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MACHINE LEARNING-BASED EXTRACTION OF LONGITUDINAL BEAM PARAMETERS IN THE LHC

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Abstract

Accurate knowledge of beam parameters is essential for optimizing the performance of particle accelerators like the Large Hadron Collider (LHC). An initial machine-learning (ML) model for beam diagnostics has been extended to extract the main parameters of multiple bunches at LHC injection. The extended model utilizes an encoder architecture to analyze sets of longitudinal profile measurements. Its development was partially driven by the need of a real-time beam energy error estimate, which was not directly available in the past. The derived beam parameters moreover include bunch length as well as RF voltage at capture in the LHC. In this paper, we compare the results of the ML model with conventional measurements of bunch length, energy error, and RF voltage from the beam quality monitor (BQM), the orbit acquisition system, and the beam-based voltage calibration system, respectively. These benchmarks demonstrate the potential of applying the ML model for operational exploitation in LHC.

INTRODUCTION

In the era of the High-Luminosity Large Hadron Collider (HL-LHC), the bunch intensity will be required to double wwith respect to its original design value [1]. Among other systems, also the Radio-Frequency (RF) system of the LHC will be pushed to its limits in terms of its power requirements at beam injection, and it will have to cope with tighter operational margins [2]. In order to operate in the HL-LHC regime, some parameters, such as the SPS-LHC energy matching, will have to be constantly monitored and frequently re-adjusted, calling for new, online beam diagnostic tools.

Longitudinal beam profiles from wide-band pick-ups provide the raw information, from which bunch length, energy mismatch, RF voltage, and many more parameters can be derived. In the LHC, high-resolution bunch profiles can be extracted using the APWL wide-band pick-up signal [3], processed by a 40 GS/s oscilloscope [4].

To calculate the energy error, bunch length and RF voltage, conventional methods can be used [5]. In this paper, a Machine Learning (ML) model that leverages only the longitudinal bunch profiles to calculate the above beam parameters is presented. The model is trained specifically for the injection at the LHC but can be re-trained or extended for other phases of the acceleration, synchrotrons, or particle types.

A realistic dataset is generated to train the supervised ML model. The model is then benchmarked against the most precise methods for measuring three relevant longitudinal beam parameters in the LHC: the bunch length, the energy error at injection, and the RF voltage. Finally, by making use of CERN's ML integration infrastructure, and the unified framework for diagnostics and display in the CERN Control Center (CCC), a pipeline is established that provides in real-time and with permanent storage, the beam parameters predicted by the ML model at each injection in the LHC.

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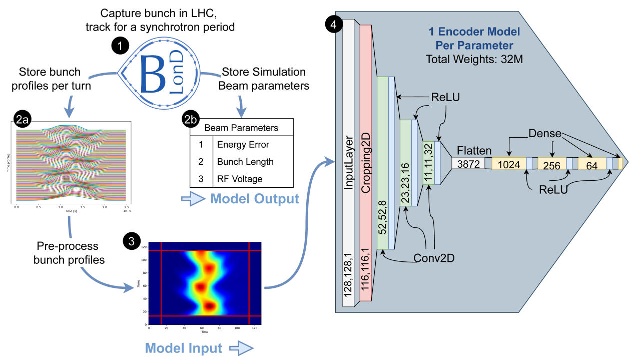

Figure 1: Training dataset generation and model architecture.

INPUT DATA PREPARATION

Supervised and unsupervised learning are the two primary approaches in machine learning, each with distinct advantages and use cases. Our specific application, which involves inferring three bunch parameters from longitudinal bunch profiles, supervised learning is an ideal choice, provided we have a well-labeled training dataset.

Assembling a high-quality dataset is on of the most important first steps in every supervised ML application. To this end, we utilize the well established beam longitudinal dynamics simulator BLonD [6,7], that can replicate measurement data in various scenarios [8]. Our simulation scenario starts with a single-bunch beam at flat-bottom in the SPS just before transfer to the LHC. The bunch is tracked for an interval longer than one synchrotron period, taking into account intensity effects. The profile of the bunch is recorded after each LHC revolution period (turn), together with the values of the three bunch parameters that the model will be trained to predict, as sketched in Fig. 1.

To ensure that the simulation-based training dataset covers a broad spectrum of operational configurations, we decided to sample a design space composed of seven beam parameters listed in Table 1. In total, $2 \cdot 10^4$ training samples were generated, partitioned in 85% for training, 7.5% for validation, and 7.5% for testing.

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Table 1: The minimum and maximum values of the sampled parameters. In total $2 \cdot 10^4$ random combinations were selected, each leading to a unique simulation.

