

ADAPTIVE ACCELERATOR TUNING *

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Abstract

A recently developed, model-independent feedback controller is presented, which is robust to measurement noise, and able to tune an arbitrary number of coupled parameters of an unknown system, simultaneously, based only on a user-defined cost function. Unlike genetic algorithms, which are a useful model-based tool for the optimization of a well known fixed system, the algorithm presented here is actually useful for implementation in hardware on actual machines as a feedback tuning and control loop, because it can compensate for the unknown time-varying disturbances/changes that all large machines experience. We present recent in-hardware experimental results obtained at the Los Alamos Neutron Science Center and at the Facility for Advanced Accelerator Tests (FACET), demonstrating the scheme's ability to simultaneously tune many parameters and its robustness to noise and system time-variation.

INTRODUCTION

Model-based schemes have been utilized for the design and optimization of particle accelerators, genetic algorithms (GA) in particular have become popular in recent years. When sufficient computer resources are available, lengthy GA searches have successfully found good starting points for machine designs by sampling a large parameter space. However, large complex machines are time-varying systems with time dependent, unpredictable disturbances and uncertainties including misalignments, thermal cycles, phase drifts, damage, and regions with limited beam measurements. Therefore, following a GA-based or any other model-based optimization approach, once an actual machine is constructed, many parameters have to be re-tuned, and re-tuned often as the system's characteristics drift with time.

When performing feedback on the beam or RF systems, there is a need for model-independent controllers which can handle the time-varying systems, especially for future accelerators such as MaRIE [1]. We present a model-independent feedback controller [2,3], which is robust to measurement noise, and able to tune an arbitrary number of coupled parameters of an unknown system, simultaneously, based only on a user-defined cost function. The algorithm is especially useful for implementation in-hardware on actual machines as a feedback tuning and control loop, because it can compensate for the unknown time-varying disturbances/changes that all large machines experience.

OPTIMIZATION SCHEME

In an accelerator there are many important parameters

$$\mathbf{x}(t) = (x_1(t), \dots, x_m(t)), \quad (1)$$

some of which are observable and others that can only be estimated or averaged, such as RMS beam width, various measures of emittance, beam current, etc... These evolve according to some complicated nonlinear, time-varying dynamics, such as

$$\frac{\partial \mathbf{x}(t)}{\partial t} = \mathbf{f}(\mathbf{x}(t), \mathbf{s}(t), \mathbf{p}(t), t), \quad (2)$$

where $\mathbf{f}(\mathbf{x}(t), \mathbf{s}(t), \mathbf{p}(t), t)$ is usually linearized or approximated in some other way so that the dynamics (2) can be numerically evaluated. In these dynamics there may be an arbitrary number of uncertain, uncontrollable, time-varying parameters

$$\mathbf{s}(t) = (s_1(t), \dots, s_m(t)), \quad (3)$$

which include misaligned components, noise, disturbances, jitter, magnetic fields that depend on currents in an uncertain way due to hysteresis, and environmentally caused temperature variations which lead to phase drifts, to name a few, which makes the simulation of anything other than an estimate of the actual system impossible. Also, there may be an arbitrary number of controlled parameters

$$\mathbf{p}(t) = (p_1(t), \dots, p_n(t)), \quad (4)$$

including magnet current settings, phase and amplitude set points in RF systems, and control loop feedback gains, to name a few. The goal of the adaptive scheme presented here is the same as the goal of beam physicists and operators: the minimization of some chosen "cost" associated with accelerator performance such as the tuning of magnet and RF systems to minimize beam loss along the accelerator or to minimize the deviation of the final beam energy from a desired set point. The cost is some analytically unknown, but available for measurement function of the many controlled and uncontrolled parameters and states of the system, $C(\mathbf{x}(t), \mathbf{s}(t), \mathbf{p}(t), t)$. In practice, the actual cost, C , is rarely available for measurement, rather a noise-corrupted version $\hat{C} = C + n(t)$ is what arrives at the control system. The adaptive scheme is incredibly robust to random noise, the parameter tuning dynamics are

