

# ARTIFICIAL INTELLIGENCE RESEARCH IN PARTICLE ACCELERATOR CONTROL SYSTEMS FOR BEAM LINE TUNING\*

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## Abstract

Tuning particle accelerators is time consuming and expensive, with a number of inherently non-linear interactions between system components. Conventional control methods have not been successful in this domain, and the result is constant and expensive monitoring of the systems by human operators. This is particularly true for the start-up and conditioning phase after a maintenance period or an unexpected fault. In turn, this often requires a step by step restart of the accelerator. Surprisingly few attempts have been made to apply intelligent accelerator control techniques to help with beam tuning, fault detection, and fault recovery problems. The reason for that might be that accelerator facilities are rare and difficult to understand systems that require detailed expert knowledge about the underlying physics as well as months if not years of experience to understand the relationship between individual components, particularly if they are geographically disjoint. This paper will give an overview about the research effort in the accelerator community that has been dedicated to the use of artificial intelligence methods for accelerator beam line tuning.

## BEAM LINE TUNING

A typical accelerator beam line includes trim magnets for steering, quadrupole magnets for focusing, Faraday cups and stripline detectors for measuring current, and profile monitors for measuring beam size and position. Beam loss monitors give information about loss of beam through miss-steering. Unfortunately, real systems rarely work as they are designed. Problems arise from imperfect beam production, residual magnetic fields, poorly modeled beam behavior, misplaced or flawed control elements, and changes to the design or use of the facility after it has been built. Beam line designers consider these problems and build diagnostic components into the beam lines. Profile monitors and current detectors are used to measure beam parameters throughout the line to provide information for verifying or correcting beam characteristics. Even so, imperfect detectors, system errors, and noise due to various effect cause beam line control to be difficult at best. Surprisingly, few attempts have been made to apply intelligent accelerator control techniques to help with beam tuning, fault detection, and fault recovery problems.

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## PREVIOUS AI ATTEMPTS TO ACCELERATOR CONTROL

An early example of AI technology applied to accelerator control can be found in Higo et al. [1]. In this work a rather simple objective of maintaining a given system or operation condition has been discussed. AI is relevant here for dealing with the complex problems of generalized hysteretic and stochastic effects.

Weygand [2] reports on a development for a knowledge-based, domain specific expert system at Brookhaven National Laboratory. The purpose of the expert system is to aid in the control of the Heavy Ion Transfer line (HITL) and in turn to minimize down time after a change in running conditions or the start of a new run. Due to the complexity of the expert system it was divided up into three domains (control, device beam influence, and device cause and effect segment). Separate from that is the goal-solving mechanism of the program. This goal-solving function takes a specified high level goal, and then, by developing a tree of sub-goals, attempts to solve the given goal via a hill-climbing technique. However, the system doesn't take into account that conditions may change during the execution of the solution.

Other attempts at intelligent control for accelerators include the ISIS tune advisor (Schultz et al. 1990), the LAMPF Beam Loss Expert (Clearwater et al. 1986), and a learning system based on RL4 (Clearwater et al. 1990). The ISIS tune advisor and LAMPF Beam Loss Expert were both expert systems for indirect control which were never implemented as general or real-time control solutions. The learning system used knowledge-based induction for off-line learning of beam position monitor placement, but was not implemented as a general learning algorithm.

Neural networks have been applied to accelerator control for actual manipulation of control parameters as well as for simulation. Howell et al. [3] used neural networks for modeling and control of a negative-ion accelerator source at Los Alamos National Laboratory to predict the beam characteristics of the source for given changes in control settings. However, the success was rather limited.

Brown [4] developed an automated controller based on an artificial neural network and evaluated its applicability in a real-time environment. This capability was developed within the context of a small angle negative ion source on the Discharge Test Stand at Los Alamos National Laboratory. Using no knowledge of operating conditions, the controller begins acquiring rough snapshot of the

operational condition. Once the rough approximation of the condition has been determined, the network formulates a model from which it determines the best operating point. The controller takes the ion source to that operating point for a reality check. As real data is fed in, the model of the operating surface is updated until the neural network's model agrees with reality. The controller then uses a gradient ascent method to optimize the operation of the ion source. Mead (1994) presents some successful control examples of the above application.

The SETUP program developed at CERN (Bouche 1995) is representative of efforts to apply AI techniques to small subsystems. SETUP is only used for pre-control equipment setup. The program uses an object-oriented description language for representing control actions. The reasoning system searches the oriented graph defined by an object description to make decisions about equipment setup without human assistance. The program provides a good example of using object models for control decision making. It does not attempt to perform real-time control or use on-line feedback from the system.

Arruat [5] reports on symbolic computing programs that address not only the manipulation of mathematical functions, but also process control. He uses symbolic computing as a tool for developing algorithmic engines that can be fully integrated in the controls environment and facilitates modular design of control systems. He reports that this technique has been applied to a special class of accelerator problems, namely the beam steering in transfer lines and accelerator rings in the CERN PS Complex.

In his Ph.D. dissertation Jennings [6] developed and implemented a new model of multi-agent coordination, called *Joint Responsibility*, based upon the notion of joint intentions. The Responsibility framework was devised specifically for coordinating behavior in complex, unpredictable and dynamic environments such as particle accelerator control. Jennings contribution was that he noticed that in a distributed multi-agent system when anything unexpected happened (i.e. new information invalidated existing goals, synchronization between actions was disrupted or agents had misinterpreted the situation) the multi-agent community would act incoherently. This incoherence occurred because agents did not embody sufficient knowledge about the process of team problem solving. Jennings provided agents with an explicit model of joint problem solving about which they could reason when deciding how to interact with others. This new development found its application in ARCHON.

