SuperKEKB positron beam tuning using machine learning

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Abstract. In the KEK injector linac, four-ring simultaneous top-up injection has been achieved, and beam tuning is always performed in various beam modes. As there are four beam modes, the optimum magnet current and RF phase must be selected for each. There are numerous tuning knobs for each mode; thus, it takes significant time and manpower to find the optimum state for all modes. In particular, tuning the positron primary electron beam requires delicate parameter adjustment due to its large charge. Significant time has been spent on this tuning. Therefore, an automatic tuning tool has been developed. Automatic tuning is realized using Bayesian optimization and the downhill simplex method. This tool can be used for any beam tuning on our system and has been particularly useful for positron beam tuning.

1 Introduction

KEK Tsukuba campus has four ring accelerators: the high-energy ring (HER), low-energy ring (LER), PF ring, and PF-AR. The HER and LER are SuperKEKB main rings. The PF ring and PF-AR are light source rings. The KEK electron/positron injector linac has been injecting these four rings with one beamline[1]. Figure 1 shows a schematic of the KEK injector linac. It has eight acceleration sectors: Sectors A, B, C, and 1-5 and a bending sector called J-arc. The injector also has two types of electron guns as electron sources. One is a photocathode RF gun and the other is a thermionic DC gun. The photocathode RF gun generates the low-emittance electron beam for HER. The positron primary beam is an electron beam from a thermionic electron gun with a charge of 10 nC, which generates positrons by hitting a tungsten target in the Flux Concentrator (FC). A positron target is in Sector 1. The positron beam generated by the target and the FC is injected into the LER after being damped by the damping ring between Sector 2 and 3. The thermionic DC gun is also used as an electron source for the PF ring and PF-AR.

The injector has many pulsed magnets and varies the beam optics pulse-to-pulse to achieve simultaneous top-up injection into four rings[2]. The RF phase is also changed pulse-to-pulse to match the energy to each ring. In recent years, the number of tuning items has increased with the increase in the number of pulsed magnets, and quality of the beam has improved accordingly. However, although the number of tuning items has increased, the required tuning time and manpower have not. Therefore, we decided to introduce an automatic tuning tool using machine learning. Previously, experienced operators had to spend significant time tuning the beam, but with the introduction of automatic beam tuning, anyone

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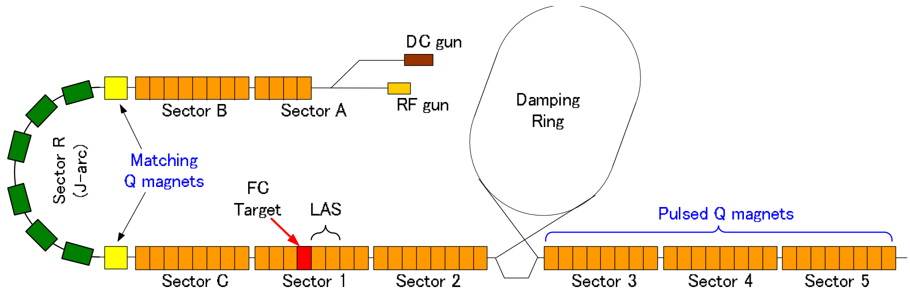

Figure 1. The KEK injector linac.

can tune the beam to a certain quality in a short time. In particular, the automatic tuning contributed significantly to improving the transmission of the positron primary beam, which has a large amount of charge. The automatic tuning was also effective in tuning the DC quadrupole magnet (Q magnet) after the positron capture section, which had been left unattended due to lack of time for adjustment. The automatic tuning using machine learning outperformed human performance in several examples. Examples of actual tunings are presented in Section 4.

2 Principle

2.1 What is tuning

Machine tuning is the process of changing the tuning parameters to improve the output. In the case of an accelerator this means, for example, changing the current value of the magnet to bring the beam orbit closer to the center. There are usually several tuning parameters, for example, the current value of the steering magnets or Q magnets and the RF phases. It is also necessary to define what constitutes a "good state"; this depends on the purpose. It may be a state where the beam orbit is zero for both holizontal and vertical, a state where the ring injection rate is high, a state where the positron generation rate is high. In any case, a good state is defined as when a certain scalar value is defined from a single or multiple monitor values and that value is at its minimum or maximum. For example, if we define a good state as a state when the beam orbit is near zero and the charge is large at a certain monitor point, then, according to the equation

