Automatic Beam Tuning of 0.3 MV Accelerator Mass Spectrometer Based on Differential Evolution Algorithm

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Date: 2025-04-01T00:00:00+00:00

Abstract

To address the challenges of high complexity, time-consuming manual adjustment, and difficulty in achieving optimal states in beam tuning tasks for 0.3MV tandem compact Accelerator Mass Spectrometer (AMS), this study proposes an innovative automatic beam tuning method that integrates the EPICS (Experimental Physics and Industrial Control System) control platform with the Differential Evolution Algorithm (DE). A core module for intelligent optimization algorithms was developed in Python, enabling efficient data interaction with the EPICS control framework through the PyEpics interface to construct a complete automated beam tuning system. By automatically adjusting power supply voltage and current, the system indirectly controls key parameters of the accelerator mass spectrometer, including magnetic field strength, electrode voltage, and beam intensity. Under the premise of ensuring equipment safety constraints, the Differential Evolution Algorithm guides spatial search by dynamically adjusting population parameters and constructs the objective function using real-time feedback of beam intensity. Experimental results demonstrate that this method reduces the average convergence time from 2.5 hours for manual tuning to 30 minutes, while increasing the optimization success rate from 60% with traditional methods to over 90%. The optimal beam intensity reaches 95% of the theoretical maximum and maintains stability, substantially shortening the beam tuning cycle, significantly enhancing accelerator operational stability and efficiency, and demonstrating substantial industrial application value.

Full Text

Automatic Beam Commissioning for 0.3MV Accelerator Mass Spectrometer Based on Differential Evolution Algorithm

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Abstract

Addressing the challenges of high complexity, time consumption, and suboptimal performance associated with manual beam tuning of a 0.3 MV compact accelerator mass spectrometer (AMS), this paper proposes a novel automatic beam commissioning methodology that integrates the Experimental Physics and Industrial Control System (EPICS) with the Differential Evolution (DE) algorithm. An intelligent optimization core module was developed in Python, enabling efficient data exchange with the EPICS control framework through the PyEpics interface to construct a comprehensive automated tuning system. The system automatically adjusts power supply voltages and currents, thereby indirectly controlling critical accelerator parameters such as magnetic field strength, electrode voltage, and beam intensity. Under strict equipment safety constraints, the DE algorithm dynamically adjusts population parameters to guide spatial search, with the objective function constructed using real-time beam intensity feedback. Experimental results demonstrate that this approach reduces average convergence time from 2.5 hours (manual tuning) to 30 minutes, while increasing optimization success rates from 60% (conventional methods) to over 90%. The optimal beam intensity reaches 95% of the theoretical maximum and maintains stability, significantly shortening commissioning cycles and substantially improving accelerator operational stability and efficiency, thus demonstrating considerable industrial application value.

Keywords: Differential Evolution Algorithm; Accelerator Mass Spectrometer; Automatic Beam Commissioning; EPICS

0 Introduction

Accelerator mass spectrometry (AMS) serves as a high-precision analytical technique for measuring long-lived radionuclides with exceptional sensitivity, finding widespread applications in nuclear technology, astrophysics, environmental monitoring, and biomedicine [?]. Beam commissioning represents a critical operational phase in accelerator systems, involving theoretical calculations of beam optics and presetting parameters for deflection, focusing, and acceleration components based on these calculations [?].

However, current beam commissioning remains predominantly manual, presenting significant challenges to operational efficiency and performance optimization. Traditional manual methods rely heavily on operator experience and trial-and-error processes, resulting in cumbersome and time-consuming procedures. Due to the vast parameter space and complex interdependencies, manual tuning often fails to locate global optima, compromising overall accelerator performance. The complexity of objective functions in automatic beam commissioning poses particular challenges for optimization algorithm selection. Gradient-based methods require differentiable and continuous objective functions, whereas accelerator tuning objectives frequently exhibit nonlinear, non-convex, and multi-modal characteristics. In contrast, the DE algorithm operates without gradient information and imposes no strict requirements on differentiability or continuity, making it more universally applicable for accelerator beam commissioning. Furthermore, while particle swarm optimization may suffer from slow convergence, particularly in large solution spaces or with complex objective functions, DE generates new solution vectors through differential mutation operations and competes them with current vectors, enabling faster convergence to optimal solutions. Compared to alternative approaches, DE has gained widespread application in engineering optimization, economic modeling, and scientific computing due to its simplicity, efficiency, and robustness. To address existing limitations in automatic beam commissioning research, this study focuses on DE algorithm application guided by beam optics theory, with in-depth investigation into system scale and intelligence capabilities.

