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PHOTOINJECTOR OPTIMIZATION STUDIES AT THE AWA

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Abstract

With a variable charge range of 0.1 nC - 100 nC, the Argonne Wakefield Accelerator facility (AWA) has a unique and dynamic set of operating parameters. Adjustment of the optics and occasionally the rf phases is required each time the bunch charge is changed. Presently, these adjustments are done by the operator during each experiment. This is time consuming and inefficient, more so at high charge and for complex experimental set ups. In an attempt to reduce the amount of time spent adjusting parameters by hand, several optimization methods in simulation are being explored. This includes using the well-known Genetic Algorithm (NSGA-II), incorporated into OPAL-T. We have also investigated a model-based method and novel structure based algorithms developed at Argonne National Laboratory (ANL). These optimization methods will be implemented to improve operations at the AWA. Simulation results will be compared to measured beam parameters at the AWA, and one or more optimization methods will be selected for use in guiding operations in the future.

AWA FACILITY

The AWA Facility houses two rf photoinjectors, both operating at 1.3 GHz. A large range of experiments are performed at various charge levels, and several methods for simulating the beam lines have been used. Recent experiments include emittance exchange [1], structure tests [2], thermal emittance measurements [3], and Two Beam Acceleration (TBA) [4]. Simulation codes used for these and other experiments at the AWA include: PARMELA [5], GPT [6], ASTRA [7], and more recently OPAL [8]. The latter is the code used for all simulations in this study. We also take advantage of the computing resources provided by the Laboratory Computing Resource Center (LCRC), at ANL. Access to the Blues, and recently installed Bebop clusters has significantly increased simulation productivity by providing the capability to run all simulations in parallel, and large optimization cases on many cores.

MODEL BASED METHOD

Last year, we began with the optimization of the front end of the high charge photoinjector at the AWA. A charge of 40 nC was chosen to target the needs for upcoming TBA experiments at AWA. The simulation model included the gun, two solenoids, and six accelerating cavities, as shown in Fig. 1. The quadrupoles and bending elements were not included in this first effort, they will be included later. We choose ten variables for the optimization parameters: laser radius, laser full width half maximum, solenoid strength (S_2), gun cavity phase, and the six accelerating cavity phases ($\phi_{L_1} - \phi_{L_6}$).

The objective was to get an optimal combination of small emittance, and short bunch length at the entrance of the quads. We choose to use a local optimization method that is freely available in the NLOPT package [9]. Bounded Optimization By Quadratic Approximation (BOBYA), is a model based and derivative-free method that builds a quadratic using the results of simulation evaluations. The next point to evaluate is chosen by minimizing the quadratic. The initial probe of the parameter space was done with 1,000 random simulations. Simulations with the best emittance and bunch length were chosen as starting points for ten BOBYQA runs. These local optimization runs were carried out until they converged. The results from all ten runs were used to form a Pareto front comparing transverse emittance and bunch length. Details of this work were presented at IPAC'17, and can be found here [10].

The initial results were promising, and attempts to measure several points on the Pareto front took place. Experimentally, some of the parameter values were found to be outside the normal operating conditions at the AWA. Using this experience, a second round of optimization was done using the same procedure and method as outlined in [10]. The boundaries for the second round of optimization work can be found in Table 1. Note that $\phi_L = [\phi_{L_1}, \ldots, \phi_{L_6}]$.

Table 1: Parameter Bounds for Linac Optimization

Variable	Range	Unit
Solenoid Strength	$50 \leq S_2 \leq 440$	amps
Phase of Gun	$-45 \leq \phi_g \leq 45$	degrees
Laser Radius	$3.5 \leq R \leq 9$	mm
Laser FWHM	$1.5 \leq T \leq 10$	ps
Cavity Phase	$-40 \leq \phi_L \leq 40$	degrees

The parameter values of the new Pareto front in Fig. 2 were analyzed, and several key points were learned from this work. First, it is clear that varying the laser radius is unnecessary for high charge simulations. All points on the Pareto front had a laser radius of 9 mm, the maximum value for this parameter. Due to the strong space charge forces at the AWA, it is beneficial to let the laser radius be as large as possible. This mitigates space charge and improves the emittance. Ongoing and future high charge optimization work will exclude the laser radius as an optimization parameter.

