Machine learning application for particle accelerator optimization-a review

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ABSTRACT

Particle accelerators receive significant attention from researchers. This machine consists of various interdependent elements, so it is complex. Efficient system tuning and diagnostics are essential for utilizing accelerator technology. In addition, machine learning (ML) has been applied in several applications. ML methods such as artificial neural networks, random forest, reinforcement learning, genetic algorithm, and Bayesian optimization have been used for accelerator optimization. The optimization of particle accelerators covers their performance and efficiency. This paper reviews the application of ML techniques in optimizing particle accelerators, highlighting their importance in addressing the complexity inherent in accelerator systems and advancing accelerator science and technology.

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1. INTRODUCTION

Particle accelerators accelerate charged particles at atomic and subatomic sizes [1]. Particle accelerators play crucial role in industrial applications, scientific research, and healthcare, including production of radioisotopes [2], nuclear forensics [3], genetic mutation [4], [5], accelerator-driven systems [6]–[8], nuclear laboratories, materials research [9]–[12], and boron neutron capture therapy. Protons and electrons, which are charged with atomic particles, comprise most of the particle stream. Generally, particle accelerators are developed according to their specific purposes, and the type of application depends on accelerator's energy.

Some particle accelerators have complex experimental installations and produce directed beams of high-energy particles toward targets. The main components of an accelerator consist of the charged particle beam source or injector, acceleration system, vacuum tube system, optic system, target system, and instrumentation and control system. The interrelationships among the systems result in high complexity. Considering the complexity of each subsystem and the unpredictability of interactions among them, it is pretty challenging to avoid failures and operational errors [13]. Navigating the nonlinear functions of the components and dynamic machine settings in accelerator optimization is a significant challenge affecting particle beam design, operation, and control [14].

Particle accelerators are nonlinear systems, and further research is necessary due to their complexity [15]. There are many intrinsic nonlinear interactions between its system components. It is challenging to navigate through the nonlinear functions of thousands of components and dynamic machine settings in particle accelerator optimization [16]. These factors affect particle beam design, operation, and control. Conventional methods have not been successful in this domain, leading to constant and costly system monitoring by human operators. Artificial intelligence (AI) itself has been widely applied in several applications [17]–[19]. AI algorithms are essential for control, tuning [20], diagnostics [21], and modeling of accelerators. Various machine learning (ML) methods have been utilized for accelerator development.

Designing accelerators more efficiently may be accomplished by utilizing ML techniques. Using sophisticated optimization methods and data-intensive approaches, ML may boost productivity, accelerate design, and enhance the accelerator's performance. The algorithms might examine large datasets from previous accelerator designs and simulations to find trends and optimize settings for desired results. Using massive datasets containing past performance and experimental outcomes, researchers may train ML models to find patterns and associations that help guide the design and management of vital accelerator parts. For instance, ML algorithms can assist in optimizing the design cavity's form and material composition to increase particle acceleration efficiency.

Moreover, ML can support particle accelerator systems' stability and control. ML algorithms can enhance the control settings for strength and performance, resulting in more efficient operation, by evaluating real-time sensor data and using predictive modeling. The techniques follow the goals to be achieved. This paper reviews various ML techniques and applications for accelerators. By conducting a review, it is expected that knowledge will be obtained, namely knowing what techniques exist in ML, grouping ML methods based on problems faced in particle accelerators, the advantages of these methods, and the requirements that must be met to optimize using ML.

2. METHOD

The research questions for ML in particle accelerators revolve around optimizing parameters, identifying utilized ML methods, and understanding trends in accelerator ML applications. Keyword and literature search is vital for identifying relevant literature through appropriate keywords and search strategies, using Boolean operators to refine searches. We review retrieved document titles and abstracts to assess relevance to the research question, documenting the search process meticulously for transparency and reproducibility. Knowledge extraction involves synthesizing pertinent insights from various sources to address research objectives and organizing and interpreting information systematically to derive meaningful insights. Critical evaluation ensures the integrity of extracted knowledge, facilitating subsequent analysis and interpretation. Knowledge differentiation categorizes and organizes extracted knowledge based on themes, patterns, or variations, deepening understanding and enabling more effective analysis.

