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A LITERATURE REVIEW OF THE EFFORTS MADE FOR EMPLOYING MACHINE LEARNING IN SYNCHROTRONS*

A. Khaleghi[†1], Z. Aghaei, K. Mahmoudi, H. Haedar, I. Imani, Computer Group, Imam Khomeini International University, Qazvin, Iran
M. Akbari, M. Jafarzadeh, F.A. Mehrabi, P. Navidpour, Iranian Light Source Facility Institute (ILSF) for Research in Fundamental Sciences (IPM), Tehran, Iran
[1]also at Iranian Light Source Facility Institute (ILSF) for Research in Fundamental Sciences (IPM), Tehran, Iran

Abstract

Using machine learning (ML) in various contexts is increasing due to advantages such as automation for everything, trends and pattern identification, highly error-prone, and continuous improvement. Even non-computer experts are trying to learn simple programming languages like Python to implement ML models on their data. Despite the growing trend towards ML, no study has reviewed the efforts made on using ML in synchrotrons to our knowledge. Therefore, we are examining the efforts made to use ML in synchrotrons to achieve benefits like stabilizing the photon beam without the need for manual calibrations of measures that can be achieved by reducing unwanted fluctuations in the widths of the electron beams that prevent experimental noises obscured measurements. Also, the challenges of using ML in synchrotrons and a short synthesis of the reviewed articles were provided. The paper can help related experts have a general familiarization regarding ML applications in synchrotrons and encourage the use of ML in various synchrotron practices. In future research, the aim will be to provide a more comprehensive synthesis with more details on how to use the ML in synchrotrons.

INTRODUCTION

Synchrotrons light sources are very large-scale experimental facilities. A synchrotron is a large machine whose size is about a football field (Fig. 1). In these facilities, electrons are accelerated to almost the speed of light. By deflecting electrons through magnetic fields, they create incredibly bright light. The electrons are deviated in the storage ring by different magnetic components such as bending magnets, undulators, wigglers, focusing magnets. This deviation results in a tangential emission of X-Rays by the electrons. The resulting X-rays are emitted as dozens of thin beams, each channeled down "beamlines" surrounding the storage ring in the experimental workstations where the light is used for research. Each beamline is designed for use with a specific technique or type of analysis [1]–[3]. The produced light is advancing research and development in fields as diverse as biosciences, medical research, environmental sciences, agriculture, minerals exploration, advanced materials, engineering, forensics [1]. The intense and highly focused light is used to study the dynamic and structure of materials down to atomic level using various techniques offered by different beamlines like diffraction, spectroscopy, tomography, and imaging [4]. Please see the references [1]–[3], [5] to see how a synchrotron works in more detail. Also, the list of light sources of the world can be found in [6].

Synchrotrons light sources worldwide are experiencing fast changes from traditional 3rd generation to multi-bend achromatic (MBA)-based 4th generation storage ring light sources to achieve high-brightness and low-emittance upgrades [7], [8]. The Advanced Photon Source (APS) and the Advanced Light Source (ALS) are both being upgraded to MBA-based new rings. Diamond Light Source (DLS) designed a machine lattice based on double triple bend achromats [8]. The upgrades will substantially harness the light beam brightness from what is offered by the existing rings (the light brightness is much more greater than the sunlight) [7].

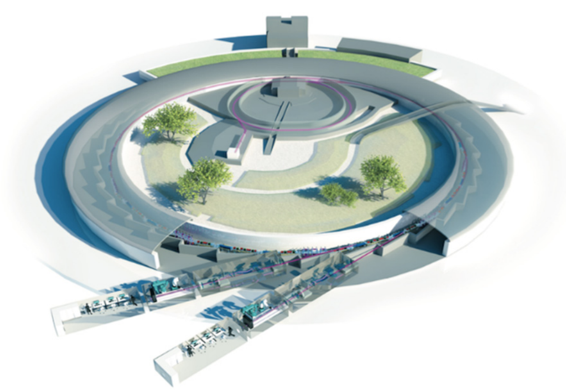

Figure 1: A 3D illustration of a synchrotron [2].

