AI-READY LATTICE REPRESENTATION AND ML OPTIMIZATION FOR THE BNL BOOSTER-TO-AGS TRANSFER LINE*

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Abstract

As part of the Nuclear Physics AI-Ready Accelerator Data (NARAD) project, Brookhaven National Laboratory is developing a demonstration use case based on the Booster-to-AGS (BtA) transfer line. We establish an AI-ready representation of the BtA lattice using the Particle Accelerator Language Standard (PALS), extended with semantic metadata linking lattice elements to control system signals and device capabilities. This NARAD-PALS model enables direct mapping between simulation, operational devices, and machine data. We implement this framework for the BtA line and demonstrate semantic device queries and control-channel resolution within the BNL Accelerator Device Objects (ADO) system. This unified representation supports integration of streaming and archived data and provides a foundation for ML-based optimization of AGS injection and cross-facility interoperability.

INTRODUCTION

Modern accelerator facilities increasingly rely on machine learning (ML) techniques for applications such as online optimization, anomaly detection, and digital-twin development. However, these efforts are often limited by heterogeneous, facility-specific data structures and control system representations. Existing infrastructures, including Brookhaven National Laboratory's Accelerator Device Objects (ADO) [1] and EPICS [2], provide essential operational interfaces but lack the semantic structure needed for scalable interoperability, automated reasoning, and reusable ML workflows across facilities.

The DOE Nuclear Physics AI-Ready Accelerator Data (NARAD) initiative addresses these challenges by developing standardized, AI-ready schemas for accelerator data and lattice models. Within this effort, the Booster-to-AGS (BtA) transfer line at Brookhaven National Laboratory serves as a demonstration use case. The BtA line contains a diverse set of magnets and diagnostics integrated into a legacy ADO-based control system, making it a representative testbed for challenges related to device modeling, signal consistency, and control system semantics. Figure 1 illustrates the high-level NARAD architecture, showing how facility-specific models are represented using Particle Accelerator Language Standard (PALS) and integrated into a knowledge graph and data services layer to support downstream applications.

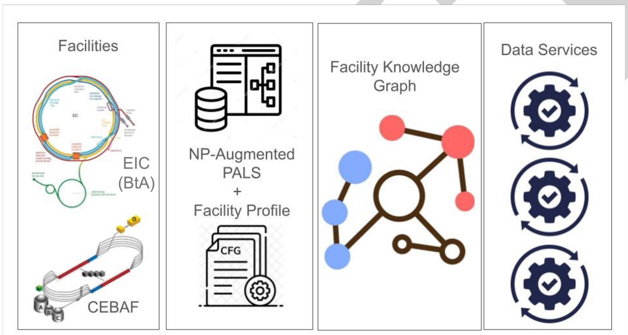

Figure 1: High-level architecture of the NARAD framework, illustrating the integration of facility models, PALS representations, knowledge graph infrastructure, and data services for AI-ready accelerator workflows.

Building on this architecture, we extend PALS with NARAD semantic metadata that unifies physics-based lattice descriptions with machine-queryable control system information. The resulting framework links lattice elements, control signals, device capabilities, and operational constraints within a single structured representation. Building on this representation, we develop methods for semantic device queries, control-signal mapping, and integration of streaming and archived machine data from the BNL accelerator database. The framework also enables higher-level orchestration workflows using large language model (LLM)-based tools.

Using these components, we aim to construct an AI-ready BtA model suitable for simulation-driven ML optimization studies, including optimization of AGS injection quality. This work demonstrates how standardized semantics and shared data representations can accelerate AI applications in accelerator facilities while providing a prototype for cross-facility interoperability within the emerging NARAD ecosystem.

BTA TRANSFER LINE OVERVIEW

The Booster-to-AGS (BtA) transfer line transports beam from the Booster extraction point at F6 to the AGS injection

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point at L20 while matching the Twiss parameters and dispersion of the circulating AGS beam [3]. The line consists of 15 quadrupoles, 5 dipole bends, 2 horizontal correctors, 4 vertical correctors, a stripping foil for heavy-ion operation, and four multi-wire profile monitors [4], as shown in Fig. 2.