Figure 1 shows the analysis using VOSviewer. There is a strong connection between the fields of particle accelerator technology and AI analysis using VOSviewer. This is because neural networks and other AI techniques are increasingly used to control and optimize particle accelerators. The use of neural networks and other AI methods in particle accelerator technology is a rapidly growing field. As AI techniques continue to develop, we can expect to see even more innovative applications in this field.

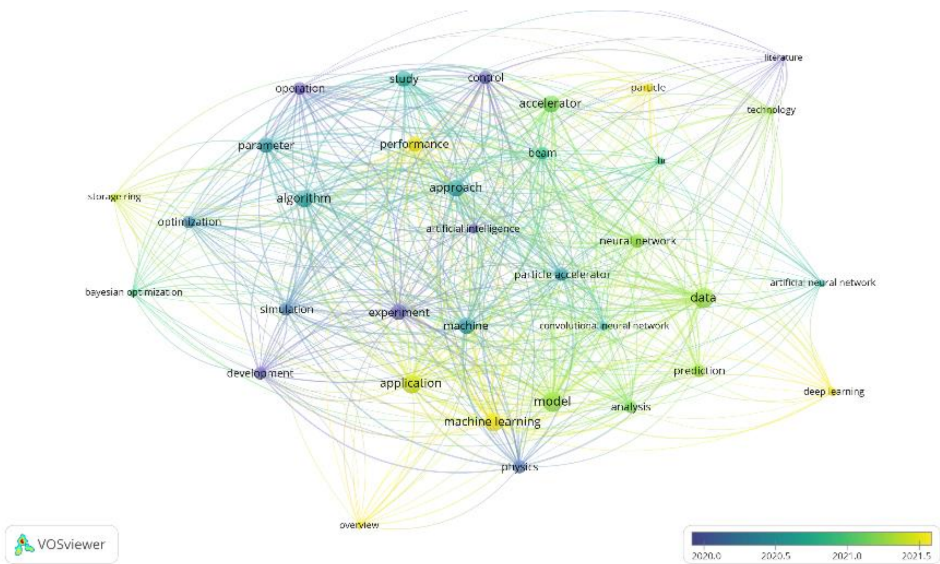

Figure 1. Trends of ML applications for particle accelerator optimization

3. MACHINE LEARNING ALGORITHM

ML becomes attractive due to the abundance of data. It can learn complex patterns, predict outcomes, and automate processes. ML generally learns relationships between input and output from existing data [22]. Tasks performed by ML include regression, classification, clustering, and anomaly detection problems [23], [24]. Several ML methods, often combined with optimization techniques, are explained in the following sub-sections.

3.1. Artificial neural networks

One of the most famous and commonly used ML algorithms is artificial neural networks (ANN) [25]. ANN is well-suited for learning tasks where data includes noise, complex signals, and target output functions that may consist of multiple parameters. A neural network can be defined as a collection of functions with weighted connections among them. These weighted connections can be adjusted or trained through an automated optimization process until the desired output behavior is achieved. Training may also involve changes to the structural components of the network, such as the number of nodes and layers [26]. Neural networks can be trained using simulation data, measurable data, or a combination of both. Many training approaches and architectures are available, each suitable for specific problem classes.

ANN is widely used in various fields, from safety to critical areas such as accelerators [27]. ANN belongs to familiar ML methods that are frequently used in accelerator applications. Several studies have been conducted on the use of neural networks [28]. ANN, especially deep learning models, are powerful tools for learning complex patterns and relationships from data. They can be used for tasks such as surrogate modelling, where the neural network learns to approximate the performance of particle accelerator components based on input parameters. ANN can also be integrated into optimization algorithms to guide the search process more effectively. The applications of ANN include beam dynamics optimization [29], control [30], surrogate model particle accelerators [31], phase space diagnostics [32], and optics reconstruction.

3.2. Random forest

Random forest is an algorithm that can be used for regression and classification analysis. Random forest is a versatile ML method that can be effectively applied to various aspects of particle accelerator optimization, including surrogate modelling, feature importance analysis, anomaly detection, and ensemble optimization. The random forest method is effective for instrumentation error detection, for example, for identifying and correcting errors in magnets.