$$Y = x_m + y_m + \frac{1}{Q_m} , \tag{1}$$

the state is good when Y is the minimum (x_m, y_m: holizontal and vertical beam positions at monitor point, Q_m: Charge at monitor point). Monitor values vary depending on tuning parameters. For example, if the amount of charge Q_m is determined with multiple magnet current values $x_1, x_2, x_3, ...$, it is expressed as an unknown multivariable function $Q_m = Q_m(x_1, x_2, x_3, ...)$. In general, the monitored values are unknown for the tuning parameters. The machine state Y determined from multiple monitor values is similarly represented as an unknown multivariable function

$$Y = f(\boldsymbol{x}) . \tag{2}$$

Here, $\boldsymbol{x} = (x_1, x_2, x_3, ...)$ are arbitrary tuning parameters, e.g., magnet current, RF phase, etc.

2.2 Optimization method

The previous chapter described how to convert machine tuning to a problem of minimizing an unknown multivariate function. Solving this minimization problem is the tuning. Bayesian optimization [3] can be used to solve minimization problems for unknown functions. This method uses a Gaussian process to predict the function and its variance, from which the next point to search is derived. This method is very efficient in obtaining the best point, making it suitable for practical machines with a limited number of measurements citeBO2.

The downhill simplex method (Nelder–Mead method) is also known as a classical method for solving unknown function minimization problems [5]. The downhill simplex method is a very simple algorithm, but if the function is smooth, it converges reliably to a minimum point. However, if the function shape is complex, it may fall into a local minimum.

Bayesian optimization is effective when the beam tuning is poor and a wide area must be searched. Downhill simplex is effective when the best point is nearby, such as when the beam condition shifts slightly from a good state due to instrument drift.

3 Implementation

All KEK injector linac instruments are controlled by EPICS. The adjustment knob and measurement items vary depending on the purpose of the tuning. EPICS is very compatible with autotuning tools because it allows various devices to be controlled from the same interface. We used Python for the software implementation, including the GUI. A Python library called GPyOpt was used for Bayesian optimization [6]. The downhill simplex method was coded from scratch.

The actual operation panel and its description are shown in Fig.2. In this panel, EPICS recode can be selected as a control item (X setting) and monitor item (Y setting). The control item allows the selection of the tuning range. The value obtained from the monitor item is used to define the evaluation value, and automatic tuning is performed so that the evaluation value is minimized. The tuning algorithm is selectable between Bayesian optimization and downhill simplex. Normally, the operator can simply load a pre-produced setting file and execute it for automatic tuning.

4 Practical examples

4.1 Increase positron generation

One example is the initial parameter search for positron generation. At machine start-up, the primary beam does not hit the target well and positron generation rate is low. If the primary beam has a certain amount of transmission, the positron beam generation rate can be increased by upstream beamline tuning. Usually, subharmonic bunchers (SHB) and several upstream pulse steering magnets are adjusted. We have two SHBs. The following are the results of the automatic tuning with Bayesian optimization using six tuning knobs (two SHB phases and four steering magnet currents). Figure 3 is a time series graph during tuning. The number of iterations was 50, and in this case, the tuning took 10 min. Figure 4 shows the panel for checking tuning in actual operation. This panel allows the user to check the status of tuning parameter changes (upper graph) and evaluation value updates (lower graph) in real time. Usually, 50 iterations are sufficient for tuning within 8 parameters. If the number of parameters exceeds 10, we tune over approximately 100 iterations.