$$\frac{\partial p_i}{\partial t} = \sqrt{\alpha \omega_i} \sin \left(\omega_i t + k \left[\underbrace{C(\mathbf{x}, \mathbf{s}, \mathbf{p}, t)}_{\hat{C}(\mathbf{x}, \mathbf{s}, \mathbf{p}, t)} + n(t) \right] \right), \quad (5)$$

where $\omega_i \neq \omega_j$ for all $i \neq j$, which for large $\omega_i \gg 1$, results in average parameter dynamics

$$\dot{\bar{p}}_i = -\frac{k\alpha}{2} \frac{\partial C(\mathbf{x}, \mathbf{s}, \bar{\mathbf{p}}, t)}{\partial \bar{p}_i}, \quad (6)$$

a gradient descent which minimizes the *actual* C , not \hat{C} , as long as the noise is random, a result that is both mathematically proven and demonstrated in hardware [3,5]. This

* This research was supported by Los Alamos National Laboratory.

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dynamic update scheme, (5), can be implemented in an iterative fashion, as in [4, 5], for systems which require settling time between parameter setting changes, and in which it is infeasible or may be destructive to continuously vary parameter settings. The iterative update law is simply the finite difference approximation of (5):

$$p_i(n+1) = p_i(n) + \Delta\sqrt{\alpha\omega_i} \sin(\omega_i n\Delta + k\hat{C}(n)), \quad (7)$$

where $\Delta \ll 1$ and time between updates is arbitrarily long.

Remark 1 In the adaptive scheme (5), $\sin(\cdot)$ may be replaced by $\cos(\cdot)$ or a triangle or square wave, or any other highly-oscillatory periodic function. The term α can be thought of as the dithering amplitude which controls the parameter search, increasing which may lead to escaping local minima. The term k is like a control gain, increasing k leads to faster convergence. The dithering frequencies ω_i must dominate all system dynamics in order to track time-dependent changes. The approach can be thought of intuitively, as similar to stabilizing an inverted pendulum by quickly vertically oscillating its pivot point [6]. Although the cost function, C in (5), is analytically unknown, because it enters the scheme as the argument of a known, bounded function, the overall scheme is very stable and we are guaranteed chosen bounds on parameter update rates.

SIMULATION STUDY

We utilized a simulation of the LANSCE low energy beam transport (LEBT) and drift tube linac (DTL) with a bunch of 32000 macro particles to demonstrate simultaneous tuning of 24 parameters [4]. The first approach was to start with all 22 magnets in the LEBT turned off, and then tune their settings according to (5) with the cost $C = (I_0 - I_s)^2$, where I_0 was the initial beam current entering the machine and I_s was the surviving beam current at the end of the LEBT. The magnets automatically tuned up to minimize C in what would be equivalent to a few hours taking into account realistic magnet settings changes. At the end of the adaptive scheme, > 80% of the beam was surviving through the end of the LEBT, slightly more than what is typically achieved by beam physicists and operators at LANSCE during a lengthy (few weeks) start up. In the second simulation study, a beam is transported all the way through the LEBT and DTL and 24 parameters are simultaneously tuned, 22 magnets and 2 buncher cavity phase settings. While survival through the LEBT is a good measure of correct magnet settings, the DTL is a good measure of the beam being bunched correctly by the pre and main RF buncher cavities, whose phase drift will cause the beam to lose synchronization with the DTL accelerating RF fields and will result in major beam loss by the end of the DTL. The adaptive scheme is able to continuously adjust both the magnet and RF buncher settings despite a time-varying initial beam distribution and drifting phase offset of the buncher cavities, all based on only the cost $C = (I_0 - I_s)^2$, a measure of surviving beam current at the end of the DTL. The results are shown in Figure 1.

