

## USE OF MULTIOBJECTIVE EVOLUTIONARY ALGORITHMS IN HIGH BRIGHTNESS ELECTRON SOURCE DESIGN

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*Abstract.* We describe the use of multiobjective evolutionary algorithms (MOEAs) for the design and optimization of a high average current, high brightness electron injector for an Energy Recovery Linac (ERL). By combining MOEAs with particle tracking, including space charge effects, and by employing parallel computing resources, we explored a multidimensional parameter space with 22 independent variables for a DC gun based injector which is being constructed at Cornell University. The simulated performance of the optimized injector is found to be excellent, with normalized rms emittances as low as 0.1 mm-mrad for a 77 pC bunch, and 0.7 mm-mrad for a 1 nC bunch. We detail the advantages and flexibility of MOEAs as a powerful tool well suited for wide application in solving various problems in the accelerator field.

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## Abstract

We describe the use of multiobjective evolutionary algorithms (MOEAs) for the design and optimization of a high average current, high brightness electron injector for an Energy Recovery Linac (ERL). By combining MOEAs with particle tracking, including space charge effects, and by employing parallel computing resources, we explored a multidimensional parameter space with 22 independent variables for a DC gun based injector which is being constructed at Cornell University. The simulated performance of the optimized injector is found to be excellent, with normalized rms emittances as low as 0.1 mm-mrad for a 77 pC bunch, and 0.7 mm-mrad for a 1 nC bunch. We detail the advantages and flexibility of MOEAs as a powerful tool well suited for wide application in solving various problems in the accelerator field.

## INTRODUCTION

Cornell University is planning an ultra-bright x-ray light source based on the Energy Recovery Linac (ERL) concept. The key component of the ERL is a high average current low emittance electron injector. We have chosen an injector system based on DC gun technology. The injector system is described elsewhere [1]. The high-voltage DC gun is followed by two focusing solenoids, one before and one after a single-cell, normal conducting buncher cavity. A cryomodule containing five 2-cell superconducting cavities is capable of accelerating the beam to energies as high as 15 MeV. The fundamental RF frequency is 1.3 GHz.

Determining the optimal parameter set for the injector is not a simple task. In general, one expects the optimal solution to be dependent on the bunch charge, the cathode field strength and gun voltage, the transverse and longitudinal profiles of the laser illumination at the photocathode, and the locations and field strengths of the focusing, bunching, and accelerating elements following the electron gun. There are many practical constraints involving the physical size of the elements, practical field strengths, and the realities of the vacuum system. The nonlinear nature of the space-charge force precludes obtaining meaningful analytic estimates. Present day codes allow good quality results to be obtained in tracking a bunch through a complete injector, but the large number of parameters and constraints involved makes a complete injector optimization formidable.

In this paper we describe a solution to the problem of optimized injector design by means of parallelized multiobjective evolutionary algorithms combined with particle tracking [1].

## ALGORITHM

Multiobjective optimization problem (for example, an injector design which simultaneously seeks smaller emittance and shorter bunch length at its output) can be defined as following:

$$\left. \begin{array}{l} \text{maximize} \quad f_m(\mathbf{x}), \quad m = 1, \dots, M; \\ \text{subject to} \quad g_j(\mathbf{x}) \geq 0, \quad j = 1, \dots, J; \\ \quad \quad \quad x_i^{(L)} \leq x_i \leq x_i^{(U)}, \quad i = 1, \dots, n. \end{array} \right\}$$

To compare between two possible solutions one can employ the concept of *dominance*: a solution  $\mathbf{x}_1$  is said to *dominate* another solution  $\mathbf{x}_2$  if solution  $\mathbf{x}_1$  is no worse than  $\mathbf{x}_2$  in all objectives  $f_m$  ( $m = 1, \dots, M$ ) and is better at least in one objective. Then, in the set of feasible solutions, the sought *optimal Pareto front* is defined as a set of  $\mathbf{x}$  not dominated by any other solutions.

We have used modified versions of evolutionary algorithms SPEA-II [2] and NSGA2 [3] to use with particle tracking code ASTRA [4] to obtain optimal fronts in the injector performance. Evolutionary algorithms mimic the natural selection process in nature and the optimization proceeds by ‘improving’ a fixed size set of trial solutions  $\{\mathbf{x}\}$ , called the *population*. The fittest individuals in the population (e.g. the non-dominated ones) are the primary candidates to produce ‘offspring’ trial candidates. Upon evaluation of all objectives and constraints (i.e.  $f_m$  and  $g_j$ ) these individuals are either purged or carried over to the next generation cycle depending on whether they improve over their predecessors.

The computational bottleneck in injector optimization is the calculation of objective and constraint functions, as this step requires particle tracking through the injector with space charge included. To reduce the wall-clock time for these calculations to a reasonable value, parallel processing is used.