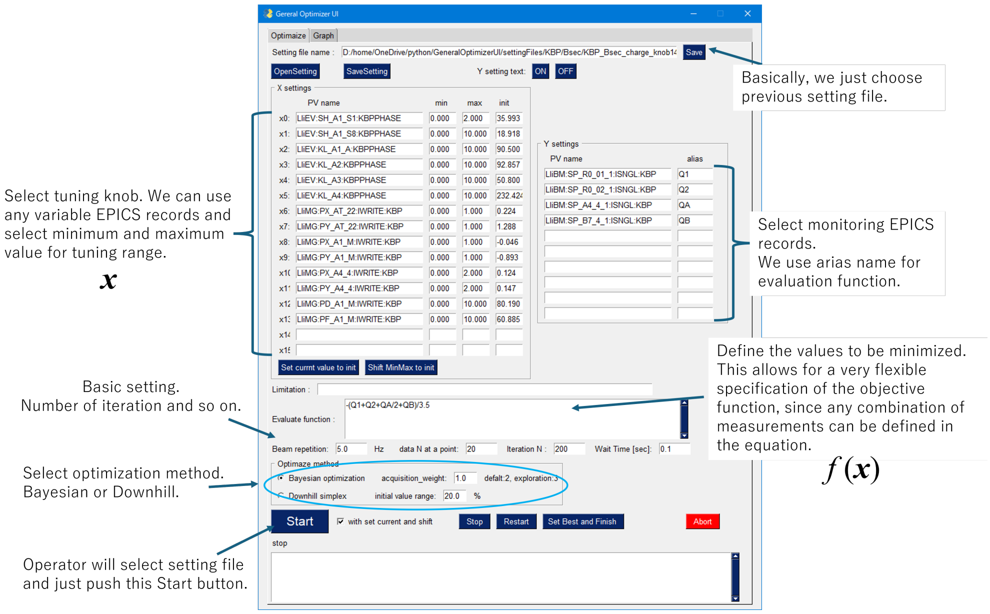

Figure 2. The automatic tuning panel.

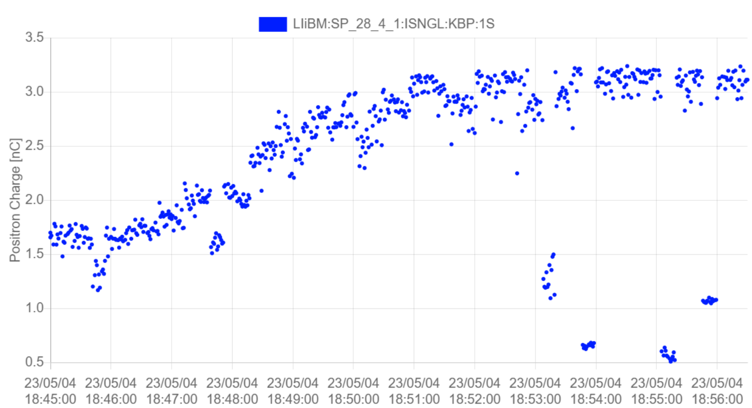

Figure 3. Graph of positron beam charge increase during tuning; tuning was completed in approximately 10 min.

4.2 Improvement of positron transmission

The positron beam loss in the acceleration line from the capture section to the damping ring has been simulated and was predicted to be only approximately 10%. However, the actual beam loss was higher than in the simulation, approximately 40%. The positron beam charge could not reach the target value of 4.0 nC, and remained at around 3.0 nC. The positron beam has a large emittance upstream of the damping ring, and the beam profile is approximately the same as the aperture of the accelerating structure. Therefore, a small orbital error or focusing error can easily cause beam loss. In addition, many Q magnets are installed in this

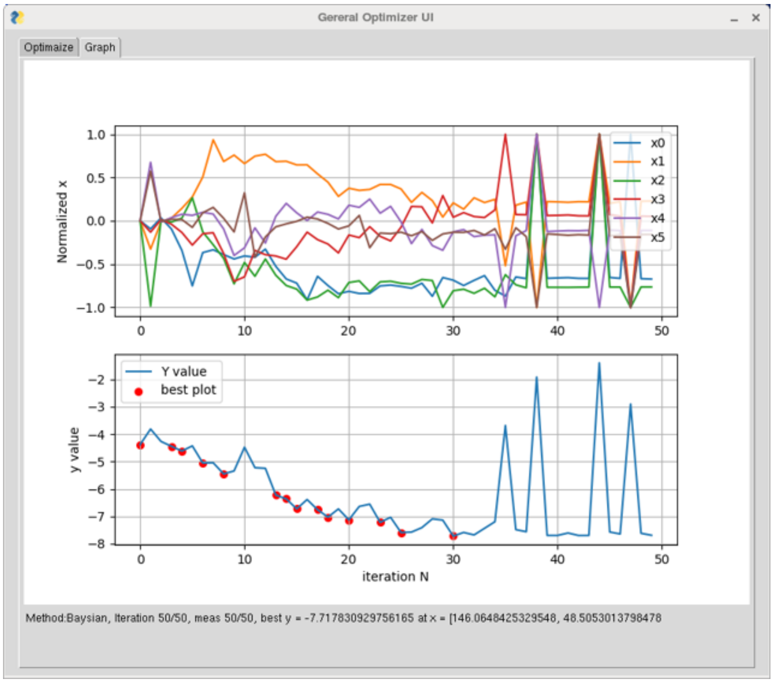

Figure 4. Panel for checking tuning in actual operation. The upper graph is the status of tuning parameter changes. The lower graph is the status of evaluation value updates.

section to keep the beam size small. The number of tuning parameters for these magnets is approximately 200. Furthermore, because the magnets in this section are DC magnets, other beam modes are affected, so long study time was not possible.