Second, it was clear that the phase boundaries were also too large. None of the gun phases were positive. An upper bound of $\phi = 0°$ will be used in the future. Some of linac phases were positive, but very few. Five out of ten local optimization runs had no positive linac phases. Four out

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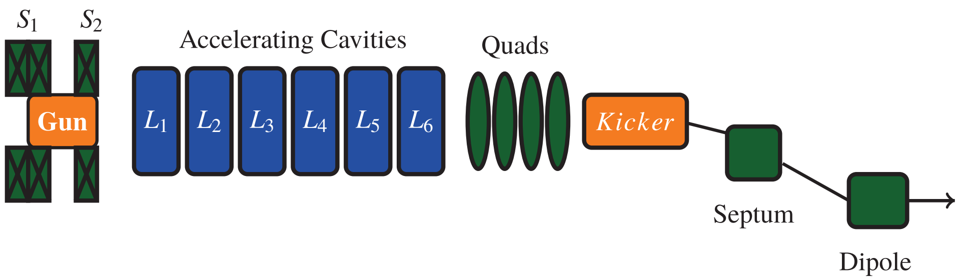

Figure 1: Partial beam line layout at the AWA.

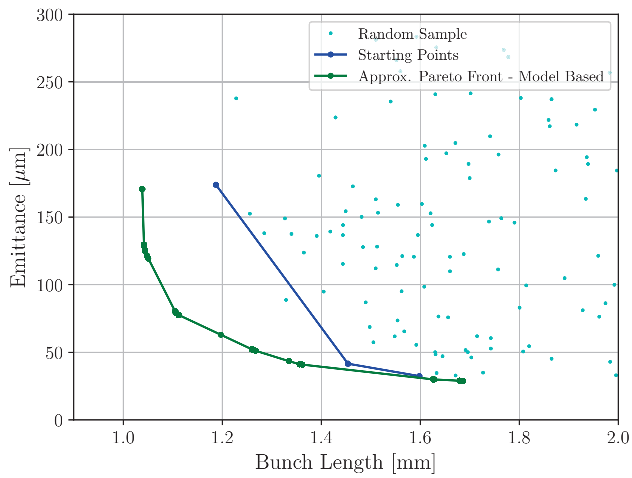

Figure 2: Pareto front for adjusted variable bounds at 40 nC.

of ten local optimization runs had only one positive linac phase(ϕ_{L_6}), and only two out of the ten runs had two or three positive linac phases ($\phi_{L_4} - \phi_{L_6}$). Therefore, the upper bounds for $\phi_{L_1} - \phi_{L_3}$ can also be set to 0°.

The last lesson learned from the initial model based work deals with the bunch length and energy spread. As stated earlier, every gun phase was negative as were ϕ_{L_1} and ϕ_{L_2}. These negative phases are reducing the energy spread in the bunch. This result is expected based on work by others [11], and is called velocity bunching. Validation of a known behavior adds credibility to the the model based work.

GENETIC ALGORITHMS

Genetic Algorithms (GAs) have been used successfully for over two decades in the accelerator physics community. They are used to tackle large multiobjective optimization problems on wide variety of machines. A nice review of work done in the field using GAs can be found here [12]. In general, this class of algorithms aims to mimic the natural selection process often seen in biology. In this way, there are several steps that most GAs follow:

1. Start with a finite population (simulation evaluations). This is the first generation.
2. Decided which individuals (simulations) in the population are the best based on a selection criteria.
3. Mix the best individuals to generate new individuals (new generation).
4. Repeat many times.

There has been much research on how to implement these steps, and what types of selection and mutation criteria should be used. A widely used implementation is the NSGA-II [13] method. This is also the algorithm built into the simulation code OPAL, which was the code of choice for the initial optimization work. It was decided to take advantage of the built in optimizer for verification of the model based method and future work.

To verify the model based method, a low fidelity model of the photoinjector was used to do a quick comparison. The number of particles and grid size was reduced to shorten the simulation time to two minutes. GAs require several thousand simulations to converge. Reduction in the fidelity allowed us to complete a comparison using a reasonable amount of computing resources and within one weeks time. The optimization variables (Table 1) and objectives are these same as those given in the previous section, with one important difference. The boundaries were reduced based on the information learned in the first round of optimization.

In total, 2,393 simulations (from the 1,000-point sample plus 1,393 points of BOBYQA optimization runs) were used to generate the model based approximate Pareto front. This approach required approximately 80 core-hours of computation. We compared this with similar fronts generated by the GA. With 128 simulations in each generation, the GA required 3,200 simulations (107 core-hours) to reach the 25th generation, and 64,000 simulations (2,133 coure-hours) to reach the 500th generation. Comparison of the three Pareto fronts is shown in Fig 3. As expected by the "no free lunch" theorem, both methods give acceptable results, with only the total simulation time being the difference.

The next round of optimization will include the four quadrupoles, kicker, and septum shown in Fig. 1. This work will support upcoming TBA experiments at the AWA.