3.3. Reinforcement learning

Reinforcement learning (RL) is a framework in which artificial agents learn by interacting with their environment. RL can be used to develop surrogate models that reproduce real-world systems' behaviors and train online agents to take control actions in those systems [33]. These online agents will ultimately control the actual accelerator system. RL has been applied in control, orbit correction [34], and real-time feedback control loop [35].

3.4. Genetic algorithm

Genetic algorithm (GA) is an evolutionary optimization technique inspired by natural selection. They are well-suited for problems with an ample search space and complex, nonlinear relationships. GA can efficiently explore the design space of particle accelerators and identify optimal configurations for components such as cavities, magnets, and radio frequency (RF) systems.

3.5. Bayesian optimization

Bayesian optimization is a probabilistic optimization technique that uses surrogate models to approximate the objective function [36], [37]. It efficiently balances exploration and exploitation to find the global optimum while minimizing the number of evaluations. Bayesian optimization is effective for optimizing black-box functions, making it suitable for optimizing complex simulations of particle accelerator systems.

4. MACHINE LEARNING IMPLEMENTATION FOR PARTICLE ACCELERATOR

Particle accelerators are necessary for many scientific projects, but optimizing their performance and reliability presents significant challenges. ML techniques offer promising solutions for enhancing design components, parameter optimization, control, diagnostics, and modelling particle accelerators. Particle accelerators benefit significantly from applying ML techniques, offering promising solutions to better design components, prediction, anomaly detection, parameter tuning, real-time adaptive control, and beam dynamics. Figure 2 shows several ML methods and their applications for particle accelerator optimization.

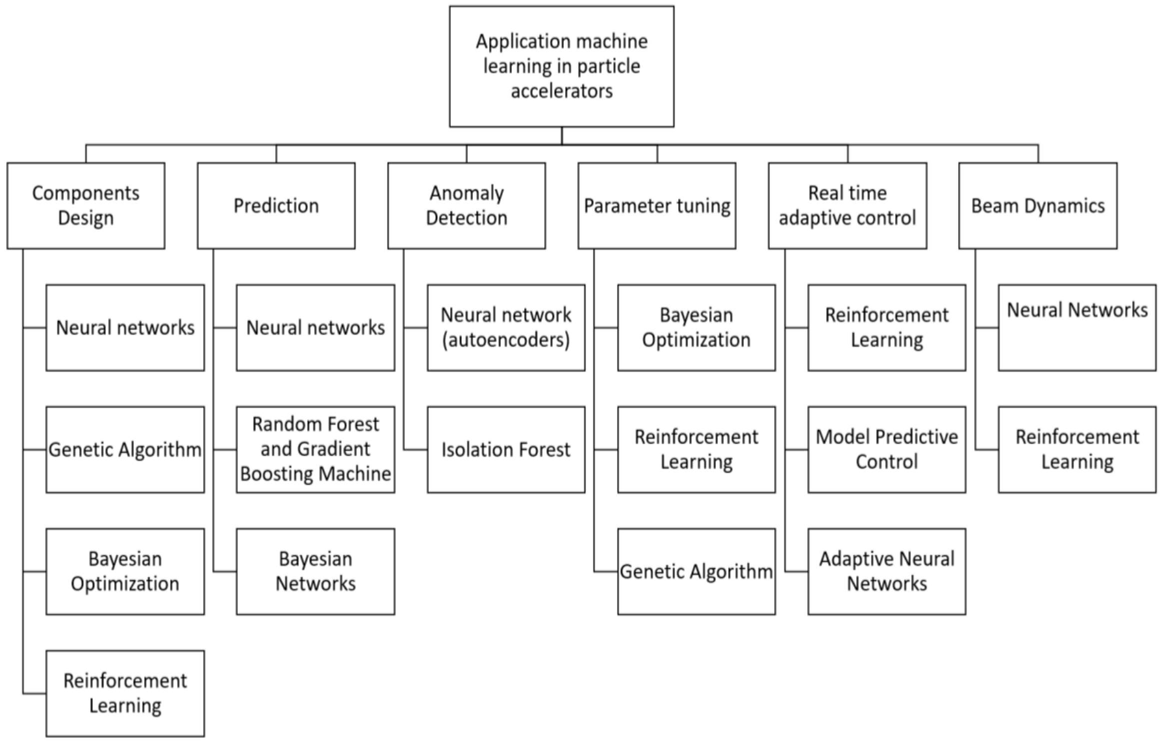

Figure 2. ML methods and their applications for particle accelerator optimization