The rapid development of synchrotrons massively is accompanied by two significant challenges. First, the new rings drive for significantly lower emittances. Therefore, the beam dynamics in the rings become extremely nonlinear, causing smaller dynamic aperture and potentially smaller momentum aperture [7]. The extremely small emittance in a new ring needs much higher beam stability, which raises the need for a good understanding of the impact of environmental factors on the accelerator and

* Work supported by Iranian Light Source Facility (ILSF)
† khaleghiali@ipm.ir

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beams [7]. Second, the speed of doing experiments and the amount of raw data collected during each experiment is increasing [9], [10]. Typically, each light source theoretically can produce one petabyte of data per day [11]. Or accelerators can generate three-petabyte data just in one experiment [12]. The manual analysis of such massive data volumes is no longer possible [9], [10].

Moreover, the lack of automatic data analysis prevents the delivery of new science from analyzing many collected raw data. These effects are collectively called "data deluge", which is a prevalent problem in synchrotrons [9]–[11]. To overcome issues such as data deluge, Machine Learning (ML), a subset of artificial intelligence that studies algorithms able to learn autonomously and directly from the existing datasets, can be very effective [13], [14]. Using ML in many contexts is increasing due to advantages such as automation for everything, trends and pattern identification, highly error-prone, and continuous improvement [15]. Even non-computer experts are trying to learn simple programming languages like Python to implement ML models on their data. Despite the growing practice towards ML, no study has reviewed the efforts made on using ML in synchrotrons to authors' knowledge. ML can be used to achieve benefits like:

- Reducing unwanted fluctuations in the widths of the electron beams produced at synchrotrons that, in turn, can prevent experimental noises obscured measurements. This work can stabilize the photon beam without the need for manual calibrations of measures [16].
- Preventing data deluge [9], [10]
- Reducing user-in-the-loop decision-making [9], [10], [17]
- Harnessing the brightness of light sources [17]
- Supporting efficient and clever monitoring and fault detection [17]
- Optimal setup using automatic alignment [17]
- Supporting stable conditions by providing real-time feedback to the experiments and end-users [17]
- Allowing users to focus on experiments at hand and best use the allocated beam time rather than manual setups and justifications [17]
- Providing instant and straight feedback from speedy physics-based simulations [17]

In this paper, we are focusing on efforts investigated ML applications in synchrotrons. Also, the challenges of using ML in synchrotrons and a short synthesis of the reviewed articles were provided. Our literature review can help related experts have a general familiarization regarding ML applications in synchrotrons and encourage the use of ML in various synchrotron practices.

MACHINE LEARNING AND ITS RELEVANT CONCEPTS

Machine learning is widely used to make predictions or decisions, a subfield of artificial intelligence and the process of making a mathematical model without being explicitly programmed and using sample data, famous as "training data". In other words, ML algorithms can learn to complete tasks using raw data [14], [18]. ML is usually applied for classification, regression, clustering, anomaly detection, dimensionality reduction, and reward maximization [13]. Generally speaking, ML techniques can be classified into three main categories, namely, supervised learning, unsupervised learning, and reinforcement learning (RL) [9]. Supervised learning is valuable when pairs of input and desired output are available. An algorithm can generalize the problem from the given structured data and predict unknown input. Unsupervised learning algorithms solve the tasks where only input data is available [19]. Recently, Reinforcement Learning (RL) has also attracted particular attention. RL is based on dynamic environment-agent interaction, similar to a Markov decision process [4], [20]. The agent starts an action on the environment, and the environment reacts to produce a reward, which the agent uses to learn how to enhance its subsequent actions. RL approach does not require a prepared data set consisting of input-output pairs since the agent learns by the continuous interaction with the environment, varying depending on the action and its dynamics [19]. Finally, semi-supervised learning is halfway between supervised and unsupervised learning. In this case, the algorithm is provided with both unlabeled and labeled data. This category is instrumental when available data are incomplete and to learn representations [21].