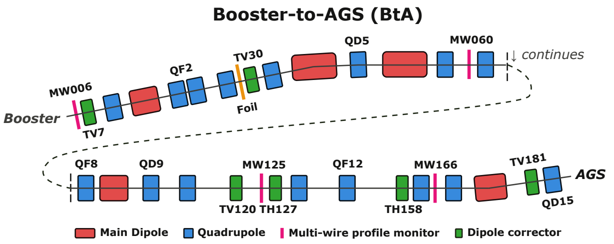

Figure 2: Schematic layout of Booster-to-AGS line.

Proper injection requires the optics at the end of the transfer line to match the AGS lattice conditions. Because the BtA lattice does not contain phase advances that are simple multiples of $\pi/2$, the responses of quadrupoles and correctors are strongly coupled. As a result, beam steering and envelope shaping cannot be tuned independently, making the line a challenging and realistic environment for ML-based optimization studies.

NARAD–PALS FRAMEWORK FOR BTA MODELING

PALS provides a physics-based, simulation-oriented description of accelerator components, including optics, geometry, and lattice relationships. To support AI workflows and cross-facility interoperability, the NARAD project extends PALS with semantic metadata describing device capabilities, control system associations, and machine-queryable signals.

These extensions introduce a structured representation that links lattice elements to their corresponding operational context, including control interfaces and measurement channels. This unified model enables consistent interpretation of accelerator components across simulation tools, control systems, and data infrastructures, providing a common semantic layer for downstream applications. For example, a semantic query for horizontal corrector current setpoints resolves the corresponding BtA ADO manager and device names and returns the associated live or archived current signals.

To support semantic queries and ML workflows, the NARAD-PALS representation can be materialized as a knowledge graph [5], encoding relationships between lattice elements, devices, and signals in a machine-navigable form. This approach enables device discovery, relationship queries, and integration with both static lattice descriptions and dynamic machine data.

By coupling lattice physics with control system semantics, the NARAD-PALS framework provides a foundation for AI-ready accelerator models, enabling seamless transitions between simulation, operations, and data-driven applications.

CONTROL SYSTEM MAPPING AND DATA INFRASTRUCTURE

A key requirement for AI-ready accelerator workflows is a machine-readable interface connecting semantic device descriptions to control system channels. For the BtA line, we implemented a query mechanism that maps NARAD-PALS device definitions to ADO manager and device names, analogous to channel-finding services in EPICS environments. This enables structured queries, such as retrieving corrector currents or profile-monitor measurements, providing a consistent bridge between the semantic model and the physical control layer.

In addition, we developed methods to access both live and archived machine data from the BNL accelerator database, with interfaces compatible with Jefferson Lab's Streaming Monitoring Optimization and Control System (SMOCS) [6] for streaming data integration. Within the NARAD-PALS model, each signal is associated with its corresponding lattice element, enabling consistent linkage between device semantics and measured data. Together, these capabilities form the operational layer of the AI-ready BtA model and support downstream data-driven applications.

WORKFLOW INTEGRATION AND ML OPTIMIZATION PATH

The NARAD-enabled BtA model provides a unified interface linking lattice descriptions, control system mappings, and machine data, forming a foundation for ML-based optimization workflows. The semantic representation enables consistent access to device settings and diagnostics, supporting data-driven tuning and analysis.

Previous studies at BNL have demonstrated that Bayesian Optimization (BO) is effective for tuning complex transfer lines [7, 8], achieving efficient convergence under coupled magnet responses and noisy measurements. Reinforcement learning (RL) studies [9] using Bmad simulations have similarly shown the ability to steer the system toward near-optimal Twiss and dispersion matching.

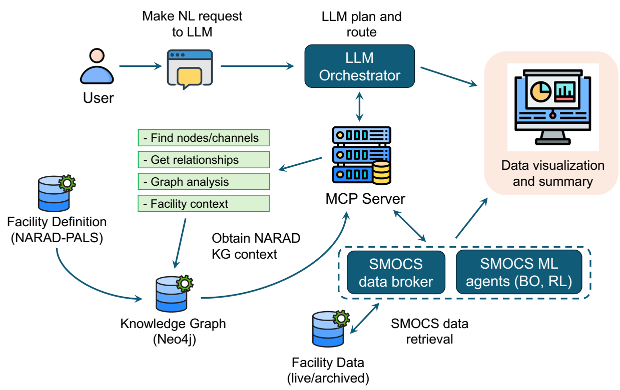

Figure 3: NARAD workflow integrating PALS lattice files, the semantic knowledge graph, SMOCS data services, and downstream ML agents, with high-level LLM orchestration enabling natural language interaction.

