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# APPLYING MACHINE LEARNING TECHNIQUES TO THE OPERATION OF THE SUPERCONDUCTING ECR ION SOURCE VENUS*

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*Abstract*

An operator of the superconducting ECR ion source VENUS tasked with optimizing the current of a specific ion species or finding a stable operating mode is faced with an operation space composed of ten-to-twenty knobs in which to determine the next move. Machine learning techniques are well-suited to multidimensional optimization spaces. Over the last three years we have been working to employ such techniques with the VENUS ion source. We will present how the introduction of computer control has allowed us to automate tasks such as source baking or to utilize optimization tools to maximize beam currents with no human intervention. Finally, we will discuss control and diagnostic changes that we have employed to exploit the faster data collection and decision making abilities when VENUS is under computer control.

## INTRODUCTION

Electron cyclotron resonance (ECR) ion sources are employed as injector sources for many accelerator facilities around the world. The reason for this is simple: these sources are capable of producing high current, highly-charged ion beams from any material that can be introduced to the ECR ion source plasma without destroying the plasma.

The typical ion source has an operation space defined by ten-to-twenty control parameters, depending on the ion beam being produced. Though this results in an enormous operation space, the operator is typically tasked with maximizing or minimizing some beam quantity. For example, it may be required that the species current be maximized, its emittance be minimized, its stability kept below some threshold, or some combination of these. Therefore, though the operation space is broad, the problem is made somewhat more tractable by the fact that much of that space may be eliminated from contention.

Bayesian optimization [1] operates in this spirit: an operation space is populated (typically) randomly with some number of exploratory measurements . The code models a distribution over the operation space using these measurements and, using a user-determined balance between exploring far from measured points and searching near currently known extrema, searches a new point where it has determined the probability of being an extrema is largest. The newly-measured point is used to update the modeled distribution and the process repeats. In this work, we use Bayesian optimization to maximize the beam current of a species of interest from LBNL's superconducting ECR ion source, VENUS, discuss the results, and use these results to motivate and implement improvements to data collection times that will aid our continued machine learning efforts with this ion source.

## VENUS ION SOURCE AND COMPUTER INTERFACE

LBNL's VENUS ion source is a fully-superconducting ECR ion source optimized for 28 GHz operation [2]. The plasma-confining magnetic field is produced through a superposition of solenoidal and sextupolar NbTi coils. A sextupole at each end provides radial confinement while one in the center opposes these fields and helps set the center minimum field. The source is able to produce over 2 tesla fields on the radial walls and on axis at extraction, and up to 4 tesla axially opposite the plasma from extraction. Two frequency heating, 28 and 18 GHz, is used with up to 10 kW and 4.4 kW available, respectively.

In recent years we have established the ability to both completely control and read all of VENUS' diagnostics by computer. This was achieved by employing the Python library pylogix [3] to interface with VENUS' programmable logic controller (PLC). We created a Python class so the computer could set and read all parameters that a human operator can when running VENUS.

Controlling VENUS through the PLC has the distinct advantage that the computer is operating the source just as human operators do, and the more-than-two-decades of safety logic written into the PLC to preserve safe operation immediately applies to computer operation. However, this comes at the cost of speed as the PLC has been designed for human interaction rates, so data can only be written or read at about 3 Hz.

Using this interface, we have been able to automate a number of tasks that previously were time-consuming. Experimental data taking (e.g. sweeping a parameter between two values and recording all source data) is now trivial. Baking, the process where materials on plasma chamber surfaces from previous runs, contaminants, or exposure to atmosphere are removed by plasma-chamber interaction, has been performed many times now with absolutely no human interaction with the source. The heating microwave power is brought up by the computer in a controlled manner until full power is reached. At that point the confining magnetic fields are adjusted by computer to alter the wall-plasma interaction and accerate the removal of material from the wall. The methods of doing this are no different than those that might be undertaken by a human, but the computer is continually

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monitoring and making changes in a way that all but the most attentive operators do not. The data retrieved from these computer-driven baking efforts will be used to inform future machine learning efforts to reduce this process that typically takes tens of hours.