Among ML algorithms, clustering and deep learning (DL) are very popular. Regarding clustering is categorized as unsupervised learning (needs no labeled data). It groups data in some clusters. The similarity between the data within each cluster is maximum, and the dissimilarity between the data assigned to different clusters is minimum. Clustering algorithms are whether based on centroid research such as k-means or are density-based like DBSCAN. They see clusters as areas of high density separated by low density instead of determining the centroids. K-means is the simplest and most common clustering algorithm [19], and DBSCAN is robust against outliers. It can be applied to eliminate them on different stages of measurements and correction processes [22]. In recent years, deep learning has emerged as the leading class of ML algorithms, now almost synonymous with ML to the public. Deep learning uses neural networks (NNs) (Fig. 2) composed of hidden layers carrying out different operations to find and explore complex data's representations. It improves the performance of classifiers beyond that common ML algorithms offer, especially in the circumstances involving large datasets with high dimensions [23], [24].

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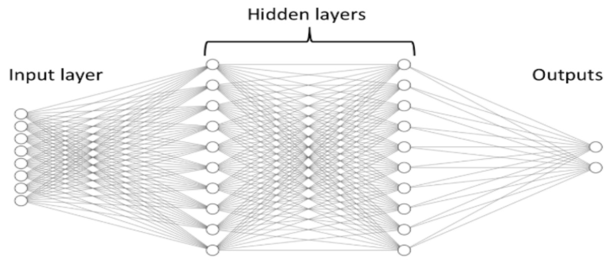

Figure 2: A fully connected NN with eight input features, two output labels, and two hidden layers including ten neurons each (Figure courtesy Alex LeNail).

CHALLENGES OF USING MACHINE LEARNING IN SYNCHROTRONS

Many AI/ML platforms for beamline tuning have been planned. However, most of them can not eventually be used regularly as part of an accelerator's central control system, mainly due to limitations such as required hardware, algorithms, software packages, and limited accessibility of large and suitable datasets [14]. The most critical challenges to scientists and end-users at synchrotrons for utilizing machine learning are [10]:

- the necessity for long-term data preservation and transfer, as well as the demand for data analysis pipelines
- The requirement for instant feedback helping on-site scientific and technical decisions during beamtime: Such feedback dramatically depends on the accuracy and automation implemented using sufficient hardware and software infrastructure for the real-time data evaluation and processing at synchrotrons.
- The need for user-friendly software packages to effectively control the extensive data generated in synchrotrons experiments: most beamlines users are not experts in data computing and management.

Alizadeh and Khaleghi also listed the most critical data management issues, which include: multiple source data, data analysis, data storage, data accessibility, data process, data format, data transfer, expensive data analysis tools, online processing, clustering, storage reliability, data mining, replication, real-time data collection and visualization [12].

Regarding these problems, a cross-domain and cross-facility solution that can accelerate creating a real-time user-friendly, advanced data processing platform at synchrotrons is needed [10]. The solutions must be versatile and flexible enough to be integrated at various experimental stations and cope with the heterogeneous requirements of different beamlines and experiments [25]. For example, supervised learning algorithms need advanced data management platforms because they require large amounts of reliable training data to construct reliable models [19], [26]. Unfortunately, while experimentalists have access to large datasets, these data are typically not tagged appropriately and thus are not suitable for supervised ML methods. Continual advances in hardware and software have enabled tremendous increases in the data collection rate. However, this boost in data throughput is not accompanied by a corresponding rise in identifying useful data and the value of each datum [27].

Some studies reported that a big data center which is termed a super facility is required for data management and processing [9], [10], [18]. Because the success of ML can be increased by the explosion in Big Data, advances in computational power, particularly the use of graphics processing units, and the development of more sophisticated ML techniques such as DL [18], [26].