FUTURE WORK: NOVEL METHODS

In the following months, we plan to continue our work by investigating novel optimization methods and comparing their efficiency and precision. We will take advantage of the open source Python library libensemble:

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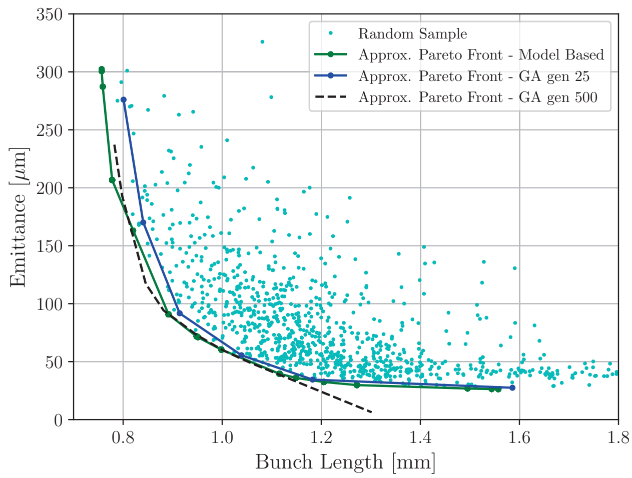

Figure 3: Comparison of model based optimization and the GA implemented in OPAL at 40 nC.

`https://github.com/Libensemble/libensemble`

which is being developed at ANL. This framework allows for massively parallel ensemble simulations in combination with a mechanism for easily interchanging optimization methods. We will work to deploy Asynchronously Parallel Optimization Solver for finding Multiple Minima (APOSMM). This multistart algorithm considers all results from previously evaluated simulations when determining where to start or continue a local optimization run [14]. This allows for an efficient search for a global minimum. This method has already been tested (with success) on problems where derivatives are unavailable, as is the case in many non-linear accelerator physics problems.

CONCLUSION

Photoinjector optimization projects are ongoing at the AWA. Two optimization methods have been used with success: BOBYQA and NSGA-II. In the future, novel optimization methods developed at ANL will be tested. The first of which will be APOSMM. All optimization efforts aim to improve operating conditions at the AWA and aid in the completion of the beamline designs needed for upcoming experiments.

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REFERENCES

[1] G. Ha *et al.*, "Demonstration of Current Profile Shaping using Double Dog-Leg Emittance Exchange Beam Line at Argonne Wakefield Accelerator", in *Proc. IPAC'16*, Busan, South Korea, May 2016, paper TUOBB01.

[2] J. Shao *et al.*, "Recent Progress towards Dielectric Short Pulse Two-Beam Acceleration", presented at Proc. IPAC'18, Vancouver, Canada, May 2018, paper TUYGBE3.

[3] L. Zheng *et al.*, "Measurements of Thermal Emittance for Cesium Telluride Photocathodes in an L-Band RF Gun", in *Proc. IPAC'17*, Copenhagen, Denmark, May 2017, paper TUPAB074.

[4] J. Shao *et al.*, "Recent Two-Beam Acceleration Activities at Argonne Wakefield Accelerator Facility", in *Proc. IPAC'17*, Copenhagen, Denmark, May 2017, paper WEPVA022.

[5] L. M. Young, "PARMELA", Los Alamos National Laboratory, Los Alamos, NM, USA, Rep. LA-UR-96-1835 (Revised April 22, 2003).

[6] GPT, `http://www.pulsar.nl/gpt`

[7] ASTRA Manual, April 2014, `http://www.desy.de/~mpyflo/Astra_manual/Astra-Manual_V3.2.pdf`

[8] A. Adelmann *et al.*, "The OPAL (Object Oriented Parallel Accelerator Library) framework", PSI, Zurich, Switzerland, Rep. PSI-PR-08-02, 2008-2017.

[9] M. Powell, "The BOBYQA algorithm for bound constrained optimization without derivatives", University of Cambridge, U.K., Rep. NA2009/06, Oct. 2009.

[10] N.Neveu, J.Larson, J. G. Power, L. Spentzouris, "Photoinjector optimization using a derivative-free, model-based trust-region algorithm for the Argonne Wakefield Accelerator", in *Proc. IPAC'17*, Copenhagen, Denmark, May 2017, paper WEPVA022.

[11] C. Mitchell *et al.*, "RF Injector Beam Dynamics Optimization and Injected Beam Energy Constraints for LCLS-II", in *Proc. IPAC'16*, Busan, South Korea, May 2016, paper TUPOR019.

[12] A. S. Hofler *et al.*, "Innovative applications of genetic algorithms to problems in accelerator physics", *Phys. Rev. ST Accel. Beams*, vol. 16, p. 010101, 2013.

[13] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II", *IEEE Trans. on Evolutionary Comp.* , vol. 6, no. 2, pp. 182-197, Apr 2002.

[14] J. Larson, and S.M. Wild, "Asynchronously parallel optimization solver for finding multiple minima", *Math. Prog. Comp.*, vol. 10, p. 1-30, Feb. 2018.