## BAYESIAN OPTIMIZATION

Though somewhat limited by the slow interface speeds, we were able to perform full optimizations of a $^{124}Xe^{37+}$ beam from VENUS where all source control parameters were under computer control. It is worth noting that the computer has no information about VENUS: the computer sets the nine control parameters within the operation range, sends these settings to the PLC, and reads out a beam current. The first 50 points are explored randomly from within the operation space listed in Table 1. The computer uses currents measured at these random points to estimate the operation space topography and predict what point in the operation space (balancing exploratory searches away from measured points and exploiting attained knowledge and searching nearer measured extrema) is most likely to provide the peak $^{124}Xe^{37+}$ current and measure there. The new point is used to better estimate the operation space, and the process is repeated for a set number of new measurements. All measured data can be used to initialize additional searches in the same operation space.

Table 1: Exploration Range for Bayesian Optimization of $^{124}Xe^{37+}$ Beam Current from VENUS

| Parameter [unit] | Minimum | Maximum |
|---|---|---|
| Bias voltage [V] | 40 | 105 |
| Oxygen valve [arb] | 11.6 | 12.5 |
| Xenon valve [arb] | 8.0 | 13.0 |
| Injection coil [A] | 185.6 | 186.0 |
| Extraction coil [A] | 136.6 | 136.8 |
| Middle coil [A] | 152.0 | 152.3 |
| Sextupole coils [A] | 430.3 | 430.5 |
| 28 GHz RF [W] | 5200 | 6000 |
| 18 GHz RF [W] | 1400 | 1800 |

As can be seen in Fig. 1, a Bayesian optimization of the operation space defined in Table 1 was able to achieve approximately 7.5 µA of $^{124}Xe^{37+}$. Though this result is much less than the ~50 µA record beams seen at IMP in Lanzhou, China with their SECRAL II source, this result compares favorably with the performance of relatively experienced VENUS tuners. Additionally, it should be noted that the operation space in Table 1 was severely limited to prevent any damage to the VENUS plasma chamber while a spare is being produced, and it is known that VENUS settings that produced over 40 µA beams are outside the prescribed range.

Each of the search points took approximately 5 minutes to complete. Part of the reason for this is that changes to the superconducting coil setting, even for small current changes, usually require a couple of minutes to complete. Additionally, after any changes are complete, the source is allowed to settle and then 50 beam current measurements at 3 Hz were taken to provide beam current statistics.

Later Bayesian optimizations were performed where the optimal coil setting was maintained from a full optimization in order to speed up the exploration. For these runs, charge state distributions (CSDs) taken at each search point indicated that many of the higher current results had nearly the same species current but wildly different current distributions, as shown in Fig. 2.

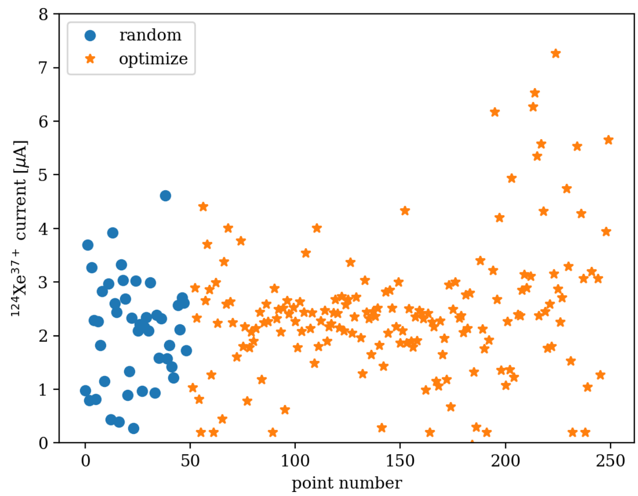


Figure 1: $^{124}Xe^{37+}$ current plotted as a function of Bayesian optimization search number. The first 50 searches are random while later searches are based on the model's understanding of the space based an all explorations to this point.

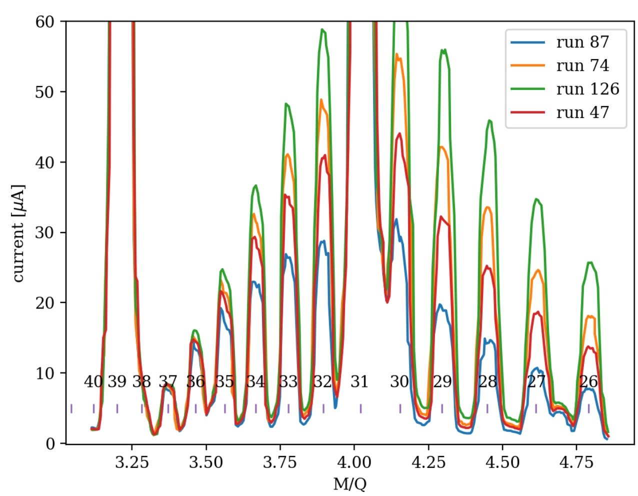


Figure 2: Charge state distributions for four control parameter settings ("runs") yielding nearly-identical $^{124}Xe^{37+}$ currents during a Bayesian optimization of that species. This distribution information was not provided to the optimization code.