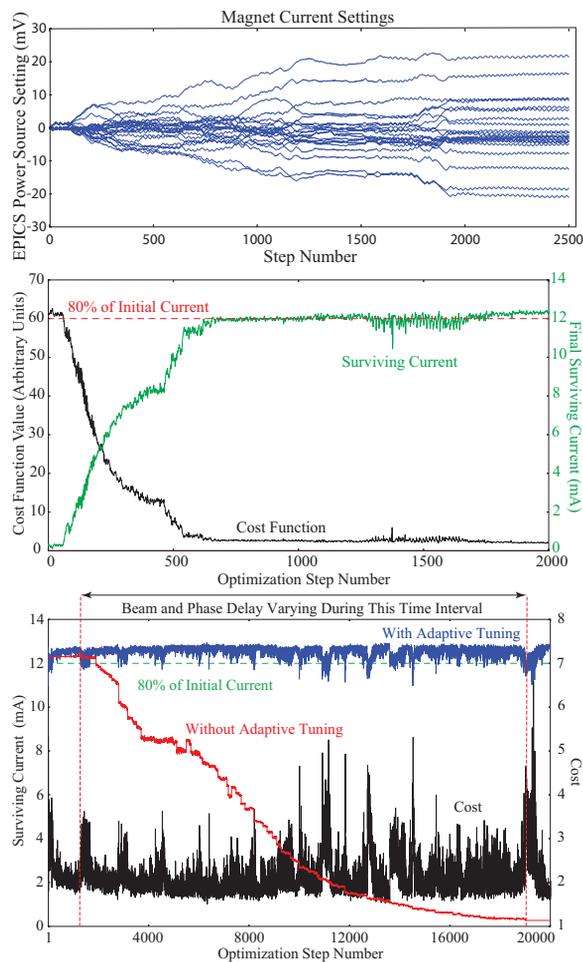


Figure 1: As the magnets are automatically tuned (top) the surviving beam current (middle) reaches and exceeds the operator-based level. Despite time variation of both beam and RF phase properties, the system automatically tunes all parameters to maintain > 80% surviving beam current, a value typically achieved by operators after a lengthy tune up for specific, fixed phase and beam settings (bottom).

APPLICATION AT LANSCE FOR RF BUNCHER CAVITIES

The scheme was implemented in hardware at the Los Alamos Neutron Science Center (LANSCE) linear accelerator, to automatically tune the phase settings of the pre and main buncher RF cavities that bunch the CW beam before its entrance into the accelerating DTL [5]. The phases of the buncher cavities must be correct relative to the RF fields of the DTL in order for the beam to be properly accelerated and matched to the quadrupole magnets throughout the machine. These RF systems, like all RF systems, suffer arbitrary time-varying phase drifts due to, amongst other facts, temperature-dependent cable length changes. In order to test the scheme the buncher phases were purposely detuned and then the adaptive scheme automatically re-tuned them based a very noise sampling of the cost $C = (I_0 - I_s)^2$, a measure of surviving beam current at the end of the DTL.

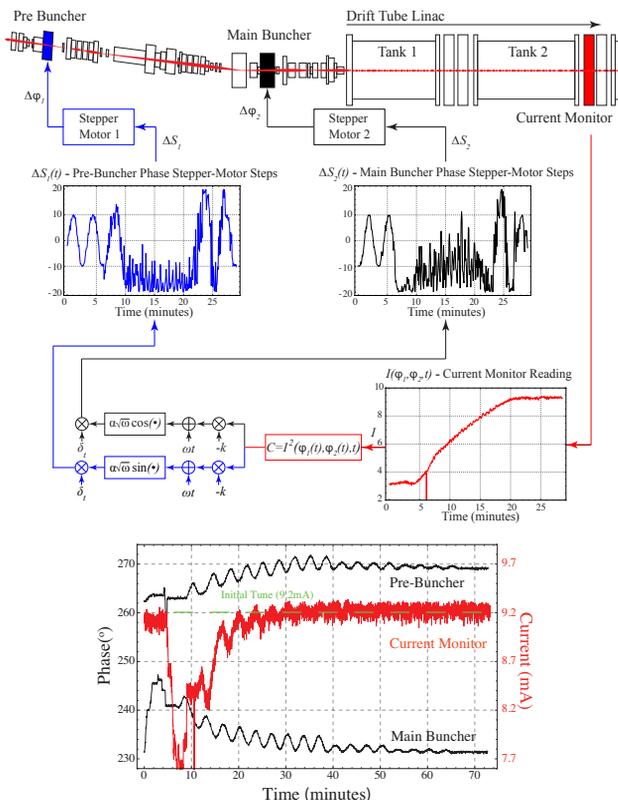


Figure 2: Feedback setup (top), parameter and cost evolution (bottom).

