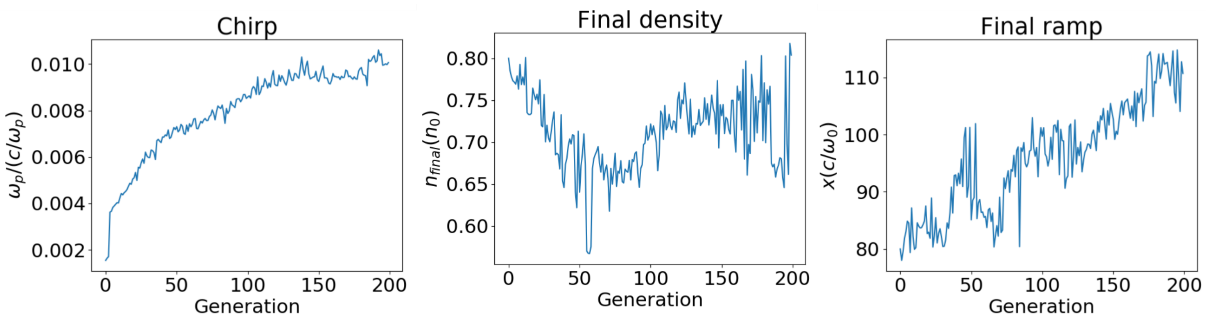

Figure 4: Evolution of the chirp (k_1 in figure 2, right) , ramp final x and final density (coordinates of red point in figure 2, middle

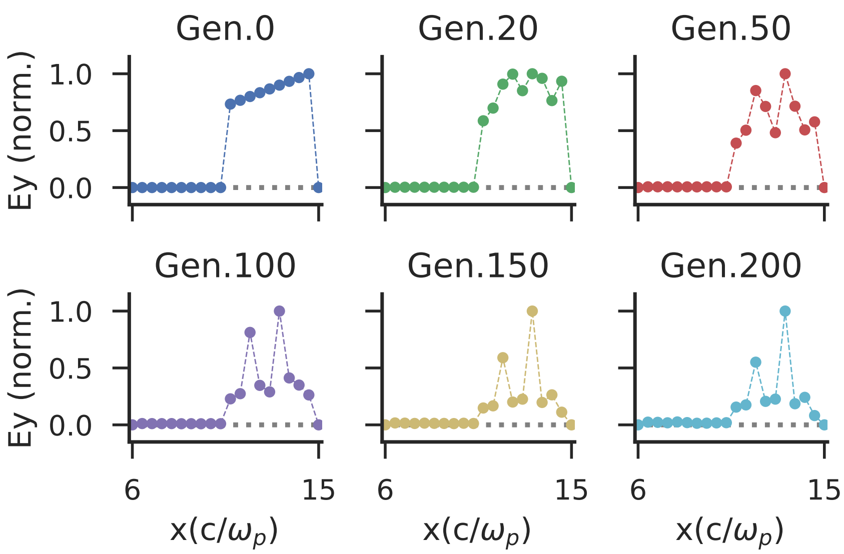

Figure 5: Evolution of the laser envelope. The effective length of the laser is smaller than the maximum length defined by the user (9 c/ω_p)

Conclusions

In this paper we show beam optimization using genetic algorithms. The optimization variable l takes into account the most important characteristics of the electron beams, such as the mean energy and energy spread. The code is ready to be applied in some other plasma physics problems. The results suggest that a fine control over the laser longitudinal profile allows for the creation of multiple sets of electron beams, with varying mean energy, spread and number of particles, which means that a single compact machine should be able to produce electron beams adapted to each necessity, which shows flexibility of this technology. we are now developing a two-dimensional optimization with ZPIC that will allow for more quantitative predictions.

References

[1] Z.-H. He et al., Nature communications **6** (2015)

[2] https://github.com/zambzamb/zpic/

[3] D. Guénot et al., Nature Photonics **11**, 293 (2017)