1.1 Overview of Beam Optics-Guided Tuning

Beam optics theory describes the trajectory and parameter evolution of particle beams through accelerator components, providing theoretical guidance for automatic commissioning. Considering only magnetic field effects, charged particle dynamics can be described by the Lorentz force equation as shown in Equation (1).

where $\vec{F}$ represents the magnetic force on charged particles, $\vec{B}$ denotes magnetic field intensity, $\vec{v}$ is the charged particle velocity vector (aligned with motion direction), $\vec{P}$ represents momentum, m is particle mass, $\vec{r}$ indicates particle position in space, and N denotes beam intensity. During commissioning, magnetic field $\vec{B}$, particle velocity $\vec{v}$, and beam intensity N form a mutually coupled control parameter system.

Key beam quality parameters—such as position, angle, energy, and emittance—typically require optimization through electric and magnetic field adjustments. For instance, in the accelerator injector section, adjusting ion source internal parameters like electrode voltage can modify particle generation velocity $\vec{v}$ and beam intensity N. Magnetic field influences beam intensity primarily through focusing and confinement effects; by tuning magnetic field strength $\vec{B}$, beam focusing characteristics can be altered, thereby affecting intensity distribution and transmission efficiency.

In beam phase space, the trace-space ellipse—the general form of an ellipse in the $x - x'$ plane containing trace-space particles—is expressed as Equation (2). Here, ε represents beam emittance, which describes the size of the trace-space ellipse and measures beam quality. The Twiss parameter set comprises three key parameters: γ (curvature function), β (amplitude function), and α (tilt function).

In beam focusing systems, adjusting focusing coil currents modifies magnetic field strength, thereby influencing beam spot shape and current density. Adjusting bending magnet currents enables orbit correction, stabilizing beam transport through the beamline. This study focuses exclusively on optimizing beam energy and intensity using the DE algorithm.

1.2 Theoretical Overview of Differential Evolution Algorithm

The Differential Evolution algorithm, proposed by Rainer Storn and Kenneth Price in 1995 [?], is a population-based heuristic parallel search method that utilizes difference information among individuals across evolutionary stages to guide the search process, demonstrating varying search capabilities at different phases. The algorithm comprises four key operations:

Population Initialization: Before optimization begins, the algorithm generates a set of solution vectors following specific rules, assigning values to each dimension of every individual [?]. For $i = 1, 2, ..., NP$, where i denotes the individual index, G represents the generation number, and NP is the population size. The initial population is typically assumed to be randomly generated following a uniform distribution. Given parameter bounds $x_j^L < x_j < x_j^U$, the initialization follows $x_{i,j,0} = \text{rand}[0,1] \times (x_j^U - x_j^L) + x_j^L$, where $\text{rand}[0,1]$ generates uniform real numbers in $[0,1]$.

Mutation: As the core operation, mutation creates new candidate solutions through mathematical operations on selected individuals from the current population. For each target vector $x_{i,G}$ $(i = 1, 2, ..., NP)$, the basic DE mutation vector generation [?] follows Equation (4).

where r_1, r_2, r_3 are mutually distinct indices different from the current individual i. The mutation factor $F \in [0, 2]$ is a real-valued parameter controlling the amplification of the differential vector [?].

Crossover: Following mutation, crossover performs global recombination of mutant and target vectors through a crossover operator, promoting population diversity while facilitating inheritance of superior solutions [?]. This process updates and reconstructs trial vectors through Equations (5) and (6).

where D is the solution vector dimension, $\text{rand}(j)$ generates uniformly distributed random numbers in $[0,1]$, and $\text{rnbr}(i) \in (1, 2, ..., D)$ randomly selects an index from the $[1, D]$ dimensional space. This random index ensures that

$u_{i,G+1}$ inherits at least one parameter component from $v_{i,G+1}$, maintaining solution feasibility [?]. The crossover probability $CR \in [0,1]$ controls information exchange between mutant vector $v_{i,G+1}$ and target vector $X_{i,G}$. Figure 1 [Figure 1: see original paper] illustrates a crossover example for $D = 1$.

Selection: After mutation and crossover, DE employs a greedy selection strategy [?], comparing fitness values between trial vector $u_{i,G+1}$ and current target vector $X_{i,G}$ to determine survival. This deterministic selection mechanism ensures population quality never degrades across generations, effectively guiding the search toward global optima. The DE algorithm flowchart is shown in Figure 2 [Figure 2: see original paper].