Parameter	**Min**	**Max**
Phase error $\Delta\phi$, [deg]	-50	50
Energy error ΔE, [MeV]	-100	100
Bunch length 4σ, [ns]	1.2	1.8
Bunch intensity N_b, [$\times 10^{10}$ p]	1	30
LHC RF voltage $V_{\mathrm{RF,LHC}}$, [MV]	3	9.2
SPS 200 MHz voltage $V_{\mathrm{RF,SPS}}$, [MV]	5	12
Binomial distribution μ, [a.u.]	1	5

The recorded bunch profiles as input dataset for the model are organized in a two-dimensional image with the columns corresponding to the time ($\delta\tau$) coordinate and the rows correspond to the number of simulated turns. To reduce the model's input dimensions, only one profile out of three from the first 300 turns is retained. To obtain simulated profiles which are directly comparable with the raw measured ones, the remaining time profiles are convolved with the transfer function of the signal acquisition path for the beam profile. Finally, the convolved data is padded with zeros, which is known to improve the performance of the two-dimensional convolutional layers in certain occasions. The final input data dimension is 128 × 128. The training data generation and pre-processing steps are also illustrated in Fig. 1.

MODEL DESIGN AND OPTIMIZATION

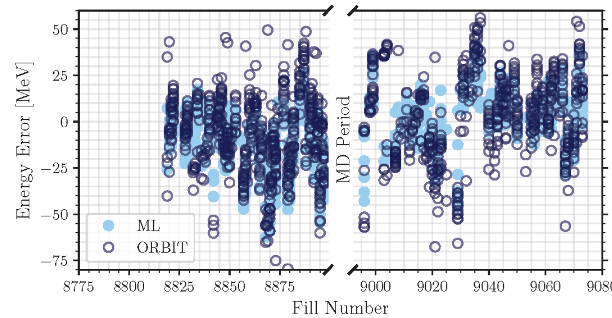
Convolutional Neural Networks (CNNs) take advantage of the local connectivity between the input features, represented by pixels of the two-dimensional waterfall image in our case. This allows CNNs to be translation invariant, meaning that they can recognize patterns found in the input regardless of their specific location in the image. This inherent property of CNNs has made them particularly effective in the field of computer vision.

Our model architecture is composed of a sequence of two-dimensional CNN layers. Typically, deeper layers encode more complex and abstract features. Strided convolutions are used to gradually reduce the input's dimensions. Next, a series of fully-connected layers enables the cross-association of all features detected by the CNN layers. The number of nodes of the fully-connected layers is progressively reduced down to a single output node, which corresponds to one of the three desired beam features. The loss function is simply the mean square error between the predicted and true values of the beam features.

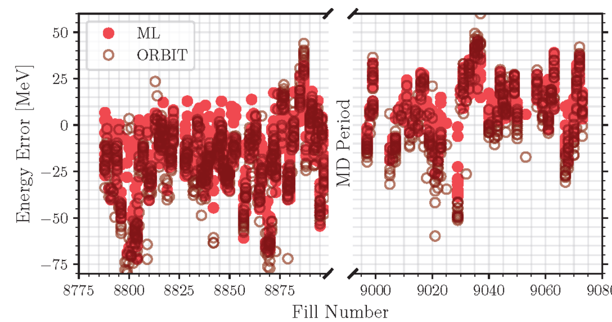
Initially, a single model was used to predict all three beam parameters simultaneously. However, it soon became apparent that the loss function of the model would saturate near the level of the hardest to predict parameter. To mitigate this premature saturation, we trained a separate model per parameter, which led to improved prediction accuracy.

Table 2: Model evaluation on simulation-generated test data, unseen during the training process.

Parameter	**MAE**	**95-%ile**
Energy Error ΔE, [MeV]	0.467	1.193
Bunch Length 4σ, [ns]	0.005	0.012
LHC RF Voltage $V_{\mathrm{RF,LHC}}$, [MV]	0.018	0.045



(a) Beam 1. Median deviation: 7.01 MeV



(b) Beam 2. Median deviation: 5.79 MeV

Figure 2: Energy error from orbit measurement versus ML benchmark.

MODEL BENCHMARKING

The ML model was evaluated on a set of measurement data collected over a two-month period spanning from mid-May to mid-July 2023. Injections designated for purposes other than physics production, such as pilot beams, were filtered out. Due to limitations in the data storage system, only the first bunch of each injected batch was recorded, and utilized as input for the model. Notably, a dedicated, one-week long, machine development (MD) period in mid-June, was excluded from the analysis due to irregular beam settings.

Energy Error from Orbit

As any energy mismatch at injection translates to a radial offset, the energy error in the LHC is traditionally measured from the orbit displacement of the beam. Figure 2 shows that the orbit-based and ML-based energy error measurements agree globally well over the entire period.

