

OVERVIEW OF THE MACHINE LEARNING AND NUMERICAL OPTIMISER APPLICATIONS ON BEAM TRANSFER SYSTEMS FOR LHC AND ITS INJECTORS

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Abstract

Machine learning and numerical optimisation algorithms are getting more and more popular in the accelerator physics community and, thanks to the computing power available, their application in daily operation more likely. In the CERN accelerator complex, and specifically on the beam transfer systems, many promising numerical tools have been put in place in the last years. Some of the state-of-the-art machine learning models have been explored and used to solve problems that were never fully addressed in the past. In this paper, the most recent results of application of machine learning and numerical optimisation for injection, extraction and transfer of beam from machine and to experimental areas are presented. An overview of the possible next steps and shortcomings is finally discussed.

INTRODUCTION

The CERN accelerator complex went through a large refactoring over the last few years with the LHC Injector Upgrade project. All the accelerators are now capable of providing better beam brightness, which has the final goal of feeding High-Luminosity LHC (HL-LHC). Nevertheless, all the experiments linked to the different injectors will also benefit from the increase in performance.

Transfer lines, injection and extraction systems have been a core part of the machine renovations, not only with new hardware but also with new analysis methodologies and more thorough studies. One of the possible sources of performance boost is to move manual tuning and scanning of system parameters to numerical methods. This is highly relevant in cases where models are not available, where instrumentation is not adequate, as well as situations where the machine time is expensive or not always available.

In this context, numerical optimisers and machine learning algorithms can play a significant role to boost our system performance, improve stability and speed up commissioning and tuning. Taking as an example the impressive progress across the accelerators in the world, in this paper we summarise the effort ongoing to test and explore ML techniques on beam transfer systems and transfer lines in the CERN accelerator complex.

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NUMERICAL OPTIMISERS APPLICATIONS

During recent years, many of the most common and powerful numerical algorithms are made available to simple implementation via the Python Package Index (PyPI). Thanks to the support of python in the CERN control system, the application of numerical methods directly to the accelerators is now streamlined. Also, thanks to the additional software layer put in place [1], we now have available a simplified manner to deploy solutions via numerical optimisations to problems which were addressed with lengthy manual scans.

Transfer Line Steering with BLMs

The Proton Synchrotron (PS) routinely delivers protons to the neutron Time-of-Flight (n_TOF) experiment via the FTN transfer line. From the same extraction channel, the PS provides anti-protons to the Anti-proton Decelerator (AD) after production via the proton-target interaction at the end of the so-called FTA line. Both transfer lines are equipped with almost no beam diagnostics for steering or beam size measurements, but beam loss monitors (BLM) are available along their lengths. To address both steering issues, derivative-free numerical optimisers are now applied to minimise the BLM readings. The main algorithm used for this type of minimisation is BOBYQA [2] as it was the one showing the best results in terms of convergence and machine time needed. Studies to assess the performance of different algorithms are ongoing.

Slow Extraction Losses Optimisation

The Super Proton Synchrotron (SPS) physics program is dominated by the North Area (NA) users, which are provided with a 400 GeV beam which is split among three primary targets. The protons provided to the NA are slowly extracted from the SPS using third-integer resonant slow extraction [3]. The main drawback of this technique are the beam induced losses at the electrostatic septum (so-called ZS), due to the direct interaction of primary protons with the anode wires. The main contribution to the approximately 3% proton lost at the ZS is the wires' alignment, as the projected size on the beam transverse coordinate increases in case of misalignment. In order to reduce to the minimum the effective thickness of the ZS, numerical optimisers have been shown to successfully reduce the time needed for this procedure [4]. This is now routinely applied and the time has also been significantly reduced using the BOBYQA algorithm: it went

