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# TOWARDS CONTINUAL MACHINE LEARNING FOR PARTICLE ACCELERATORS*

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*Abstract*

Machine Learning (ML) has become an essential tool in modern scientific and engineering applications, enabling predictive modeling for complex systems. Many particle accelerator facilities are adopting ML-based solutions to accelerate time-consuming optimization tasks through fast inference, and to enable low-latency anomaly prediction. However, ML models assume stationary data distribution, as such, when data distribution drifts away from the training data, ML models' performance degrade. In particle accelerators, data drift is inevitable. These drifts can originate from either changes in the machine settings or non-measured factors such as equipment degradation. In this paper, we present an application of rehearsal based continual learning method to maintain model performance on drifting data. We present an ML surrogate to reconstruct beam current data from Spallation Neutron Source accelerator that can be used for downstream tasks such as anomaly detection. We use the data from different beam settings that demonstrate systematic known shift in the data. We demonstrate that a model trained incrementally on new data lose performance on previous data distributions due to catastrophic forgetting. In contrast, integrating rehearsal based continual learning can maintain model performance in such scenarios and limit forgetting on previous data distributions.

## INTRODUCTION

Particle accelerators are among the most complex and fast paced scientific instruments in the world, supporting a wide range of applications from high-energy physics to medical diagnostics and material science. The efficient operation and optimization of these facilities require continuous monitoring, calibration, and adaptation in response to changing machine conditions, environmental factors, and evolving experimental requirements. Traditional diagnostics and control strategies, while effective, are often limited by their static nature and inability to generalize across varying operational regimes.

In recent years, machine learning (ML) methods have emerged as powerful tools for diagnostics and control applications within particle accelerators [1]. These approaches are shown to be very good at learning complex, nonlinear dynamics directly from data, enabling more flexible and adaptive modeling schemes. However, a significant limitation of ML techniques, particularly Deep Neural Networks (DNN) is their reliance on fixed training datasets and their tendency to degrade in performance when exposed to new or non-stationary data—a phenomenon known as catastrophic forgetting.

At the Spallation Neutron Source (SNS) accelerator, efforts are underway to develop ML based solutions for pre-emptive anomaly prediction, optimization of beam losses and anomaly detection in target system. The ML models perform well in short time scales and offline data, however faces significant performance degradation in deployment due to data drifts. Previous studies have adopted conditional models [2] to mitigate the effects of data drifts due to changes in beam settings. However, it is not feasible to train the conditional models on all the possible conditions expected during operation. In addition, conditional models alone can not address drifts caused by non-measured factors such as equipment degradation. As such, we have steered towards developing a self-sustained adaptive ML framework that integrates advance techniques to continuously update ML models to account for data drifts.

Continual learning [3], also referred to as lifelong learning, addresses this challenge by enabling models to learn from a stream of data over time without forgetting previously acquired knowledge. This paradigm is particularly well-suited for particle accelerator environments, where operational conditions can vary significantly across time scales, and where retaining knowledge of past configurations is critical for stable and efficient performance. By integrating continual learning into accelerator diagnostics and control systems, we can build models that not only adapt to new regimes but also retain robustness and generalization across diverse conditions.

In this paper, we present current progress on errant beam prognostication use case at SNS accelerator. The study integrates continual learning techniques, particularly, memory-based methods, to maintain performance of a Conditional Auto-Encoder (CAE) when switching among different beam settings. We demonstrate that integration of continual learning stabilizes model performance even when underlying data drifts. This shows that continual learning holds promises to bridge the significant gap between ML development and long term deployment in particle accelerators.

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# RELATED WORK

## Machine Learning in Particle Accelerators

Machine learning (ML) has increasingly been adopted in the particle accelerator applications offering powerful tools to model complex, nonlinear system dynamics and optimize performance. Applications include virtual diagnostics [4,5], fast-tuning of beam parameters [6,7], anomaly detection [2, 8–10], surrogate modeling of beamline components [11], and controls [12]. These methods leverage historical and simulated data to build predictive models that support decision-making and reduce dependence on manual tuning. In addition, a number of efforts included uncertainty quantification for ML models as applied to particle accelerators [13–15].

Despite their promise, many of these ML models are trained offline and deployed in static settings or short term studies due to challenges related to data drifts.

