MULTI-OBJECTIVE BAYESIAN OPTIMIZATION OF ELECTRON CYCLOTRON RESONANCE ION SOURCE

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Abstract

Electron Cyclotron Resonance (ECR) ion sources typically require tuning by experts to achieve best performance. We developed a Multi-Objective Bayesian optimization for the ECR of the Linear IFMIF Prototype Accelerator (LIPAc). The free parameters are: the RF power fed, the gas flow, the position of 2 RF tuners and the current of 2 solenoid coils. The machine learning approach demonstrated a fast convergence to a working point where not only the extracted beam current is >125 mA, but also the emittance is successfully constrained to be <0.25 π mm mrad, and the rms intra-pulse and inter-pulse current fluctuations are <3 mA. We present the detailed algorithm, testing methodology, results achieved and encountered challenges posed by the dimensionality of the problem and evolving state of the system.

INTRODUCTION

The physics involved in the plasma formation and the beam extraction from ECR ion sources is very complex and cannot yet be modelled and simulated to the required precision without any final tuning from experts with years of training. The use of Bayesian Optimization (BO) [1, 2] for particle accelerators has been proven very successful [3, 4, 5] and in particular for ECR too [6, 7] . From recent literature, what seems still elusive is a multi-objective approach to the ECR tuning problem. The work here presented can be easily generalized to all ECRs, as their performances are regulated by the same fundamental physics processes, though this work focus on the study case of the Linear International Prototype Accelerator (LIPAc)'s ion source. LIPAc is designed under the EU-Japan Broader Approach (BA) agreement to accelerate 125 mA of D+ to 9 MeV in continuous wave (CW) to verify all the key accelerator technologies required for a source of neutrons with energy spectrum and intensity for testing of materials relevant to fusion energy [8, 9, 10]. LIPAc's ECR operates at 2.45 GHz and it is designed to deliver 140 mA of D+ at 100 keV in pulsed mode or CW with a rms current <1 % and a transverse normalized emittance <0.25 π mm mrad [11, 12, 13]. In previous commissioning campaigns, the system achieved excellent quality beam [14, 15], yet the final optimal performances are to be achieved and fine tuning and experiments are ongoing. Furthermore the ion source requires often fine retuning after maintenances, due to ageing, when requiring different duty cycle in pulse mode, etc. For this reasons we developed a multi objective Bayesian optimization (MOBO) method to assist experts in reliably and rapidly achieving the highest possible extracted beam current within a required maximum intra and inter-pulse rms fluctuation and also a maximum transverse emittance. The tuneable source parameters we act upon are: the RF power fed, the gas flow, the position of two RF tuners and the strength of two solenoid for plasma magnetic confinement.

SINGLE OBJECTIVE

Before attempting to tackle the full scale problem, we follow a step-wise approach and perform single objective optimization of the strength of the two solenoid for plasma magnetic confinement to achieve the highest total extracted beam current *I*. All other tuneable parameters of the system are fixed. The kernel selected for the BO selected is the sum of Matern and white noise [16], while the acquisition function is Upper Confidence Bound (UCB) [17]. The model is initialized with 5 data points acquired randomly in the 2D variable phase space. Figure 2 shows the evolution of the surrogate model from Bayesian regression and its uncertainty. Each iterations, including computation of next candidate and measurement of current requires roughly 10 seconds. Figure 1 shows that after roughly only 60 iterations (~10 minutes) the algorithm is able to converge to the global maximum. From this iteration onward, the model can only rely on the further exploration of phase space and the uncertainty term of the acquisition function. Figure 2 indeed shows how the method starts to approximate a grid search.

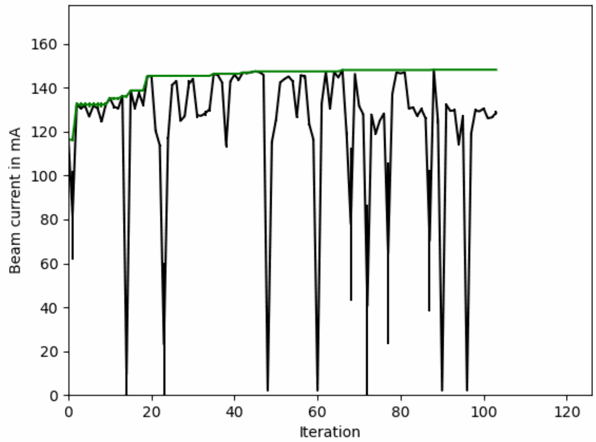

Figure 1: Convergence of single objective BO. Black: beam extracted current *I* at iteration; Green: maximum hold of *I*.