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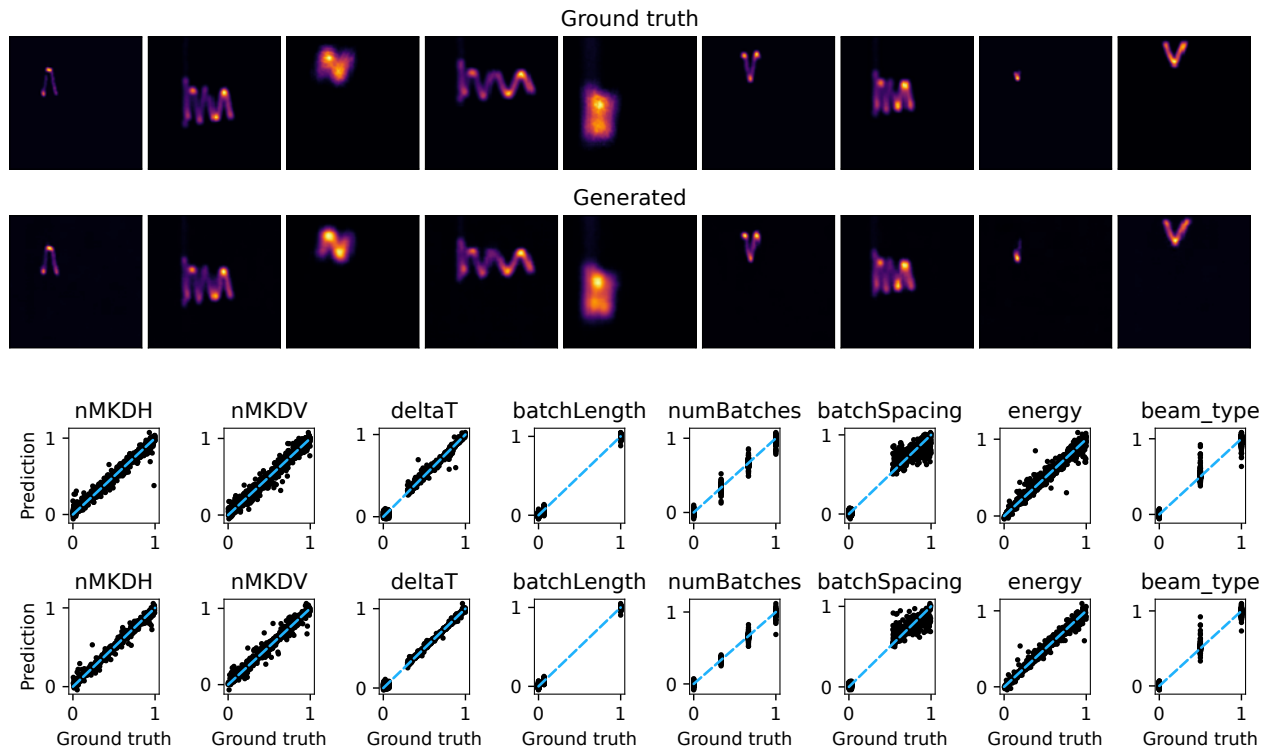


Figure 1: (Top) Images produced at the SPS BTV just upstream of the absorber block as obtained from simulations (first row) and as generated by the trained. (Bottom) Comparison between labelled generative parameters for the data used for training (first row) the VAE and the data used for testing (second row). All data shown are normalised to the totality of the dataset.

from an almost 8 h manual procedure to less than 30 min. In the same context, a large effort at CERN has produced the conception and development of the so-called crystal shadowing concept to reduce the amount of protons impinging on the ZS wires [5]. A silicon bent crystal is used as gap-opener in the separatrix to deplete the part of the beam that will hit the wires. Depending on the relative alignment of the crystal with respect to the separatrix, different deflection regimes arise, as documented in [5]. Channelling is the most profitable one for the local shadowing concept, where a loss reduction of about 45% was shown to be possible in the SPS [5]. In volume reflection, a 20% loss reduction was observed in the same machine configuration. Both alignment regimes require many extractions to scan both crystal position and angle. As detailed in [6], numerical optimisers were exploited to speed up and simplify this procedure. Depending on the optimiser choice and initial conditions, the crystal can be aligned both in channelling and in volume reflection. Channelling is reached for most of the different initial conditions, although convergence to Volume Reflection (VR) has been observed in about 30% of the optimisations.

DEEP NEURAL NETWORK APPLICATIONS

Data available in the accelerators span from time-series to images, but they can also be more “exotic” such as sound

signals or element vibrations. Very well known descriptive models are available for most of the phenomena to treat, but in many cases, noise or other imperfections make the accuracy of the prediction of low quality. Also, the computational cost may be very high when particle simulations are needed and this usually not compatible with online analysis.

Different applications have been investigated: recurrent Neural Networks (NN) to predict the beam induced heating on a kicker system, deep NN to interpolate the non-linear relation between current and field in the SPS dump kickers, and several other deep NN to make simple surrogate models to speed up parameter scans and optimisers’ experiments.

In this section, applications of deep NN for analysis of screen images is presented.