## Continual Learning in Dynamic Systems

Continual learning addresses the issue of catastrophic forgetting in neural networks trained sequentially on drifting data. Various strategies have been proposed, including regularization-based methods (e.g., Elastic Weight Consolidation) [16], memory-based techniques that use replay buffers [17] or generative models [18], gradient projection methods [19], and dynamic architectural approaches that expand the model structure over time [20], meta-learning [21], and online learning [22].

In the broader context of robotics and control systems, continual learning has been explored for tasks involving adaptation to changing environments, system aging, and fault tolerance [3]. Meta-reinforcement learning has been explored in an exploratory study at CERN [23]. A recent work highlighted continual learning needs for particle accelerators to achive long term ML deployment and provided a guide for future developments [24]. However, despite being a very good fit, its application to particle accelerators remains limited, with most existing works assuming static or periodically re-calibrated models.

# ERRANT BEAM PREDICTION AT SNS ACCELERATOR

In particle accelerators errant beams are defined as an abnormal beam that is deviated from the normal behavior. SNS accelerator at Oak Ridge National Laboratory uses a Differential Current Monitor (DCM) [25] to detect errant beam pulses. DCM is paired with a Field Programmable Gate Array (FPGA) that monitors beam current both upstream and downstream of the Super-Conducting Linac (SCL) to detect any beam loss. It is connected to Machine Protection System (MPS) with a dedicated communication link to abort the beam when significant loss is detected. This reduces possible damage or activation. As DCM acquires all the beam current waveform, it can also stream this data to an edge computer for online inference and storage for ML model training. ML models are expected to predict anomalies based on one or more pulses (prefault pulses) before an actual errant beam to allow pre-emptive abort of beam and avoid damange and activation. Previous studies [13] have shown that this is possible as there are precursors in the normal prefault pulses that indicate an impending errant beam pulse.

An initial study at SNS developed uncertainty aware ML models to predict anomalies before they occur [13]. The study did not include beam settings parameters in the model input. However, we observed that the beam current data demonstrate significant drift when beam setting knobs are changed. ML models trained for errant beam prediction experience performance degradation when beam settings are changed due to drift in the data. As such, conditional models were developed to include beam setting vector as input condition. A conditional Siamese Model [2] was shown to be about 40% better at capturing anomalies at a fixed False Positive Rate (FPR) compared to a non-conditional Siamese Model. Additionally, it was also shown to be better than conditional Variational Auto-Encoder (CVAE). The performance increase is expected to be due to conditional model being able to leverage the correlation among beam current waveforms from various configurations and its ability to learn from an increased amount of data. However, conditional models alone are insufficient, since it is impossible to include all potential beam settings in the training data that may arise during operation. Therefore, continual learning techniques must be integrated with conditional models to enable robust, long-term ML deployment.

## Data Description

The beam current waveforms at SNS accelerator are roughly around 120,000 in length, however, we only use 10,000 points from this full waveform starting from 3,000 to 13,000 since our previous studies have indicated that precursors on an impending fault are most prominent in this region [13, 26]. For conditional inputs, we record beam setting parameters belonging to each beam current waveform. We consider 21 relevant beam parameters that directly affect and shape the beam current waveform.

The dataset include fourteen different instances of beam settings during production operation at SNS accelerator. We consider any change in one or more of the 21 knobs as a different beam setting configuration. It is important to note that the beam current waveforms produce slightly different patterns when switching from one configuration to another. This is also evident from just looking at the median of these waveforms across data from different configuration instances as shown in Fig. 1.

# BACKGROUND

## Conditional Autoencoders

An autoencoder is a type of neural network designed to learn efficient representations of data by compressing inputs

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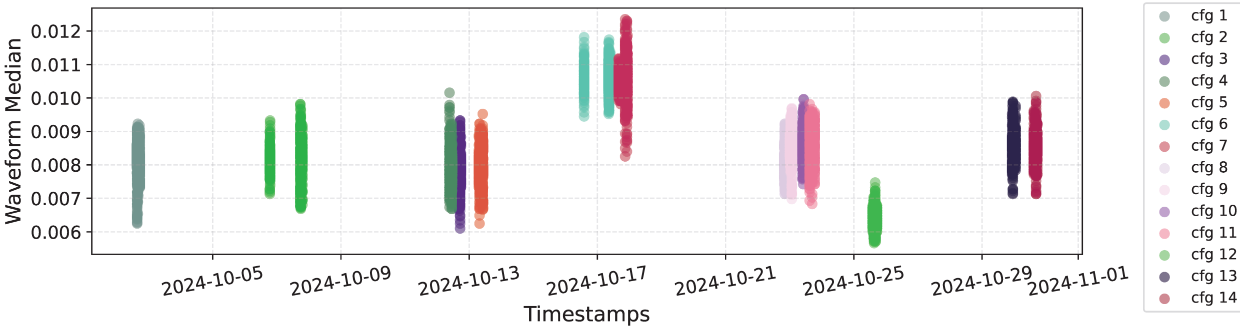