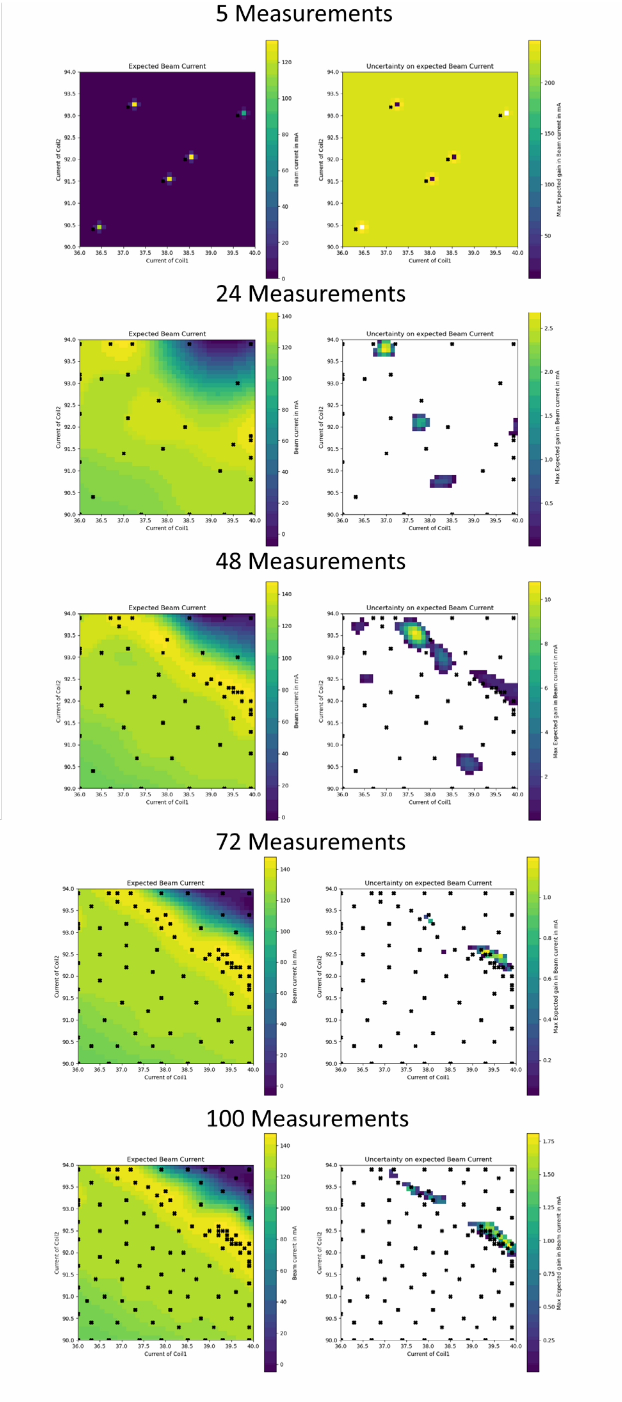

Figure 2: Surrogate model for LIPAc's ECR (left) expected total extracted beam current I and (right) expected potential improvement from highest measured current including model uncertainty. Model is refined with further measurement along the algorithm iterations from top to bottom.

MULTI OBJECTIVE

The time profile of the extracted beam current is sometime unstable shot-to-shot and within the plateau of a pulse. This behaviour is mitigated after waiting a warm up time of the order of roughly one hour, but can be persistent for some settings. In general the intra and inter-spill fluctuations of the total extracted beam current greatly varies within the phase space of tuneable parameters. We must maximize the total extracted beam current, while minimizing its rms fluctuation *Std* (measured in a time window of 30 s). The ideal solution of any multi-objective problem is to identify the Pareto front of the competing targets. This is expected to be expensive in term of number of necessary measurements, while not being strictly necessary in several cases. In particular for the vast majority of ECR tuning it is sufficient to achieve the highest extracted beam current within a required maximum fluctuation over time. We propose the following method:

- build 2 independent BO models from acquired data providing an expectation over the entire variable phase space for: $I = I_\mu \pm I_\sigma$, $Std = Std_\mu \pm Std_\sigma$
- search for phase space of input variables where Std_μ-β_{Std}·Std_σ≤3 mA
- within this subspace select candidate input variables where $I_\mu + \beta_I \cdot I_\sigma$ is max
- measure I and *Std* at this setpoint
- update models and repeat

where β_I, β_{Std} are model hyperparameters that regulate the exploration/exploitation trade off and influence the converge speed to optimum.