Evaluation of objectives and constraints of a population of solutions in evolutionary algorithms over a single generation is ideal for parallel processing. Computation of the objective and constraint functions of a particular trial solution is done on a single processor. The communication between various processes occurs only at the end of each generation, when evolutionary operations, such as selec-

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tion and crossing of the individuals in the whole population, takes place. Thus, parallelization of evolutionary algorithms does not require high-bandwidth low-latency interconnections of the various nodes in a cluster, and even computers that are part of a usual network form an effective parallel environment for doing optimizations.

Parallel implementation of the evolutionary algorithms was realized on two 64 and 32 dual-processor cluster computers, as well as nearly 100 Desktop computers within the laboratory's network. The latter were utilized as a latent computational resource, performing trial solution evaluations in the background when their normal work load was minimal. A 'Master-Slave' model for algorithm execution was used: the master processor performs all the evolutionary operations on the ordered population of evaluated trial solutions, and sends the trial solutions to the slaves for evaluation.

## RESULTS

For the injector optimizations reported here, we have used a total of 22 parameters (unless specified otherwise). In all cases, the longitudinal separation between elements has been constrained to allow for the assembly of a physically realistic vacuum system, and for realities such as the transition from room temperature to 2 K at the entrance and exit of the cryomodule. Field strengths used for different elements were technically feasible and within specifications of our injector. Four variables specified the DC gun voltage, the two solenoid fields and the buncher cavity gradient. Four other variables specified phase and gradients of the 5 SRF cavities, with the 4 last cavities having identical parameters. The longitudinal field profile in all elements were determined with suitable codes (POISSON [5] for static fields and SLANS [6] for RF fields). Two variables specified the spot size and duration of the laser pulse at the cathode. Two pairs of 3 parameters defined the transverse and longitudinal laser profiles (see description below). Finally, two parameters represented the bunch charge and the effective thermal energy  $E_{th}$  of the photocathode. The thermal emittance of the photocathode is  $\epsilon_{n,rms} = \sigma \sqrt{E_{th}/mc^2}$ , with  $\sigma$  and  $mc^2$  being the rms laser spot size and the rest mass of electron respectively. The effective thermal energy of the cathode in all of the simulations presented here is 35 meV – the measured value for room temperature GaAs cathodes illuminated with near bandgap energy photons [7].

### Optimal Pulse Shape at the Photocathode

We have carried out optimization of the initial laser pulse shape by employing 6 parameters with values over the interval  $[0, 1]$ , to specify the transverse and longitudinal laser profiles, viz., a tail parameter specified the fraction of the total width of the profile occupied by tails as opposed to a flattop region (0 corresponding to uniform, and 1 to Gaussian shapes); a dip parameter allowed creating profiles depleted in the center (0 – without depletion, 1 – zero

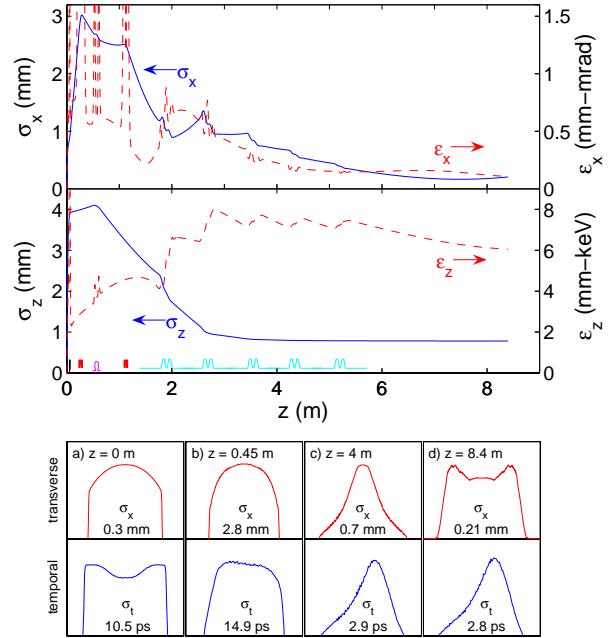


Figure 1: Beam evolution in the injector for 80 pC bunch charge: normalized transverse (top plot) and longitudinal (middle plot) rms emittances (dashed line) and sizes (solid line) versus position in the injector; transverse and temporal beam profiles (bottom plot) at various locations in the injector.

density in center); and an additional elliptical shape parameter, which ranges from 1, corresponding to a half-circle, to 0, corresponding to a top hat. The full profile is obtained by multiplication of the three respective parts.

We have found that the optimal laser shape depends on beam parameters, and no single optimum exists. In particular, for the high bunch charge (1 nC), an initial temporal distribution close to a top hat results in best emittance, while for the low charges (0.1 nC) the optimal temporal distribution has a depleted central region. The optimal transverse profile was found to be intermediate between elliptical and flattop shapes in both cases.