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From Fig. 2, one can clearly see that optimizing a specific beam species current (here, $^{124}Xe^{37+}$) while only looking at the species of interest leaves the source operator missing critical information. Human operators are able to glean general trends with this CSD information, but computers have the potential to use this information with tools like neural network techniques to better understand and optimize source performance within the operation space. However, the only way for this to be useful in reasonable timescales is to reduce the time to gather charge state distribution information from the 3–4 minutes required using the PLC's 3 Hz bottleneck.

## FASTER DIAGNOSTICS

Though the 3 Hz beam current update rate through the PLC has proven sufficient to determine beam stability for delivery to LBNL's 88-Inch Cyclotron, this is an unacceptably low rate when trying to calculate statistics to inform the machine learning effort. In order to improve the data collection rate for beam current, a faster ammeter was employed, its current read by computer, and then the rapid signal was averaged at a 3 Hz rate and fed back to the PLC to maintain current display capabilities. The ammeter, a Keysight B2983A, has the capability of reading beam current at 20 kHz, but as discussed in [4] in detail, the Faraday cup does not serve as a great diagnostic for fast instabilities. Therefore we typically do not measure currents at a rate faster than 1 kHz and use standard deviation calculations with these measurements as a gross, and faster, stability measure.

Combining the faster ammeter measurements with computer control of the VENUS analyzing dipole allows for a significant decrease in the time needed to collect charge state distribution data. By requesting dipole current changes and reading the Faraday cup at 100 Hz each, charge state distributions for M/Q from 2 to 8 to be completed in 5–6 seconds with the same amount of information as the 3–4 minute sweeps through the PLC. Sudden dipole current changes from the top of the the CSD to the bottom to start the next sweep were deemed hard on the dipole's power supply, so we now sweep the current up, sit for a second at the top of the range, sweep down, wait a second at the bottom of the range, and repeat. The full cycles take ∼12 seconds, as can be seen in Fig. 3, where a xenon-124 beam is analyzed.

In one full cycle of the dipole, as shown in Fig. 3, we get two CSDs, as visible by the near-mirroring about the center of that plot. By plotting the measured current as a function of mass-to-charge ratio, as in Fig. 4, it can be seen that the two CSDs agree relatively well. However, it can also be seen that on the downward sweep the measured currents for higher charge states are reduced relative to the upward sweep. This is a result of all of the overbent species being intercepted on a relatively small area of the wall of the beam pipe. The temperature of this area increases as does the pressure after the dipole, leading to beam losses. However, this transient has settled for the most part by the start of the next upward sweep, and therefore only upward sweeps are used for diagnostic purposes.

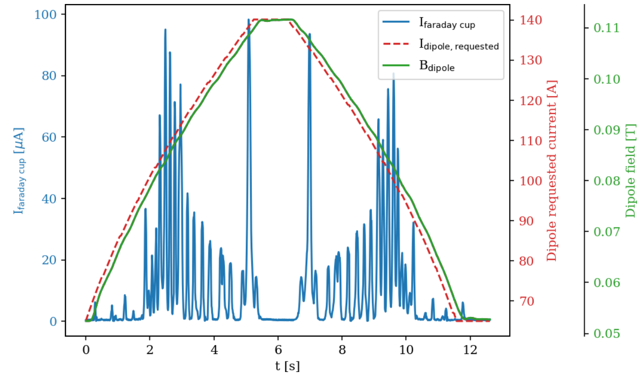


Figure 3: Faraday cup current, requested dipole current and dipole field are plotted as a function of time for one full up-down cycle when measuring fast charge state distributions. The field lags behind the requested current, so a second is spent with constant requested current before sweeping in the opposite direction.