At a higher level, this framework also supports integration with LLM-based orchestration tools such as Osprey [10] that translate user intent into structured queries and data-driven workflows, as illustrated in Fig. 3. Within this architecture, ML methods operate on a consistent, semantically enriched representation of the accelerator, enabling integration of simulation, controls, and data for future optimization studies.

CURRENT IMPLEMENTATION AND PROGRESS

The NARAD-PALS framework has been implemented for the BtA transfer line, with semantic extensions developed for key devices including quadrupoles, correctors, and multi-wire profile monitors. These extensions integrate physics-based lattice descriptions with control system metadata, enabling a unified representation that connects simulation elements to operational device semantics.

A control system query mechanism has been realized for the BNL Accelerator Device Objects (ADO) environment, allowing semantic device definitions to be resolved to corresponding channel names. This mechanism is used to programmatically identify and validate control system signals associated with each lattice element, enabling structured retrieval of device settings and diagnostics directly from the control system.

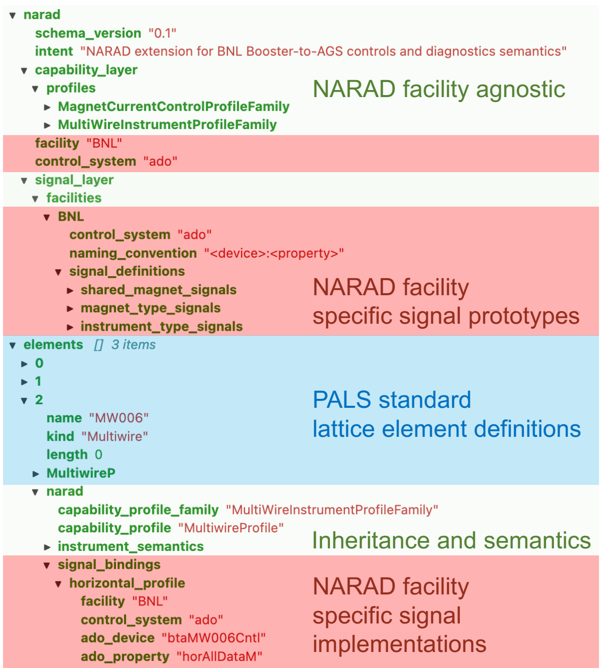

Figure 4: Excerpt of the implemented NARAD-augmented PALS YAML representation for the BtA transfer line, illustrating integration of lattice elements, semantic metadata, and ADO control system bindings.

These capabilities enable automated, query-driven retrieval of device settings and diagnostics, providing a practical interface between the semantic model and the underlying control system. Figure 4 shows an excerpt of the resulting BtA YAML representation, illustrating how lattice elements, semantic metadata, and ADO signal bindings are combined within a single structure.

In parallel, methods have been developed to access both live and archived accelerator data from the BNL database, with signals consistently associated to their corresponding lattice elements within the NARAD-PALS model. This provides a coherent interface between device semantics and measured data, supporting data-driven analysis workflows.

These components establish the core infrastructure required for integrating machine learning methods with the BtA system, providing a consistent and semantically enriched representation spanning simulation, controls, and machine data.

CONCLUSION

We have developed and implemented an AI-ready, semantically enriched representation of the BtA transfer line by extending PALS with NARAD ontology and control system semantics. The resulting NARAD-PALS model integrates lattice physics, device metadata, and ADO control mappings within a unified, machine-queryable structure.

The implemented framework enables consistent linkage between simulation models, operational devices, and both archived and streaming machine data. This provides a practical foundation for data-driven analysis and supports integration of machine learning methods for accelerator optimization.

This work demonstrates how standardized semantics and structured data representations can enable scalable AI applications in accelerator facilities, and provides a practical prototype for cross-facility interoperability within the NARAD ecosystem.

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