In other words, these super facilities allow users to focus only on meaningful scientific data leading to discoveries and insights instead of dealing with unstructured and massive raw data. It can be achieved under users' simultaneous access to the synchrotrons' experiments with the designed real-time user-friendly platforms [9], [10]. In an interview conducted by Alizadeh and Khaleghi using ten light source facility members, it was concluded that 86% of participants were not familiar with big data [12]. Also, this study first classified synchrotrons experiments based on their techniques into three classes: imaging, scattering, and spectroscopy (Fig. 3). Then based on these main techniques, the researchers proposed a conceptual model for different data management aspects required for each method (Fig. 4). Some synchrotrons like the Shanghai Synchrotron Radiation Facility (SSRF) [9], the National Synchrotron Light Source II (NSLSII) [4], [17], and the Stanford Synchrotron Radiation Light Source (SSRL) [7] have made some efforts to provide the platforms needed for robust data analysis and management. The main work of these extensive platforms is that they should support a complete automated process for real-time and offline access for data management and computations to different operations of synchrotrons by providing sufficient hardware and software infrastructure [10].

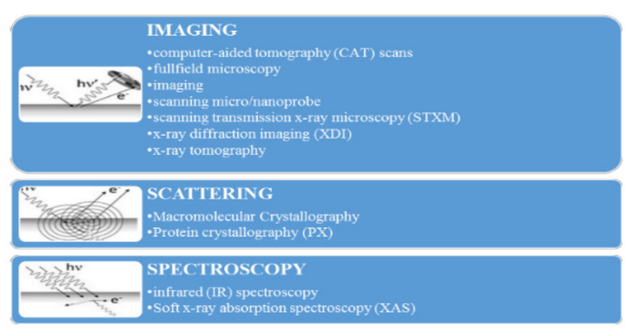

Figure 3: Synchrotrons experiments classification based on their techniques [12].

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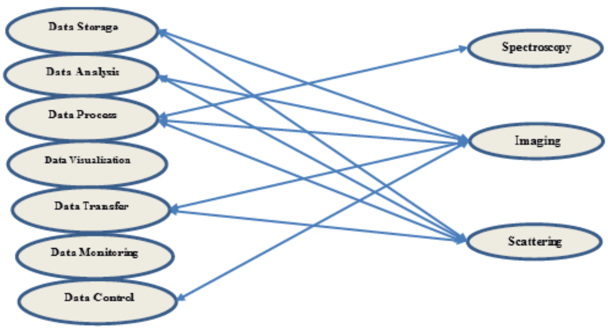

Figure 4: Different data management aspects required for each general synchrotrons experiments technique [12].

As the last point, we mention the concern that Hill et al. [22] noted that remote data analysis workflows and the use of distributed resources should be provided for ML purposes. The amount of beamtime required for a particular experiment reaches a limit as experiments become shorter. Therefore, it is no longer valuable for a user to visit the synchrotron physically. For this, remote data analysis and pipelines are essential in steering the experiment from a remote synchrotron and carrying out an optimal measurement.

THE USED/ DEVELOPED ML ALGORITHMS, SOFTWARE, AND PLATFORMS FOR DATA MANAGEMENT

High performance and low latency ML models are necessary to use ML techniques in everyday operations of synchrotrons [28]. Among these models, Neural Networks in synchrotrons have attracted particular attention due to their ability to facilitate image-centric big data science and many scientific imaging problems, such as denoising, feature segmentation, image restoration, and super-resolution [10], [29], [30]. Furthermore, NNs can explore nonlinear and dynamic behaviors [24].