Convolutional Neural Networks for BTV Image Analysis

The SPS and LHC beam dump systems are equipped with dedicated BTV [7] just before the absorber block of their dump systems. The pattern formed by the bunches hitting the surface of the screen contains information regarding the kickers that have originated the dump and the beam characteristics at that moment. In the LHC, a dedicated system takes care of checking that the pattern of the beam on the screen is indeed in agreement with the expectations, but rather often the analysis fails due to imperfections and noise,

but nothing to do with failures. In this context, we propose to use convolutional NN, specifically a slight modification of Variational Auto Encoders (VAE [8]) to retrieve anomalous dumps and to reconstruct the dump system configuration that generated that anomaly. As the simulations for both systems are of great accuracy, the proposed solution is to train a VAE with a modified loss function on simulated data and then deploy it on real BTV data.

In Fig. 1-top, the results of training for the SPS beam dump system is shown compared with the original images. In Fig. 1-bottom, the generative parameters predicted are correlated with the original labels - in most cases, the agreement is excellent but for other parameters, the information extraction from the BTV image is not straightforward and this is reflected in the quality of the reconstruction.

Work is ongoing to deploy the trained VAE on real BTV data and first results are very encouraging. The reconstruction accuracy of the images can be used as metric to isolate anomalies and latent dimension prediction of the generative parameter to suggest which system has not performed as expected.

ANOMALY DETECTION

Beam transfer equipment such as kicker systems are critical components with potential significant impact on the global performance of the entire machine complex. Identifying root causes of malfunctions is currently tedious, and may become infeasible in future systems due to increasing complexity. Looking to automate this with machine learning, a collaboration between CERN and KU Leuven was founded in 2017 in the framework of FCC Studies.

LHC Injection Kicker Installation

Several iterations of the study have yielded an anomaly detection pipeline which includes pre-processing, detection, post-processing and evaluation. Merging large quantities of data of different, asynchronous sources was an unexpected challenge. Gaussian Mixture Models and Isolation Forests are used as the main unsupervised detectors, but any detector can easily be plugged into the system. During evaluation, the detector predictions are compared to manual e-logbook entries which constitute a noisy ground truth. Lastly, expert knowledge has been incorporated by means of semi-supervised clustering with COBRAS [9]. A grid search allows for hyper-parameter optimisation across the entire pipeline, which has yielded very promising results [10] as shown in Table 1.

The model, trained on historical data, flags unexpected behaviour in unseen data. Incorporation into an expert application for daily usage is still pending.

Table 1: Incorporation of Expert Feedback From 2017 Yields Improved Performance for 2018 with GMM

	anomaly	normal
detected	6	2
undetected	1	1437

LHC Beam Dump and Pipeline Generalisation

With the previous positive results in mind, the scalable pipeline and code-base have been generalised so that they can easily be applied to various beam transfer systems installations which have all different hardware configurations with various specificities. A single configuration file contains all needed parameters.

This approach was tested on the most challenging installation, the LHC Beam Dumping System (LBDS) with 60 high-voltage pulse kicker generators with ample data. Due to the size of the stored data, local pre-processing was not possible anymore and a shift to Apache Spark™ clusters, available through the CERN logging team, was made. This has brought huge execution improvements but at the same time complicates some non-partitionable operations such as the required forward-fill after merging data from different sampling domains. In addition the pipeline was extended with explainability tools, needed for this use-case due to the low number of anomalies only (i.e. hard to train) and a high dimensionality (i.e. >1000). Among others, new evaluation and ranking methods have been added such as *Recall@k* and a HBOS score. The ground truth labelling process was altered to be more representative of a real world scenario. Lastly, an in-depth analysis of the detected anomalies was performed using an improved web-application to up the precision and recall for the LBDS.

Although the detector correctly detects anomalies, the LBDS dataset still raises questions about the practical application of this detector due to the high number of false positives. Especially the fact that some individual features of the LBDS dataset perform better than the full dataset should be investigated, as indicated by Claessens [11].

CONCLUSION

Experimentation and testing of machine learning algorithms is well advanced for the CERN accelerators beam transfer systems. A series of successful examples were briefly presented, spanning from numerical optimisation, neural networks to anomaly detection. More applications are being investigated, with special focus on system automation and online system monitoring. Work is ongoing to deploy these methods in daily operation, to finally quantify the performance gain in terms of manpower saved, beam quality and setting up time.

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