Figure 3 shows the progress of the algorithm when tuning four variables (the RF power fed, the amount of gas flow, and position of two RF tuners) with a fixed strength for the two solenoids magnets. Once more the used kernel is a sum of Matern plus white noise. The higher dimensionality of the problem prompt to initialize the first model after acquisition of 20 random sampled data points. After only 70 measurements (50 iterations of the algorithm) a very high total extracted current is achieved (I = 179 mA) with satisfactory stability (2.7 mA). This far surpasses the best achieved by expert (~150 mA) with the system condition on the specific same test day.

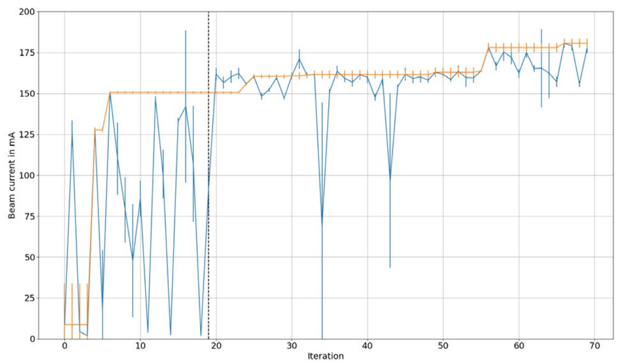

Figure 3: Convergence of MOBO method to tune RF power, gas flow, two RF tuners (4 variables) of LIPAc's ECR. Blue: extracted beam current measured I at iteration, error bar represent rms stability *Std* over 30 s. Orange: highest current measured up to iteration. First 20 data points are randomly sampled.

Finally the same method is applied for all 6 target tuning variables at the same time. Figure 4 shows that after only

~40 measurements (20 random to start + 20 algorithm iterations) the method converges again to very high extracted current (I = 176 mA) that are also extremely stable (Std = 0.4 mA).

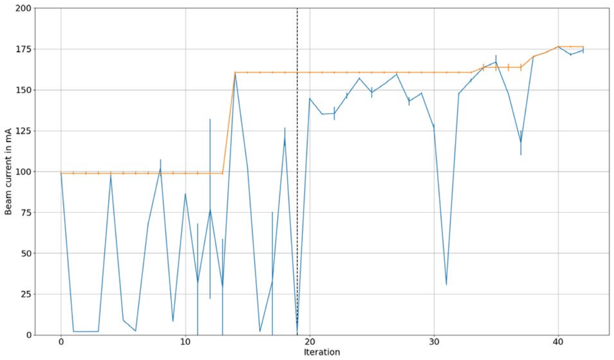

Figure 4: Same as Fig. 3, but tuned parameters additionally include the strength of two solenoids magnets for plasma confinement (6 variables).

INCLUDE OBJECTIVE ON EMITTANCE

The developed method was demonstrated to converge to ideal solutions in a very sample efficient manner. Nonetheless Figure 5 shows how the found solution exhibits transverse emittances significantly larger than optimum find by expert. It is clear that minimization of the normalized emittance ε_n must be considered as a third objective. The developed algorithm is further modified as follows:

- build 3 independent BO models from acquired data providing an expectation over the entire variable phase space for: $I = I_\mu \pm I_\sigma$, $Std = Std_\mu \pm Std_\sigma$, $\varepsilon_n = \varepsilon_{n,\mu} \pm \varepsilon_{n,\sigma}$
- search for phase space of input variables where both conditions are fulfilled: Std_μ-β_{Std}·Std_σ≤3 mA and $\varepsilon_{n,\mu}$-β_ε·$\varepsilon_{n,\sigma}$≤0.25 π mm mrad
- within this subspace select candidate input variables where $I_\mu + \beta_I \cdot I_\sigma$ is max
- measure I and Std at this setpoint
- if new setpoint is significant, measure ε_n
- update model and repeat