Therefore, we performed automatic beam tuning in this area to achieve effective beam tuning in a short period of time. However, there are too many parameters to adjust all the magnets at once, so the tuning was divided into several sections. In practice, the section was divided into 16 sections and tuned so that the transmittance increased from upstream. A series of tuning from upstream to downstream took approximately 5 h. Figure 5 shows the change in the amount of charge at the downstream end of the series of tuning. As the tuning is performed from the upstream side, the graph of Fig.5 shows that the amount of charge sometimes drops. As a result of a series of tuning, the charge increased from 3.3 nC to 4.0 nC. Figure 6 shows a graph of the BPM charge monitor. Before the tuning, there was a gradual loss of positron charge, but after the tuning, the loss was reduced.

Thus, machine learning made it possible to adjust a large number of parameters in a short time. This is an example of automatic tuning using machine learning that is beyond human capability.

5 Summary

At KEK injector linac, automatic beam tuning is performed using machine learning. In recent years, the quality of beams required for injector linac has been increasing, and machine learning has become increasingly important. We have developed an automatic tuning tool that can be used for various applications. The autotuning tool has a flexible interface and can adjust anything under EPICS control.

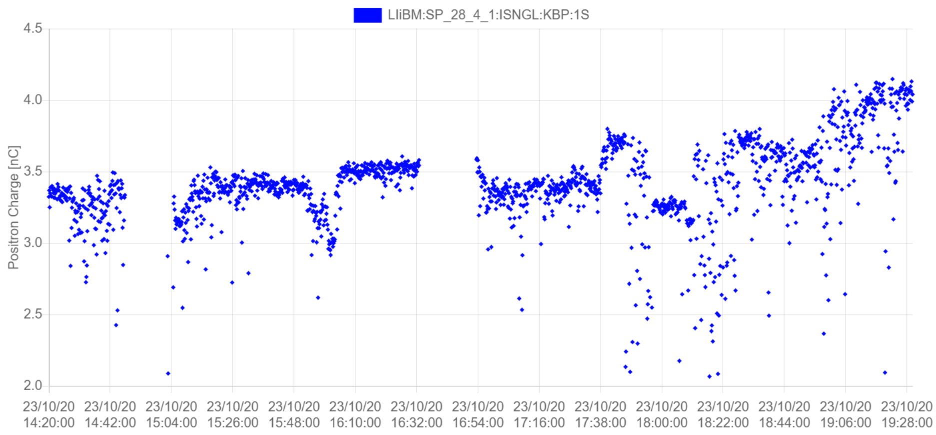

Figure 5. Time-series graph of positron transmission adjustment; over a period of 5 hours, the charge increased from 3.3 nC to 4.0 nC.

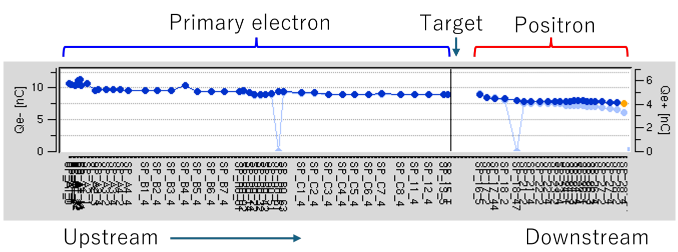

Figure 6. Graph of BPM charge monitor. The light blue dots are before tuning, and the dark blue dots are after tuning.

Automatic tuning has shown satisfactory results and is a useful tool. For simple adjustment of a few parameters, automatic tuning showed the same quality as human tuning. In some cases, it also produced better results than human tuning. The autotuning contributed significantly to the increase of the positron beam charge, in particular. We are developing the automatic tuning tool to be used more widely.

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