4.1. Design components

Ensuring adequate particle acceleration necessitates optimizing accelerator components, including the detector, high-voltage pulse transformers, magnetic components [38], RF, cavity, acceleration systems, and control monitoring systems. ML models can examine past data, simulations, and experimental outcomes to determine the best designs for the components. Utilizing ML techniques to design the components and develop surrogate models is expected to improve particle accelerator efficiency, performance, and reliability.

4.2. Prediction and anomaly detection

The particle accelerator behavior can be predicted using ML methods. This includes the prediction of low-energy beam transport tuning, time series forecasting using classification approaches [39], beam loss modelling [40], prediction of low-energy beam transport tuning, and longitudinal phase space [41]. ML can automate and expedite diagnostic processes, producing more reliable, high-performance accelerators. Other ML applications for particle accelerator diagnostics include anomaly detection [42]. Anomaly detection techniques have also been applied to clean measured data by comparing it with clustering techniques.

4.3. Parameter tuning

ML algorithms can facilitate real-time optimization of parameter control strategies based on data-driven insights. By analyzing large datasets of operational parameters and performance metrics, ML models can identify correlations, patterns, and optimal control strategies for ion sources and other critical components. This enables adaptive control mechanisms that dynamically adjust operational parameters to optimize accelerator performance under various conditions. Beam parameter optimization uses lasso regression for online tune correction and neural networks for beta function simulation correction [43]. Detection of magnetic field errors using autoencoder neural networks, linear regression, and tuned feedback storage rings [44].

4.4. Particle accelerator control and diagnostics

ML in the control of particle accelerators can be utilized for system failure prediction, anomaly detection, control optimization, and automatic control. Some applications of ML in accelerator control include detector control and calibration [45], automatic beam position control [46], predictive accelerator control, beam matching control, adaptive control for beam diagnostics [47], electron bunch profile detection, and beam dynamic control [48]. Particle accelerator diagnostics is a complex and time-consuming process that identifies and addresses issues in the accelerator. ML can help automate and expedite diagnostic processes, resulting in more reliable and high-performance accelerators. Some ML applications for particle accelerator diagnostics include multivariable diagnostics and virtual diagnostics of beam longitudinal properties [49], [50].

4.5. Modelling

Particle accelerator modelling is the process of simulating particle behavior within the accelerator. This process is essential for designing, optimizing, and commissioning accelerators. ML can help improve the accuracy and efficiency of particle accelerator modelling. Here are some ML applications for particle accelerator modelling: prediction of low-energy beam transport tuning, time series forecasting using classification approaches, modelling of beam loss, prediction of low-energy beam transport tuning, uncertainty analysis, beam dynamics [51], [52], development of other applications. The study of particle beam motion in accelerators covers particle interactions, electromagnetic fields, and other elements. ML methods can model, predict, and optimize particle beam behavior.

5. CONCLUSION

ML presents a powerful toolset for advancing particle accelerator technologies, offering control, tuning, diagnostics, and modelling improvements. The design and analysis of accelerator beam dynamics can use a GA, prediction, and anomaly detection using neural networks and random forests. In addition, linear and nonlinear regression can help analyze system parameters, and parameter tuning can use Bayesian optimization and control using RL. The combination of these techniques allows for more sophisticated optimization and responsiveness to changing operational conditions, improving the overall efficiency and performance of the accelerator. Several requirements must be addressed to implement ML-based optimization for particle accelerators. Firstly, high-quality and representative datasets are essential for training accurate ML models. The datasets should encompass various operational conditions and performance metrics, ensuring robust model training and validation. Additionally, collaboration between domain experts, data scientists, and ML specialists is necessary to develop effective optimization strategies that address the unique challenges of particle accelerator systems. Continued research and development in ML applications promises to enhance particle accelerators' performance and reliability further, driving scientific discovery and innovation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Taufik	✓			✓	✓	✓	✓			✓		✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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