Figure 1: Demonstration of data drift in beam current waveforms collected at SNS accelerator. The y-axis shows median of the 10,000 points on beam current pulses that are fed to the ML models. Although this reduction from 10,000 values to a single statistic is highly strict, it clearly highlights how switching between different beam configuration settings causes the distribution to drift.

into a lower-dimensional latent space and then reconstructing them. This structure enables feature extraction, noise reduction, and data generation without requiring labeled training data. The Conditional Autoencoder (CAE) extends the classical autoencoder by incorporating auxiliary information into both the encoder and decoder. While a standard autoencoder learns a latent representation $\mathbf{z}$ of an input $\mathbf{x}$ through an encoder $q_\phi(\mathbf{z}|\mathbf{x})$, and subsequently reconstructs the input using a decoder $p_\theta(\mathbf{x}|\mathbf{z})$, the CAE conditions both processes on an additional variables $\mathbf{c}$, that provide additional context.

Formally, the encoder learns a distribution

$$q_\phi(\mathbf{z}|\mathbf{x}, \mathbf{c}), \tag{1}$$

while the decoder generates reconstructions by modeling

$$p_\theta(\mathbf{x}|\mathbf{z}, \mathbf{c}). \tag{2}$$

The objective of the CAE is to minimize a reconstruction loss between the input $\mathbf{x}$ and the reconstructed sample $\hat{\mathbf{x}}$, typically expressed as

$$\mathscr{L}_{\text{CAE}}(\theta, \phi) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x},\mathbf{c})}\left[\ell\left(\mathbf{x}, \hat{\mathbf{x}}\right)\right], \tag{3}$$

where $\ell(\cdot)$ denotes a reconstruction error metric such as the mean absolute error (MAE) for continuous data or the cross-entropy loss for categorical data.

We use CAE model in a semi-supervised manner trained only on normal data. The inclusion of the conditioning variable $\mathbf{c}$ enables the CAE to learn to accurately reproduce normal beam current waveforms belonging to different beam settings. We use a typical auto-encoder architecture with convolutional, max-pooling, activation (relu), dropout, and dense layers. In the encoder, the convolutional layers are responsible for extracting time series features that are further processed by dense layers that produce latent 1-dimensional representation of size 256. The decoder processes the latent representation with dense layers, further processed by convolutional and upscalling layers to reconstruct original 1-dimensional waveform of length 10000. Both encoder and decoder receives beam setting vector as condition ($c$).

We use Mean Absolute Error (MAE) for supervised training, along with Adam optimizer. Learning rate is set to $10^{-4}$. Additionally, we use a learning rate scheduler with reduction fraction of 0.85 and patience of 5, and early stopping with patience of 20 epochs on validation loss plateau.

### *Memory-Based Continual Learning*

Memory-based continual learning is a family of methods designed to mitigate catastrophic forgetting by reintroducing data from previous tasks or distributions during training on new data. These approaches maintain a memory buffer of real or synthetic data that represents past experiences and periodically samples from this replay set when updating model parameters. This mechanism allows the model to maintain performance on older tasks while acquiring new knowledge.

Two main categories of replay strategies are commonly used: *experience replay* [17] and *generative replay* [18]. We use experience replay in this study. It stores a set of real samples from previously encountered data distributions, often selected through reservoir sampling, ring buffers, or prioritization schemes. These samples are combined with new data during training to ensure the model's gradient updates reflect both past and present knowledge.

Replay-based methods are particularly well suited for applications with recurrent and cyclical behavior. In particle accelerators, operational regimes often revisit prior beam configurations, tune settings, or environmental conditions, which align well with the replay paradigm.