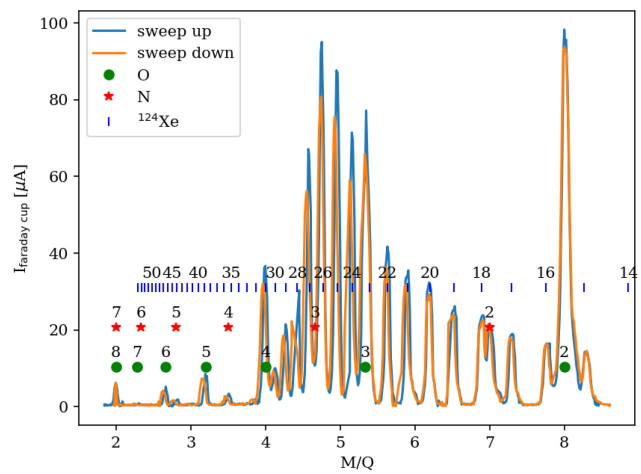


Figure 4: Charge state distributions with increasing dipole current (blue) and decreasing (orange). Expected mass-to-charge ratios for different species are indicated with symbols.

The ability to take charge state distributions faster allows for the measurement of dynamic systems and get more rapid feedback on how those changes are affecting the all ion species. As an example of this, when running a 124-xenon beam using oxygen as a mixing gas, we closed the valve in regular steps over an hour. After each closing the system was able to settle and charge state distributions were continually measured at 12 second intervals. From each charge state distribution we identified the species peaks and provided some smoothing of each species' current as a function of time to get rid of measurement noise. As is well-known in the field, the lowering of pressure caused a shift in the charge state distribution from lower to higher charge states. To visualize this, we normalized each species' current over the hour to its maximum and made the plot shown in Fig. 5.

Plots like Fig. 5 are very useful for ion source operators to understand general behaviors and trends for ECR ion sources. The data underlying this plot and similar data in

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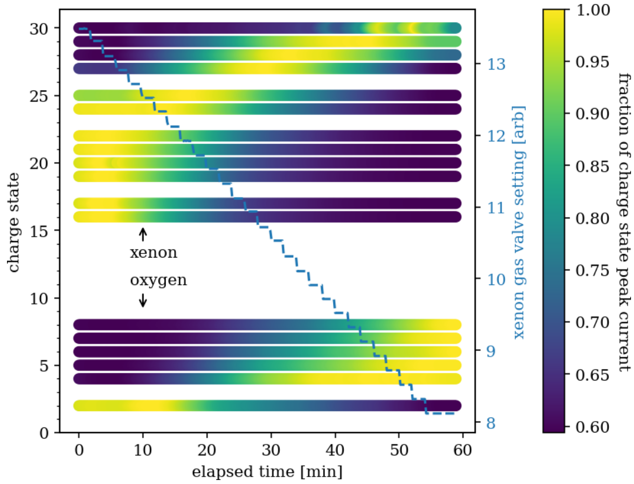


Figure 5: Beam current for twelve 124-xenon ion species and six oxygen species are plotted as a function of time as the xenon valve is closed over an hour. Each species is normalize to its maximum value during this hour. Both oxygen and xenon distributions shift to higher charge state as the valve is closed.

explorations of the ECR operation space will be essential in the application of machine learning techniques not just focused on optimizing the beam current, but also with the goal of better understanding general source operation. For example, after metals have been used in the source, metal beams still appear in extracted beams for days after. The amount of these unwanted elements in the beam decays with time, and as it goes away it affects the charge state distributions. Without the machine learning computer (or a human, even) knowing about the changing presence of these extra elements in the plasma and extracted beam, it is very difficult to generalize results. The ability to gather this information rapidly gives machine learning a much better chance at succeeding at characterizing the operation space by providing previously unobservable information and predicting how we might improve our source operation.

# CONCLUSIONS

We now have the ability to completely control the VENUS ion source by computer. Using Bayesian optimization, we are able to have the computer optimize the ion source for a given ion species and achieve currents that are comparable with those a moderately trained ion source tuner could produce. The operation space for this effort was limited and distinct from regions where significantly higher currents have been achieved with VENUS. It is expected that opening the search space will lead to significantly increase achieved currents.

The recent addition of the capability to read the source Faraday cup at frequencies of at least 100 Hz significantly reduces the time to determine the level of general beam stability, and coupling this with faster analyzing magnet operation has reduced charge state distribution times to approximately 10 seconds. We expect that these faster charge state distributions will be extremely impactful as this machine effort continues, both in terms of faster data and a more complete understanding of what is in the source and what is coming out.

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