Fig. 1 shows beam evolution in the injector for 80 pC bunch charge, as well as electron beam profiles at several locations. Under the influence of the space-charge in non-relativistic region, the specially shaped initial distribution develops into a nearly symmetrical ellipsoidal shape downstream of the DC gun. During compression the bunch begins to acquire a teardrop-like shape with a more tightly focused tail, and this asymmetric temporal distribution remains fixed after acceleration to high energy. The kinetic energy at the end of the injector is about 13 MeV. It should be noted that the optimal shape in Fig. 1 assumes a fast photoemission response on the scale of the initial laser pulse length.

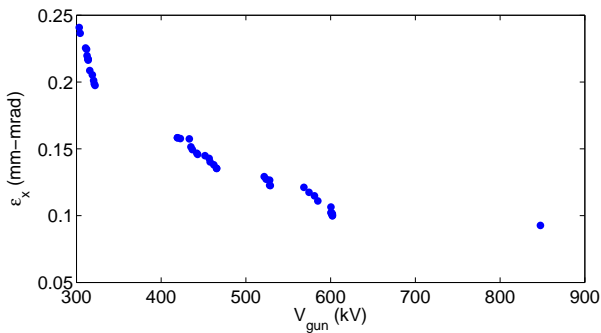


Figure 2: Normalized rms emittance vs. voltage in the gun for 80 pC bunch charge.

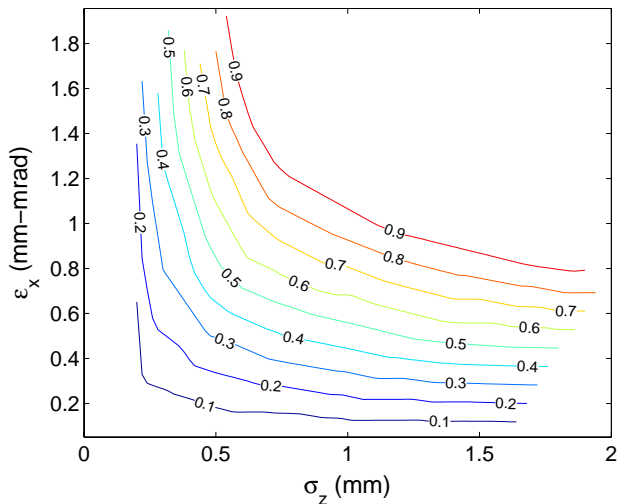


Figure 3: Transverse normalized rms emittance vs. bunch length for various charges in the injector (nC).

### Gun Voltage Dependence

It is widely believed that a very high gun voltage and electric field at the photocathode is critical to achieving good beam properties. We carried out a two-objective optimization, in which a minimum transverse emittance was sought while the gun voltage was being minimized at the same time. The cathode-anode geometry was kept fixed during this optimization, so an increased gun voltage results in a similarly increased cathode electric field strength. An additional constraint picked only those solutions that had the rms bunch length at the end of the injector less than 0.8 mm. The resulting nondominated front is shown in Fig. 2.

The gaps in Fig. 2 are algorithm specific, and to reduce this effect it is necessary to significantly increase the population size and the number of generations [1].

The salient feature of Fig. 2 is clear – a higher gun voltage is important to obtain low emittance only up to a certain point, after which the dependence on gun voltage is relatively small. We note that the gun voltage required to obtain small emittances is well within the specifications of our in-

jector system (between 500 and 750 kV). It is important to point out, however, that the optimum distances between the elements prior to the cryomodule become rather crowded at the low end of the gun voltage range. The spacing of the elements becomes more relaxed in an almost linear fashion as the gun voltage is increased: e.g. the distance from the photocathode to the center of the first SRF cavity is 1.25 m at 300 kV and 2.3 m for 850 kV.

### Injector Performance

Fig. 3 shows global performance from the injection system obtained by multiobjective optimization through minimizing the emittance and bunch length, and at the same time maximizing the bunch charge. Positions of all the elements were fixed in this optimization. The DC gun voltage was also kept unchanged and equal to 750 kV (maximum design value for the gun). It is seen that good performance is achievable from the same injector over a broad range of charge per bunch values. Even better performance is possible when element positions are allowed to change [1].

### SUMMARY

The optimizations of this DC gun injector show a high degree of emittance compensation is possible from this system. Transverse phase space quality is dominated by thermal emittance at the end of the injector, making use of low thermal emittance cathodes an important advantage. Further studies are underway which will include the merger section to the main linac as well as finite time response of the photocathode in injector optimizations.

We acknowledge MacCHESS for granting us access to their two computer clusters, which were used extensively in this work. We thank our numerous CLEO and LEPP colleagues who have tolerated our using their theoretically latent desktop computers as a parallel processing resource.

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