### *Experimental Setup*

The data belonging to 14 beam setting configuration are considered as 14 tasks for continual learning. The tasks are arranged in the same order as they have appeared in operation and assigned task ids from 1 to 14. We switch from one task to the next in a sequential order, and adapt the model with and without replay to compare the performance. To balance the number of training data points, we use 1000 samples from each configuration for training and keep remaining samples for test purpose. Within training data, the samples

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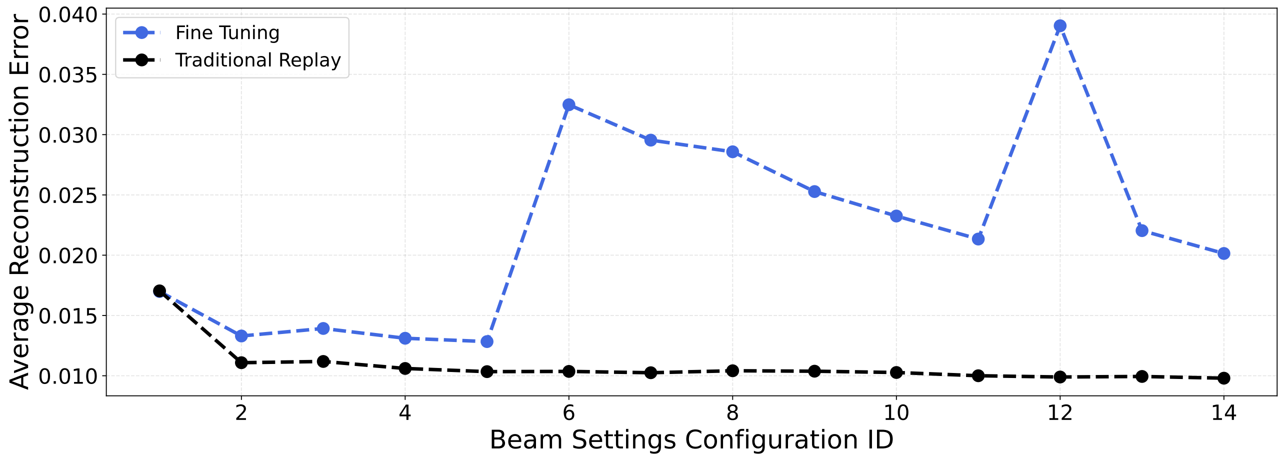


Figure 2: Performance comparison between naive fine-tuning, and memory-based replay. The y-axis shows average MAE on reconstruction compared to original input for all the configurations up to the current one. Replay is able to maintain stable performance when switching between different beam setting configurations while fine-tuning on new data without replaying data samples from previous tasks demonstrate forgetting and produce higher average reconstruction error when data drifts significantly.

are randomly divided into train and validation set with 70% and 30% shares respectively.

## RESULTS

We compare a naive online fine-tuning model that only use data from new task for training with a model trained with replay strategy that uses new task data along with historical task data stored in memory. We evaluate the models based on reconstruction error on test dataset per task. We use MAE as our error metric.

Our experimental findings, as depicted in Fig. 2, indicate that replay techniques can sustain stability without compromising performance. In contrast, online fine-tuning method that does not use historical data while training on new task, is unable to maintain stable performance in the presence of considerable task drift due to catastrophic forgetting.

Ultimately, these results demonstrate that replay techniques tailored to the specific application can significantly enhance the preservation of long-term stability in machine learning models during particle accelerator operations. It is important to note that our research presents an initial step towards developing tailored continual learning solutions for unique challenges encountered by various accelerator applications, such as selecting the right adaptation method or evaluating metrics. For example, as shown in Fig. 2, the online fine-tuned model (shown in blue) maintains a low average reconstruction error across the first five tasks, but the error rises thereafter due to significant data drift. This suggests that certain configurations share similarities, depending on which knobs are adjusted and by how much. Leveraging these configuration similarities could enable the design of more efficient continual learning approaches in the future.

## CONCLUSION AND FUTURE OUTLOOK

In this paper, we have attempted to bridge the gap between ML solution development and their long-term deployment in particle accelerator applications via integration of continual learning. We have demonstrated that integration of memory-based replay techniques can stabilize model performance on drifting data in particle accelerators. We have shown this with a practical use case at the SNS accelerator on real data when switching among different beam settings.

Though our study show encouraging results towards a long-term ML deployment, this is an initial stage as continual learning approaches are largely unexplored for accelerator applications. This study evaluates the methods based on reconstruction error of the CAE model, however, in future, we would like to compare based on practical metrics used for decision making such as anomaly prediction rate. In addition, this study did not consider various practical constraints such as memory and compute limitations, and latency constraints. The future work will include exploring tailored continual learning solutions that address unique challenges and constraints specific to anomaly prediction application within accelerators and deploy it in operation. We plan on extending our existing approach with other methods like meta-learning and adapters.

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