NNs process the feature of image pattern rather than the value of each pixel, as with classical methods [31]. Moreover, image-based diagnostics can be used directly in accelerators both as outputs and inputs [14]. NNs' accuracy and efficiency for image recognition and classification have been proved from various applications [31]. Several tools have implemented NNs for synchrotrons operations. The Xlearn toolbox implemented NNs for multiple synchrotron X-ray imaging problems, which is an open-source Python package. The Features of Xlearn are [31]:

1- Correction of instrument and beam instability artifacts
2- Improving low-dose images
3- Feature extraction and segmentation
4- Super-resolution X-ray microscopy

The Xlearn can be easily integrated into existing computational pipelines available at various synchrotron facilities [32]. Moreover, the Xlearn is based on Keras [33] and Theano [34] packages. Keras is a well-known platform for neural networks and Theano for tensor flow computing. Keras and Theano also include GPU acceleration, the critical feature of applying NNs on extensive datasets. Please see [35] for source code, documentation, and information on contributing to this library. However, NNs are powerful in removing noise from reconstructed images. For training, they require collecting a dataset of paired noisy and high-quality measurements, which is a significant obstacle to their use in practice. In this regard, the Noise2Inverse was designed, a deep NN-based denoising method for linear image reconstruction algorithms that do not require any additional clean or noisy data. Recently, Hendriksen et al. [36] used the Noise2Inverse for deep denoising for multi-dimensional synchrotron X-ray tomography without high-quality reference data. This study applied the Noise2Inverse method to datasets acquired at two synchrotron beamlines. First, they used the technique on a static and a dynamic micro-tomography dataset from the TOMCAT beamline at the Swiss Light Source (SLS). Second, to investigate the possibility of accelerating the acquisition process using an X-ray diffraction tomography (XRD-CT), a dataset from the ID15A beamline at the European Synchrotron Radiation Facility (ESRF) was used. Results showed that Noise2Inverse is capable of accurate denoising and enables a substantial reduction in acquisition time while maintaining image quality. Liu et al. [30] introduced a deep NN model for real-time computed tomography at synchrotron light sources to improve the quality of tomographic reconstructions as data is collected. In turn, this method produces high-quality output more quickly and reduces the amount of data that must be collected. This method can be integrated into the real-time streaming tomography pipeline to enable better-quality images in the early stages of data acquisition. Using real-world datasets (tomography data, a common imaging modality at synchrotrons) collected at APS, results showed significant improvement in tomography image quality and system throughput.

Usually, different beamlines exit in a light source facility covering different scientific areas and utilizing different multi-dimensional detector technologies. Moreover, at synchrotrons, each beamline typically uses an individual streamline data acquisition software developed specifically for that beamline. The types of software are often incompatible with each other, making it difficult for scientists to compare data from different beamlines and other light sources. Therefore, AI/ML tools must also be compatible with these different beamlines [17], [37]. In this way, the NSLSII [17] developed the Bluesky Suite, a collection of Python libraries for data acquisition and management and mainly to tackle the data "variety" challenge and streaming and real-time data analysis at user facilities. There are capabilities like all data and metadata generated during an experiment can be emitted in real-time to other processes in the form of 'documents', Python dictionaries with comprehensible schema. The generated documents can be distributed locally or over a network. All beamline hardware is accessed via a library called ophyd. Or, the access to historical data is through an API called DataBroker.

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In another study recently published by NSLSII investigated reinforcement learning [4]. This paper demonstrated the use of RL methods for optimizing beamline operations. This study also explained how the Python-based Bluesky suite of data acquisition software enables RL applications at a beamline. This functionality by solving a classical RL problem, cartpole, in the Bluesky environment was demonstrated. Furthermore, the use of RL methods to address a prevalent scenario existed on high-throughput beamlines: maximizing data quality across multiple samples of different scattering strength within a limited time window. Finally, the challenges and overall strategy to realizing extensive development of RL methods at large-scale user facilities were discussed.