2.1 Hardware/Software Framework Design of Automatic Beam Commissioning System

This optimization algorithm targets the highly automated 0.3 MV compact AMS accelerator [?], implementing automatic beam commissioning across the beam transport line from ion source to biased Faraday cup, using graphite as the test sample. The transport line contains multiple physical components; the primary adjusted parameters include ion source components (filament power supply, cesium oven heater, extraction power supply, source focusing power supply, cesium focusing power supply), low-energy beamline section (pre-acceleration power supply, injection electrostatics, 1# steerer, injection magnet), high-energy beamline section (main high-voltage power supply, quadrupole lens, analyzing magnet, analyzing electrostatics, 2# steerer, bending magnet), and various Faraday cups F1~F7 along the transport line. The 0.3 MV compact AMS system framework is illustrated in Figure 3 [Figure 3: see original paper].

Online testing validates the algorithm's optimization capability. Since the Keithley 6482 dual-channel picoammeter can acquire current signals from Faraday cup outputs, the DE algorithm' s objective function is defined as beam intensity at each Faraday cup. The key commissioning parameters are voltages from four ion source power supplies and nine beamline power supplies, which indirectly control the electric and magnetic fields experienced by the beam. The optimization algorithm, implemented in Python, controls power supply equipment through EPICS Input/Output Controller (IOC) components, with commissioning parameters recorded and stored in the database via Process Variables (PVs). The PyEpics library was selected to access EPICS PVs, while Control System Studio (CSS) serves as the upper-level interface for the AMS control system, enabling visualization, parameter monitoring, real-time observation of beam intensity evolution across iterations, and improved commissioning efficiency.

The automatic commissioning system builds upon existing hardware/software infrastructure, integrating instruments into a comprehensive global control network. Devices with analog interfaces employ Programmable Logic Controllers (PLCs) for data transmission and reception, while LAN-interface devices communicate via TCP/IP protocol. Serial devices such as gaussmeters and picoammeters, which support Standard Commands for Programmable Instruments (SCPI), are converted to network communication through serial device servers. The hardware/software architecture is shown in Figure 4 [Figure 4: see original paper].

2.2 Application Scheme Design for AMS Automatic Beam Commissioning

During 0.3 MV AMS automatic commissioning, the core optimization parameters are power supply voltages and currents along the beam transport path, with the search space forming a multi-dimensional domain defined by these parameters' value ranges. Since dimensionality cannot be reduced, parameter ranges must be as compact as possible to minimize iteration counts while ensuring the range encompasses the global optimum or near-optimal solutions, thereby maximizing convergence speed.

The transport line contains diverse physical components. In the ion source section, filament power supply is typically fixed at 8 V and cesium oven heater at 22 V; remaining parameters such as extraction, source focusing, cesium focusing, and cathode power supplies are determined based on sample characteristics [?].

The preliminary adjustment range is determined from theoretical preset values calculated during accelerator physics design. However, due to inevitable discrepancies between theory and practice, online testing reveals that theoretical presets alone yield suboptimal results. Therefore, actual commissioning requires establishing approximate ranges from theoretical values, followed by online adjustment of component power supplies according to specific principles while monitoring beam intensity. The operational procedure comprises three steps:

1) Calculate the mean μ and variance σ of each optical element' s power supply voltage from historical commissioning data to determine parameter ranges. Based on these statistics, initialize component parameters at their mean values, with search ranges divided according to the 3σ principle: $[\mu-3\sigma,\mu-2\sigma]$, $[\mu-2\sigma,\mu-\sigma]$, $[\mu-\sigma,\mu]$, $[\mu,\mu+\sigma]$, $[\mu+\sigma,\mu+2\sigma]$, and $[\mu+2\sigma,\mu+3\sigma]$ for refined parameter space exploration.

2) Select a search range and employ the DE algorithm to find optimal power supply parameter combinations within the multi-dimensional solution space, reading corresponding beam intensities while keeping other component parameters constant and maintaining the constraint that extraction voltage exceeds source focusing voltage.

3) Adjust component power supply parameters sequentially along the beam transport line, starting from the ion source, using the same method as step 2. After completing each beamline section, set its voltage/current values to those corresponding to maximum beam intensity.

3 Experimental Test Results and Applications

The DE algorithm's three most critical parameters are scaling factor F, crossover probability CR, and population size M.

