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EXPERIENCE WITH ON-LINE OPTIMIZERS FOR APS LINAC FRONT END OPTIMIZATION*

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Abstract

While the APS linac [1] lattice is set up using a model developed with ELEGANT [2], the thermionic RF gun [3, 4] front-end beam dynamics has been difficult to model. One of the issues is that beam properties from the thermionic gun can vary from time to time. As a result, linac front-end beam tuning is required to establish good matching and maximize the charge transported through the linac. We have been using a Nelder-Mead (or simplex) [5] optimizer to find the best settings for the gun front-end magnets and steering magnets. However, it takes a long time and requires fairly good initial conditions. Therefore, we imported other on-line optimizers, such as robust conjugate direction search (RCDS) [6], which is a classic optimizer (as is Nelder-Mead), multi-objective particle swarm (MOPSO) [7], and multi-generation Gaussian process optimizer (MG-GPO) [8], which is based on a machine learning (ML) technique. In this paper we report our experience with these on-line optimizers for maximum bunch charge transportation efficiency through the APS linac.

INTRODUCTION

APS has a long history of work related to computer optimization of the machine performance. The simplex [5] algorithm was implemented in `sddsoptimize` [9] and has been used widely for APS accelerator tuning [10], including insertion device steering optimization, injection efficiency maximization, APS storage ring beam x-y coupling minimization, booster-to-storage ring rf phase adjustment to center injected beam in the rf bucket, on-axis injection setup and closed bump setup, APS linac beam-based optimization of rf phase and power, PAR capture efficiency maximization, and linac beam trajectory optimization.

However, simplex optimization can easily get trapped in a local minimum, and it takes a long time to converge when the initial condition is far from the optimum. Sometimes it requires an experienced physicist or operations expert to perform manual tuning in the beginning, especially in the APS linac trajectory optimization and photocathode gun beam optimization. After importing RCDS into `sddsoptimize`, we often switch between simplex and RCDS for the APS linac gun front-end charge optimization, because sometimes simplex works, and sometimes RCDS works. We have been searching for an optimizer that does not strongly reply on the initial state and converges faster than the classic optimizers.

We imported the ML-based Gaussian Process (GP) Optimizer [11] in 2019 for APS linac front-end charge optimization [12]. The GP optimizer did not show an advantage over the classic optimizers, which may be a result of the large magnet hysteresis, so the pre-built GP model does not work. Classic optimizers are able to find the best operation condition as long as the initial state is relatively good; for example, the initial L3:CM1 charge is around 80% of the operation required charge. The studies two years ago showed none of the simplex, RCDS, or GP optimizers were able to find the best operation condition when the initial condition was bad [12].

Recently we imported MG-GPO [8] and MOPSO [7] to APS. The performance of the MG-GPO, MOPOS, RCDS, and simplex optimizers on the APS linac front-end charge optimization are studied and compared in this paper.

APS LINAC CHARGE OPTIMIZATION

APS linac charge transportation is maximized by `sddsoptimize` [9] with simplex or RCDS and then followed by a steering controllaw [13] to adjust the linac to PAR [14] trajectory during the operation. The objective of the optimization is the linac charge at L3:CM1. For the RG2 gun beamline, the input variables of the optimization are 16 magnets consisting of the RG2 gun front-end quadrupoles and steering magnets. Since four steering magnets are being used in the steering controllaw, we remove these four steering magnets from the optimization. Thus 12 magnets are being used for the APS linac charge optimization with the RG2 gun.

Recently RG1, a new gun that needed to be optimized from scratch, was installed in the backup beamline [15]. After trying different optimizers with different combinations of RG1 magnets, the RG1 gun beamline was successfully set up with the optimization.

APS LINAC CHARGE OPTIMIZATION WITH THE RG2 GUN

The RG2 gun is used for normal operation and has been operating with a fine-tuned configuration. None of the simplex, RCDS, or GP optimizers can further improve it from this starting point. After importing the MG-GPO optimizer, we would like to test if it can improve our current operation. Since the MG-GPO optimizer uses GP regression to determine which new solutions have a high probability of

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yielding good performances, hyper-parameters for defining the GP model are needed. The MG-GPO optimizer provides two methods for providing the GP hyper-parameters:

- hyper-parameters with optimization: hyper-parameters are optimized with current solutions,
- hyper-parameters without optimization: hyper-parameters are predefined without optimization.