The European Organization for Nuclear Research (CERN) is the Large Hadron Collider (LHC) site, the largest and highest-energy particle collider globally [13]. The CERN has mainly focused on applying supervised and unsupervised ML techniques for various domains associated with beam dynamics studies. Some of these areas include beam commissioning of the collimation system, optimization of beam lifetime and losses, detection of collective beam instabilities, heating detection from pressure readings, and numerical simulations of dynamic aperture. For example, a fully automated software for beam commissioning of the collimation system using ML algorithms was developed. This new fully automatic alignment software was successfully used throughout 2018 in the LHC operations. Furthermore, this software will be used as the default software at the LHC in 2021. The time to align the collimators at injection was decreased by 71.4%, compared to the semi-automatic alignment, namely from 2.8 h to 50 minutes. Also, this tool was incorporated into the angular alignment implementation and successfully decreased the alignment time by 70%, requiring no human intervention. For a complete review of how ML techniques have been incorporated at CERN, please see [13].

Topaz3 is data manipulation and machine learning package implemented with python libraries for Macromolecular Crystallography (MX) at DLS. Specifically, it transforms electron density map data obtained from diffraction experiments and uses machine learning to estimate whether the original or inverse hand has clearer information. Tensorflow-gpu is required to use the machine learning side of Topaz3, which speeds up the training and use of neural networks [38].

One of the decades-old problems in synchrotron light sources facilities is that they simultaneously deliver light to dozens of beamlines. One side effect of this is that the movements of specific insertion devices (IDs), i.e., undulators and wigglers with variable magnetic fields, cause the electron beam's size to fluctuate. These fluctuations affect other beamlines' performance. Usually, changes are reduced using corrections based on a combination of static, predetermined physics models and lengthy calibration measurements. It is periodically repeated to counteract drift in the accelerator and instrumentation. Researchers at the ALS in Lawrence Berkeley National Laboratory showed that NNs algorithms can predict noisy fluctuations in the size of beams generated by synchrotron light sources. Therefore, they can correct changes before they occur (feed-forward vs. feed-back correction). Consequently, this approach significantly helps attain order-of-magnitude enhancement instability that fulfils the requirements for different light sources. For training the synchrotron, researchers fed electron-beam data from the ALS, including the positions of the IDs and blips in electron-beam performance raised by ID adjustments, into a NN. One key advantage of this approach is that the required data for retraining NNs can be obtained constantly, even while the feed-forward system is active during a regular user run [16]. Furthermore, continuous retraining allows the neural networks to continually adapt to a drifting machine and changes in ID configurations during run periods, independent of static physics models. The developed algorithm then learned the complex nonlinear relationships between the ID settings and vertical beam size and made corrections to negate the blips. NNs stabilized the vertical beam size at 0.2 μm or 0.4% of the beam size compared to 2–3% without correction [16].

Another light source facility that has heavily investigated using machine learning for light source facilities is the SSRL, a division of SLAC National Accelerator Laboratory, operated by Stanford University for the Department of Energy. A recent report which the SSRL published shows the research activities and achievements during the two-year R&D project of 'beam-based optimization and machine learning for synchrotrons' at SSRL [7]. R&D project was carried out in the development of machine learning techniques for synchrotron applications in three main areas: accelerator design optimization, beam-based optimization, and analysis of accelerator operation data. First, to implement online optimizations, they developed the Teeport platform. The control systems and programming environments on different machines may be different. Therefore, online optimization algorithms developed for one machine can not be easily applied to other systems. Usually, the optimizer is a Matlab script, and the evaluator is a Python script. Teeport decouples the algorithm implementation and the experimental systems by providing a universal middle layer that communicates between the optimizer and the evaluator. Therefore, they can communicate freely. In Teeport, a middleware between the evaluator and optimizer is inserted, acting as a data normalizer and signal forwarder. The data flows through the middleware. Therefore, to make the online optimization process more controllable and visible, one can add the control and monitor layers to the middleware (Fig. 5). The features of the platform include: online optimization experiment, fast switch between different optimization settings (the only necessary actions needed to switch between the different optimization settings concerning the code are switching the evaluator/optimizer id and/or update the configurations of

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the evaluator/optimizer accordingly (Fig. 6)), optimization performance comparison, and optimization algorithm benchmark.