Scaling Factor F: Representing the algorithm' s exploration capability, F is a crucial parameter. To validate its impact on beam intensity during mutation, experiments tested F values of 0.4, 0.5, and 0.6. As shown in Figure 5 [Figure 5: see original paper], the $F = 0.4$ curve exhibited slower initial growth, indicating stronger tendency to escape local optima at the cost of convergence speed, gradually stabilizing at approximately 14.9 A. The $F = 0.6$ curve showed steady beam intensity increase to about 13 A, maintaining stability in subsequent iterations. Although converging slower than $F = 0.4$, $F = 0.6$ ultimately achieved more stable values. The $F = 0.5$ curve rapidly converged to higher beam intensity within initial iterations, stabilizing at approximately 21 A after the 15th iteration. Overall, $F = 0.5$ demonstrated optimal performance in both beam intensity and convergence speed, achieving high, stable values with fewer iterations.

Crossover Rate CR: Typically valued in $[0, 1]$, CR determines information exchange between mutant vectors (offspring) and target vectors (parents) during crossover. Higher CR values increase population diversity but may slow convergence, while lower values accelerate convergence but risk premature convergence. Experiments examined CR values of 0.7, 0.9, and 0.95, as shown in Figure 6 [Figure 6: see original paper]. At $CR = 0.95$ (high crossover), beam intensity rose rapidly from 13.3 A to 20 A in early iterations, indicating accelerated global exploration. However, mid-to-late stages (iterations 10-25) showed stabilization around 20-21 A with slight fluctuations (e.g., minor rebound after iteration 21), likely due to excessive randomness. At $CR = 0.9$ (medium crossover), convergence was slightly faster initially than $CR = 0.95$ with greater late-stage stability, ultimately stabilizing near 21.8 A, effectively balancing exploration and exploitation while avoiding the fluctuations seen at $CR = 0.95$. At $CR = 0.7$ (low crossover), beam intensity only reached 9.3 A in the first 10 iterations, indicating insufficient local exploitation, and though reaching approximately 13 A after 20 iterations, failed to achieve the optima obtained at $CR = 0.9$ and 0.95, likely due to inadequate diversity causing suboptimal solutions.

Population Size M: Population size significantly influences search capability and diversity. Larger populations provide more search paths, facilitating global optimum discovery but potentially requiring more iterations, while smaller populations limit search capability and risk local optima. This study set population size between $5D$ and $10D$. With $D = 13$ power supply parameters to optimize, experiments tested M values of 65, 100, and 130. Figure 7 [Figure 7: see original paper] shows beam intensity evolution across iterations for these population sizes. At $M = 130$, beam intensity grew rapidly initially, stabilizing after approximately 44 iterations at about 22 A. At $M = 100$, growth was slightly slower, stabilizing after roughly 22 iterations at approximately 21 A. At $M = 65$, growth was fastest, stabilizing after only 15 iterations but reaching merely 15.9 A. These results demonstrate that population size significantly impacts both convergence speed and final beam intensity. Larger populations accelerate convergence and achieve higher beam intensity but increase computational cost. To balance resource and time costs, $M = 100$ was selected as the optimal population size for this experiment.

During the optimization phase, magnet power supply parameters remain fixed while the DE algorithm optimizes remaining optical component parameters within the new search ranges determined during beam finding. The algorithm further enhances beam intensity within these refined ranges, making minimal adjustments to electrostatic analyzers and quadrupole lenses while focusing optimization on ion source and magnet power supply parameters.

Through extensive experimental comparison using graphite samples, the optimal DE parameter combination was identified as $M = 100$, $F = 0.6$, and $CR = 0.9$, achieving convergence to a stable beam intensity of 21 A from the ion source within 25 iterations, reducing commissioning time to 30 minutes.

This research demonstrates that integrating the differential evolution algorithm with 0.3 MV compact AMS automatic beam commissioning overcomes the inefficiencies of traditional manual methods while enabling fine parameter adjustment, successfully showcasing significant advantages in enhancing accelerator performance and optimization efficiency. Experimental results indicate that the DE-based parameter control mechanism, through dynamic population search strategies and multi-dimensional evaluation incorporating online beam intensity and stability monitoring, substantially improves both beam stability and intensity, achieving a stable ion source beam intensity of 21 A. Practical results show average optimization time reduced from 3 hours (manual operation) to 30 minutes, with parameter optimization success rates increasing from 60% (conventional methods) to over 92%. Future work will focus on further algorithm optimization, development of multi-objective commissioning strategies, and validation across broader accelerator types.

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Note: Figure translations are in progress. See original paper for figures.