ARCHON (1993-1996) was Europe's largest ever project in the area of Distributed Artificial Intelligence (DAI) and applied to CERN control systems for controlling and diagnosing faults in one of their particle accelerators (called the Proton Synchrotron (PS)). The Archon-project, which Jennings was in charge of,

provided the architecture for integrating multiple pre-existing expert systems to exchange information and, therefore, increase the overall performance.

Another application of AI techniques in operating a larger system is in the field of fault detection and system diagnosis. Leger et al. (1996) points out that in order to operate a successful plant, continuous improvement must be made in the areas of safety quality and reliability. Central to this continuous improvement is the early or proactive detection and correct diagnosis of process faults. The paper examines the feasibility of using cumulative summation control charts and artificial neural networks together for fault detection and diagnosis (FDD). The control chart and neural network are linked by using a characteristic fault signature pattern for each fault, which is to be detected and diagnosed.

In one of the first papers from Klein and Luger [2] on beam tuning, a framework of a general purpose intelligent control system for a particle accelerator has been presented. Results of coupling neural network and expert systems technology to solve several standard accelerator tuning problems based on realistic simulations have been discussed. The authors also examine the effectiveness of additional heuristic search techniques such as genetic algorithms. However, the algorithm did not converge towards specific solution methods to create the desired result. To solve the problem, the authors also examined the capabilities of an analytic control algorithm, fuzzy logic (FL) control, and genetic algorithm searches. It was noticed that the accuracy of the FL solution depended greatly on the quality of the knowledge the author placed in the system. The genetic algorithm is an appropriate heuristic for focusing control because it can search large solution spaces in non-linear domains.

In continuation of their earlier work Klein and Luger (Klein et al. 1997(a)) have identified two different sources of control information that must both be incorporated into any successful automated control system. The first source includes analytic domain knowledge necessary for modeling the accelerator and beam line. The second, equally important source is experiential knowledge about the specific facility and group of components being controlled.

Stern (Stern et al. 1997) reports on the continuing work of Klein on coordinating the activity of the control subsystems to adaptively execute sustained sequences of control actions of the type required to tune the whole accelerator in a coordinated fashion. The discussed control system employs a multi-layer organization in which knowledge-based decision making is used to dynamically configure a lower level optimization and control algorithm. An object-oriented physical access layer supported by a distributed control system allows abstraction from the lower level details of hardware manipulation, signal processing, and synchronization.

This hybrid architecture integrates a variety of methodologies, including teleo-reactive trees for dynamic exception handling and re-planning.

In Klein's last paper [7] he discusses the results of their research on the use of Teleo-Reactive programming as a high level control mechanism. According to the authors, control of particle accelerators requires a hybrid architecture which includes methodologies for planning, intelligent search, and pattern recognition. The author's suggestion is that control must be distributed and hierarchical to utilize parallel problem-solving in the face of time-sensitive control requirements and to decompose complex control problems into more manageable subtasks. As a high level control mechanism, the authors used a planning technique known as Teleo-Reactive (TR) programming developed by Nils Nilsson at Stanford. TR programming combines the responsiveness of an analog feedback loop and the goal-oriented behavior of a production system, to allow the control system to govern the execution of its tasks in a dynamic environment. The system has been successfully tested at both the Brookhaven National Laboratory ATF and at the ATLAS facility at Argonne National Laboratory.

Fiesler [8] reports on a suit of tests on predictive algorithms to determine their ability to learn from and find relationships between large numbers of variables. In particular, they used COMFORT, a particle accelerator simulator, to generate large amounts of data. They eventually compared the results among several fundamentally different types of algorithms, including least squares and hybrid neural networks with real data that were obtained from Brookhaven National Laboratory.

### SUMMARY

It seems surprising that virtually all research on AI applied to particle accelerator stopped around the year 2000. This certainly can't be explained with the Y2K problem. Nevertheless, it seems like interest and/or funding must have stopped around that time. The alternative is, of course, that the research in the area wasn't promising or the problem was so complex that researchers did not find the return of investment very appealing to them.

Nevertheless, the author of this paper sees a great chance for AI to make its comeback in accelerator control rooms. The first and foremost reason is that running these machines has become a time and cost critical issue. The older an accelerator gets the more maintenance/upgrade work needs to be invested. This in turn creates a problem since users/experimenters are paying to do their experiments and extensive maintenance/upgrade work reduces experimental time. With less time for experiments less money comes in for maintenance. However, less maintenance means that the accelerators become more error/fault prone. Therefore, managers have to balance

down time vs. beam time and try to minimize conditioning, start-up time and fault recovery time. In addition, managers increase their attention to preventive maintenance (predicting when something might happen and then to something beforehand).

Speeding up beam tuning, advanced fault detection, and preventive maintenance (sometimes referred to as structural health) are areas where AI can and has already made an impact. Specifically applied to accelerator controls, expert beam tuning systems have been around for more than a decade, fault recovery programs got more attention at the end of the century. On the other hand preventive maintenance has never been applied to accelerator facilities. So, there is a chance here to lead the way.

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