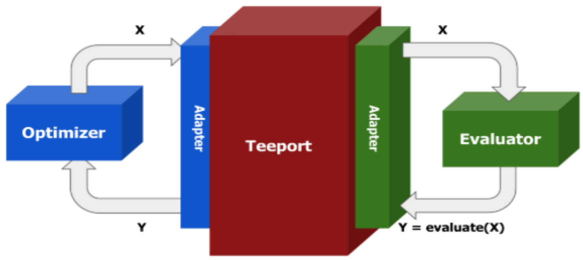

Figure 5: The architecture of Teeport. Teeport facilitates the application of optimization algorithms created in one programming environment to accelerators equipped with many different control systems and programming environments [7].

The Teeport platform can potentially become a centralized service for advanced optimization applications. It can be integrated lots of the optimization algorithms/test problems from various platforms, such as PyGMO, pymoo, PlatEMO, and Ocelot, to Teeport (Fig. 7). The R & D project also developed two ML-based global optimization algorithms for storage ring nonlinear beam dynamics optimization. The first is the multi-generation Gaussian process optimizer (MG-GPO) was used to solve multiple objective optimization problems. The second one is a neural network-based method to analyze accelerator operation data and study underlying environmental factors' impact on machine performance.

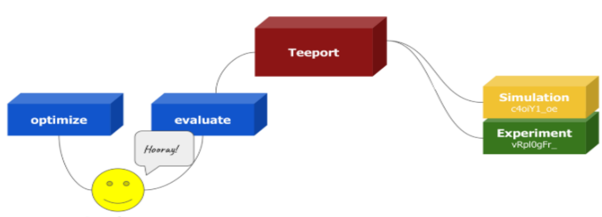

Figure 6: Fast switching between the simulation evaluator and the experimental evaluator [7].

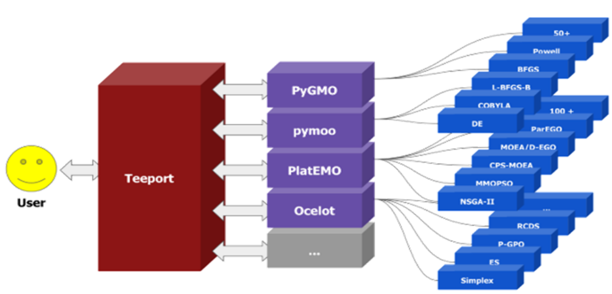

Figure 7: Teeport as a unified interface for the optimization algorithms [7].

BESSY II Light Source is another synchrotron that has started to use machine learning. The primary efforts made by this synchrotron described in [39] are: (1) beam lifetime can be successfully predicted in a time-series fashion using supervised learning models trained only with 185 accelerator variables readbacks, i.e., excluding previous lifetime measurements, and (2) the prototypes towards self-tuning of machine parameters in different optimization cases like injection efficiency and orbit correction using deep reinforcement learning agents have been implemented.

The Delta synchrotron for orbit correction used machine learning techniques [40]. Conventional Feed-Forward neural networks were trained on measured orbits to apply local and global beam position corrections to the 1.5–GeV storage ring DELTA. According to this study, it can be demonstrated that ML techniques are an alternative approach for automated orbit correction of the DELTA storage ring.

Fol et al. [19] focused on applying ML for beam diagnostics and incorporating ML concepts into accelerator problems. They identified four main areas that ML algorithms can be helpful, including virtual diagnostics, optimization and operation, beam optics correction, instrumentation fault detection. This study shows how different ML approaches can be incorporated for various functions of accelerators. For example, it has been concluded that reinforcement learning is suitable for solving complex control tasks. Or unsupervised learning is helpful for anomaly detection tasks such as detecting instrumentation defects, e.g., using clustering for faulty beam position monitors signal so that these methods can be performed directly without training in accelerator systems.