Both methods were tested in APS linac charge optimization with the RG2 gun starting from operational (good) conditions with 0.63 nC initial L3:CM1 charge, as shown in Fig. 1. The objective value is -1.0 * L3:CM1 charge: the more negative the the objective value, the higher the L3:CM1 charge. Both methods yielded better results than the normal operational configuration obtained by the simplex/RCDS optimizer.

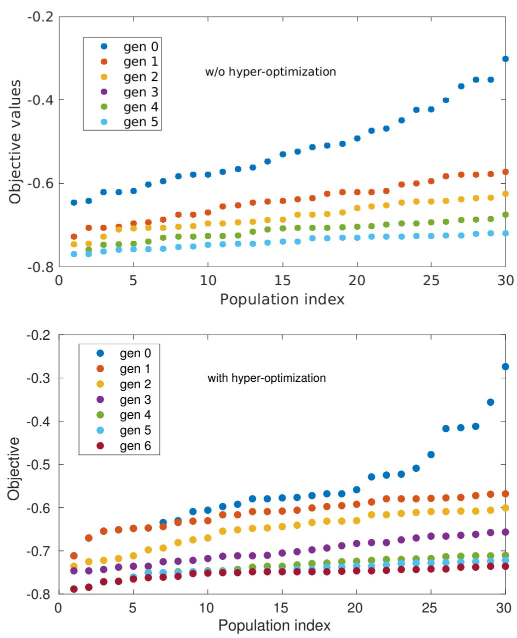

Figure 1: APS linac RG2 front-end charge optimization starting from a good configuration with MG-GPO. The objective value is a negative L3:CM1 charge. Without (top) or with (bottom) hyper-parameters optimization.

MG-GPO hyper-parameters with the optimization method was faster and got a better solution than hyper-parameters without the optimization method. Therefore, only hyper-parameters with the optimization method were used in subsequent studies.

Figure 2 shows the comparison of simplex, RCDS, MOPSO, and MG-GPO optimizers, starting from a bad state where the L3:CM1 charge is about 0.1 nC. This initial state was actually obtained by MG-GPO starting from a bad state where there is no L3:CM1 charge, for which neither simplex nor RCDS could work.

When starting from this 0.1 nC charge state, simplex performs the best and is able to find the operation state within

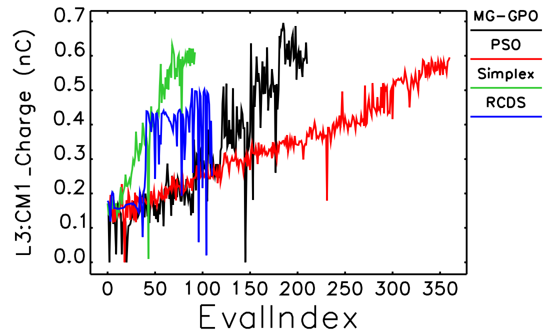

Figure 2: Comparison of all optimizers, starting from a bad condition where the L3:CM1 charge is about 0.1 nC.

100 evaluations. In other words, simplex is able to find the target within 10 minutes, with each evaluation taking about 5 seconds. RCDS does not perform well with this initial state, as it terminates with a sub-optimal result.

After running for several operation shifts or at the beginning of each run, the L3:CM1 charge drifts to about 80% of the normal operation. Restoring the previous operation configuration does not help; the simplex/RCDS optimizer is used to bring the charge back to normal operation, which takes about half an hour. This is even longer than starting from the bad state with a 0.1 nC charge, which means that this 0.1 nC charge state is in the correct track of simplex optimizer.

Our optimization studies two years ago showed that RCDS performs better than simplex when starting at a different 0.1 nC initial state [12]. The performance of both simplex and RCDS optimizers vary significantly depending on the initial state.

MOPSO is the slowest among the tested optimizers, but it steadily improves as it goes. MG-GPO takes a longer time in the first three generations and then becomes faster in the next three generations because of the randomization in each generation. Overall, it is slower than simplex in this case, but gets a better solution. Besides the hyper-parameters, there are other parameters that can change the performance of MG-GPO, such as the number of population (Npop) in each generation, the maximum step size, etc. Due to slow response and hysteresis problems of the APS linac magnets, the maximum step size has to be limited to less than 0.2 A, and the scan range is limited to ± 0.5 A of the initial state. In Fig. 2, the Npop is 30, and the maximum step size is 0.1 A for MG-GPO. A smaller Npop is expected to be faster. Three different combinations of Npop and the maximum step size are being tested for MG-GPO:

- case 1: Npop=20, maximum step size=0.15 A
- case 2: Npop=12, maximum step size=0.10 A
- case 3: Npop=8, maximum step size=0.10 A

The results, from Fig. 3, show that case 2 has the best performance, reaching normal operational performance (0.6 nC)

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within 10 minutes. It obtains about a 0.65 nC charge after 20 minutes.