The emittance of the LIPAc ECR is measured with an Alisson type scanner and requires ~10 minutes, while measurement of average total extracted beam current and its stability requires ~30 seconds. Emittance can be measured only when current is stable (<5 % Avg). Additionally, to minimize the test time, emittance is measured only at settings where: Std is within stability requirements and I is the highest seen OR the setpoint is significantly different than any previous measured. Figure 6 shows convergence of the method to I = 125 mA with Std = 2.5 mA and ε_n = 0.21 π mm mrad. The test was performed during a day in which source performances were deteriorated (cause under study; possibly from ageing from previous intensive operations) and this value is comparable with best tuning efforts from expert on the day. The limited allocated testing time and the slow method did not allow to confirm potential convergence to even better setpoints. A considerable portion of time is required by computation of next candidate measurement (~4 minutes). Faster calculation can be achieved by code parallelization and faster processing units, but the algorithm intrinsically suffers from requiring explicit calculation of BO model expectation over the entire phase space to identify subspaces of feasibility. Furthermore the method introduce a bias on the selection of candidate for emittance measurement which might results in insufficient exploration of neighbours solutions and pose too great of a significance on hyperparameter of distance from previous settings. The authors are committed to address both concerns and further perfecting the method in future works.

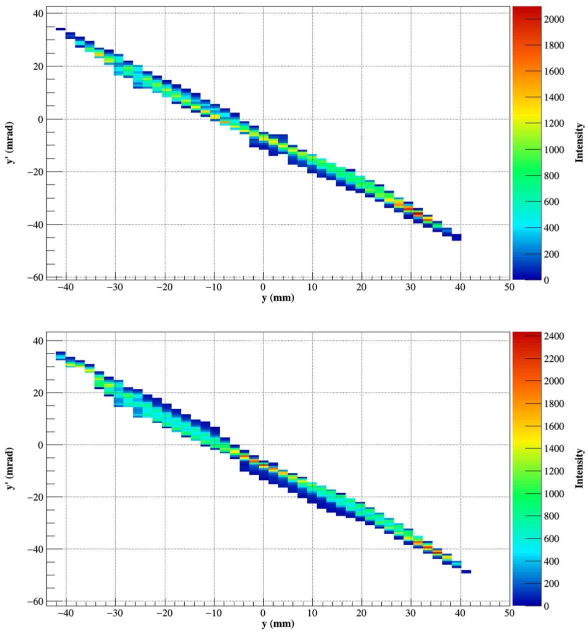

Figure 5: Transverse emittance measurement of exctracted D+ beam. Top: best expert tuning I=153 mA, ε_n= 0.31 π mm mrad; Bottom: best machine learning I=173 mA, ε_n= 0.42 π mm mrad.

CONCLUSION

A multi-objective Bayesian optimization method was developed for ECR ion source and demonstrated with the LIPAc's system as a study case. Six main variable parameters were tuned to obtain high extracted beam current with arbitrary required transverse emittance and intra/inter-spill stability. The algorithm requires order of ~50 iterations (with ~10 emittance measurements) to converge to similar solutions obtained by trained expert. The time required by the process is mainly dictated by computation and measurement speeds.

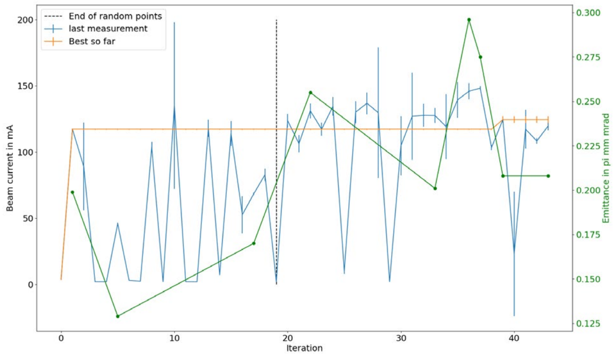

Figure 6: Same as Fig. 4, but method include minimization of emittance. Orange: the highest beam current measured up to an iteration that satisfies both stability and emittance requirements. Green: rms normalized transverse emittance.

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