A SHORT SYNTHESIS OF THE REVIEWED ARTICLES

- To advance the field of incorporating ML in synchrotrons, a game-like project defining a reward scheme to train models to optimize a beamline efficiently is very effective.
- Good works have been done to facilitate data management and computing at synchrotrons, but they are ad-hoc based on different beamlines and synchrotron facilities. Therefore, future works can focus on converging these efforts in a seamlessly integrated platform for diverse beamlines with different requirements to provide impetus to employing ML in different operations of synchrotrons like accelerator design optimization, beam-based optimization, and analysis of accelerator operation data.
- Implementing remote data analysis workflows and the use of distributed resources are very effective for synchrotron practices. Because with the advances in synchrotron technologies, the amount of beamtimes needed for experiments is reduced tremendously, and an experiment can be done quickly. Therefore, physically visiting synchrotrons is no longer worthwhile.
- As evident from the above discussions, many researchers for developing ML models have used Python. There are three main reasons for this. First, for Python, such as HyperText Markup Language

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(HTML), many existing codes are widely available for different use cases. By combining them, standalone platforms can be implemented more easily and rapidly. Considering such features, [14] suggested some people at accelerator laboratories can be determined to focus on the application of these tools to specific problems. Second, many libraries for ML purposes have been implemented in Python like Scikit-learn, TensorFlow, Keras, PyTorch, etc. Third, Python is very popular among non-computer experts due to its simplicity.

- Among existing ML algorithms and models, deep learning has been considered significantly. Almost, most of the reviewed articles have used NNs mainly due to their ability to explore nonlinear and dynamic behaviors and facilitate image-centric big data science.
- Unfortunately, on the Web, less publicly available good and large datasets are available for synchrotrons practices. It can mainly reduce the speed of using ML models in particle accelerators. By providing suitable datasets at cloud-based platforms like Kaggle in a short time, a variety of solutions can be provided for a given problem. For example, a successful competition was organized in 2014 by the high energy physics community, and it attracted over 1700 participants [14].
- Advanced online optimization using ML algorithms can support an efficient way of finding the ideal machine configuration.
- Combining big data with ML is already crucial. Storing, managing, and analyzing high-volume data are challenging problems that can be solved using this combination.
- In many contexts, usually, it is sufficient to use previously stored data for ML purposes. However, in synchrotrons, it is essential to develop online data streaming and management platforms because real-time usage of ML is vital for us in particle accelerators. Besides, processing and validating data after completing experiments lead to undetected problems and prevent online steering. Online ML algorithms and data processing platforms also can reduce the amount of data needed to be stored.
- The existing literature does not provide many direct comparisons between ML techniques using the same publicly available datasets. Therefore, to choose the best method that suits a given question, an empirical approach investigating different proposed ML methods on the same dataset is recommended.
- For storing data for ML techniques, mainly supervised algorithms, besides providing large datasets, it is essential to give techniques for tagging data and separating valuable and useful data from less or no useful data. This work reduces the amount of data needed to be stored and improves the efficiency of ML models.

CONCLUSION

The suitability of ML methods has been clearly shown in the performed review for beam energy, brightness, stability, etc. But much is expected from further application and extension of these approaches to the most diverse beamlines at synchrotrons globally, offering advanced capabilities, exploring the most varied, time-varying, and nonlinear relationships. There are many efforts to provide data management platforms for machine learning models and algorithms. However, these efforts are sparse and heterogeneous based on different beamlines and synchrotrons. It is beneficial to integrate them to propose a more efficient environment for incorporating machine learning in everyday synchrotron practices. Generally, in large experimental facilities such as synchrotron, neutron, and x-ray free-electron laser (XFEL), unifying ML-ready solutions is needed such that they should be general and transferrable to different beamlines and particle accelerators. Moreover, ML algorithms should also have the capability to be used online by providing online powerful data analysis platforms. Otherwise, some errors and anomalies may not be detected, and the amount of data that need to be stored will increase. Feed-forward correction, evaluation, and optimization (e.g., Feed-Forward Neural Networks) are more beneficial than feedback ones for many synchrotron practices, according to our review. In future research, the aim will be to present a more comprehensive synthesis with more details on how to use the ML in synchrotrons.

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