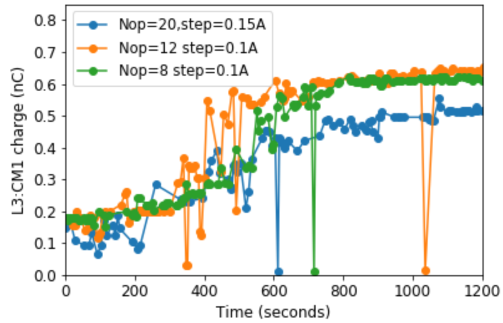

Figure 3: MG-GPO optimization of L3:CM1 charge for the RG2 gun with different Npop values and maximum step sizes.

APS LINAC CHARGE OPTIMIZATION WITH THE RG1 GUN

Recently a new type of gun [16] was installed in the APS linac RG1 beamline; this gun is longer and has six more magnets than RG2. There was no available reference configuration to start with. Simplex, RCDS, MOPSO, and MG-GPO had been tried to optimize the L3:CM1 charge with all 18 magnets in the RG1 front end as the input variables. None was successful with the initial state of about 0.2 nC charge, obtained by manual tweaking. Attempts at varying the combinations of the input variables (magnets) were also unsuccessful. However, after reducing the number of input variables from 18 to 11 and adding a constraint on the trajectory at the L1:P0 BPM, MG-GPO was able to obtain 1.1 nC L3:CM1 successfully, as shown in Fig. 4. These 11 magnets

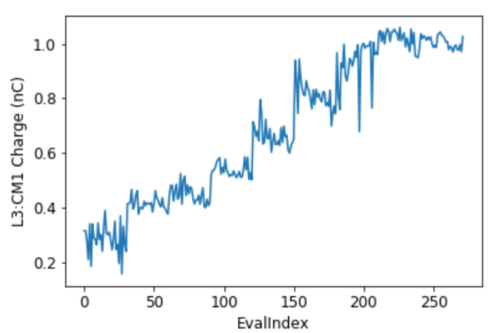

Figure 4: MG-GPO optimize on L3:CM1 charge optimization for the RG1 gun.

include 9 RG1 front-end quadrupoles and two steering magnets before the RG1 alpha magnet [17], which are the knobs most sensitive to the L3:CM1 charge. The BPM constraints for L1:P0 are important for linac beam stability and injection efficiency as it seems to prevent variable beam scraping when the trajectory varies.

RESULTS AND DISCUSSION

Our studies show that simplex and RCDS, which have been used in APS optimization applications, work well when the initial state is reasonable. MOPSO is several times slower than the classic optimizers (simplex/RCDS). The GP optimizer [11], imported to APS two years ago, was able to reach about 70% of the target charge for APS linac charge optimization when starting from a bad state. However, it was not successful when starting from a good state [12]. These conclusions are probably specific to our conditions rather than general properties of the algorithms.

GP and MG-GPO are machine learning-based optimizers. The GP optimizer is very fast when the model fits the application [11]. However, it requires a large amount of effort to fit the model. The hyper-parameter of the GP model for APS linac charge optimization took several 8-hour machine study shifts to complete, requiring a raster scan of the 16 magnets. Due to the large hysteresis of the APS linac magnets, the GP hyper-parameters obtained from the raster scans do not work well for the online APS linac charge optimization. MG-GPO performs best among the machine learning-based optimizers and does not heavily rely on the initial state as do other optimizers because of its randomization feature. Therefore, MG-GPO is the preferred non-classical optimizer for APS.

MG-GPO is based on MOGA [18] and Gaussian process regression. It uses mutation and cross-over operations for generating trials and uses Gaussian process regression to determine favorable solutions, but it has online hyper-parameter optimization and multi-generation features. Compared to the GP optimizer, it is more general and does not require a raster scan or offline hyper-parameter fitting. Instead, the hyper-parameters are obtained online during optimization. MG-GPO also works well for APS SR injection efficiency optimization in our recent studies. With the multi-objective feature, it has been applied in APS dynamic aperture and momentum aperture optimizations using two objectives.

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