The scheme was able to re-tune the bunchers and achieve a slightly better survival percentage than what was implemented by the operators, the results are shown in Figure 2.

APPLICATION AT FACET FOR BEAM PROPERTY PREDICTION

The Facility for Advanced Accelerator Experimental Tests (FACET) at SLAC produces high energy electron beams for Plasma Wakefield Acceleration [7]. For these experiments, precise control of the longitudinal beam profile is very important. A number of bunch length diagnostics are employed at FACET, including beam streaking with an x-band transverse deflecting cavity (TCAV). At FACET, we employed the above described technique as a non-invasive real-time estimate of the bunch profile [8]. The cost to be minimized was the χ^2 residual between the measured (TCAV) and simulated (LiTrack) spectra of the electron bunch. System parameters such as various arbitrary phase shifts and beam properties (β , dispersion) were the inputs to LiTrack. The adaptive scheme minimized the cost by varying an arbitrary number or parameters simultaneously. We simulate FACET with fourteen free parameters in code package called LiTrackES. The results are shown in Figure 3.

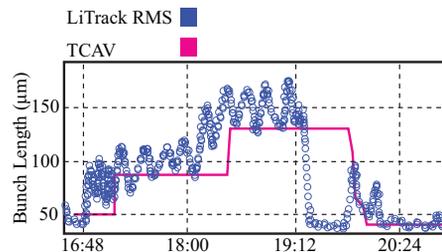


Figure 3: The LiTrackES-based RMS prediction can be seen tracking the TCAV-based measurement over the course of several hours.

CONCLUSIONS

The scheme presented is model independent and incredibly robust to noise, it depends on a noise-corrupted sample of a user-defined cost, and is therefore very general and may be useful for optimization of many beam parameters via magnet or RF system tuning. Combining virtual beam measurements from simulations with actual diagnostic signals from the accelerator into a single cost function, as was done at FACET, allows one to take into account both unknown/unmodeled machine variations and estimates of physically inaccessible beam characteristics.

REFERENCES

- [1] J. Bradley, A. Scheinker, D. Rees, R. Sheffield, "An overview of the MaRIE XFEL and electron radiography LINAC RF systems," *Proceedings of IPAC'15*, Richmond, VA, USA, 2015.
- [2] A. Scheinker, "Model Independent Beam Tuning," *Proceedings of IPAC'13*, Shanghai, China, 2013.
- [3] A. Scheinker, M. Krstic, "Extremum seeking with bounded update rates," *Systems & Control Letters*, vol. 63, pp. 25-31, 2014.
- [4] A. Scheinker, X. Pang, L. Rybarczyk, "Model-independent particle accelerator tuning," *Physical Review Special Topics - Accelerators and Beams*, vol. 16, 102803, 2013.
- [5] A. Scheinker, S. Baily, D. Young, J. Kolski, M. Prokop, "In-hardware demonstration of model-independent adaptive tuning of noisy systems with arbitrary phase drift," *Nuclear Instruments and Methods in Physics Research A*, vol. 756, pp.30-38, 2014.
- [6] P.L. Kapitza, "Dynamic stability of a pendulum when its point of suspension vibrates," *Soviet Phys. JETP* **21**, 588592, 1951.
- [7] M. J. Hogan, T. O. Raubenheimer, A. Seryi, P. Muggli, T. Katsoleas, C. Huang, W. Lu, W. An, K. A. Marsh, W. B. Mori, C. E. Clayton, and C. Joshi, "Plasma wakefield acceleration experiments at FACET," *New Journal of Physics*, vol.12, 055030, 2010.
- [8] A. Scheinker and S. Gessner, "Extremum Seeking for Parameter Identification, Implementation for Electron Beam Property Prediction," *Proceedings of the 2014 Conference on Decision and Control*, Los Angeles, CA, USA, 2014.