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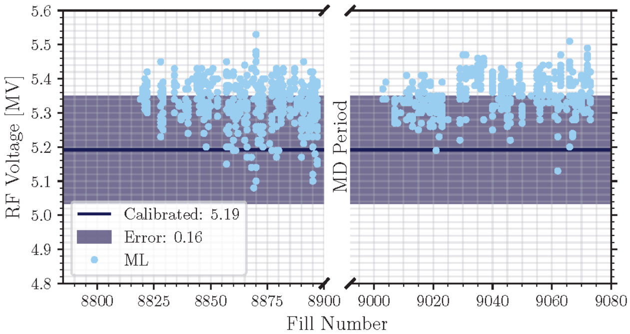
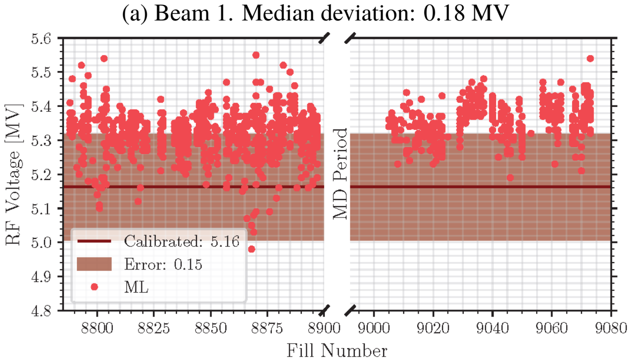
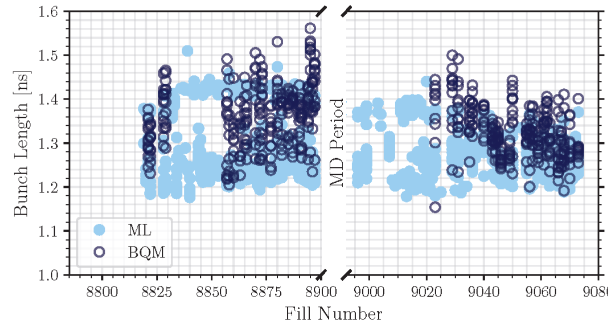


(a) Beam 1. Median deviation: 0.18 MV

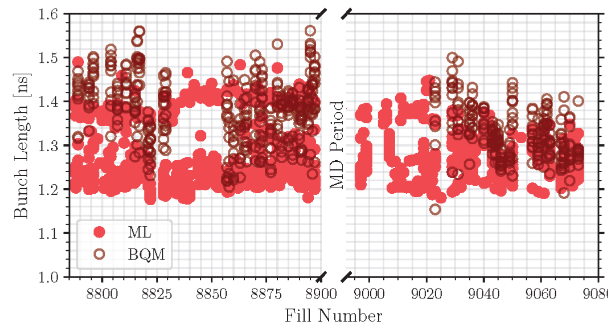


(b) Beam 2. Median deviation: 0.18 MV

Figure 3: Calibrated RF voltage versus ML benchmark.



(a) Beam 1. Median Deviation: 70 ps



(b) Beam 2. Median Deviation: 90 ps

Figure 4: BQM versus ML benchmark.

RF Voltage from Low-Level Acquisition

The RF voltage can be acquired from the cavity field antenna acquisition in the low-level RF system. These acquisitions were calibrated by conventional RF measurement techniques, and we further apply correction factors from the recent beam-based observations, in which the synchrotron frequency at a given voltage has been accurately measured, cavity by cavity [9]. Figure 3 summarizes the ML-based voltage estimates with respect to the calibrated RF voltage with its error bar. The calibrated voltage is well established and is expected to be re-confirmed by beam-based measurements this year. The V_{RF} derived by the ML set-up seems to be systematically overestimating the LHC voltage by ~3 %. The source of this error will have to be investigated in conjunction with the SPS V_{RF} and bunch length estimates.

Bunch Length from BQM

Operationally, bunch lengths are obtained from measurements of the beam quality monitor (BQM) [10], which acquires the bunch profiles with 8 GS/s and extracts from it the bunch length in regular intervals. The ML model provides us with an estimate of the first-turn bunch length, while the BQM only measures the bunch length after filamentation. In first approximation, the bunch length at LHC injection can be reconstructed from the BQM measurements for a constant longitudinal emmetance, and using the SPS and LHC RF voltages. Comparing then the BQM and ML bunch lengths, see Fig. 4, the ML-based values seem to be systematically lower, and more strikingly, in certain periods of time, two groups of bunch lengths are detected by the ML model, which is not seen on the BQM data. A more detailed fill-by-fill analysis is planned to understand the origin of this behaviour.

Deployment in the CERN Control Center

Our beam diagnostics ML model has been integrated with CERN's Machine Learning Platform (MLP) [11], to standardize and simplify its storage, versioning and deployment within the CCC. In addition, a UCAP [12] node has been setup, triggering the model's inference for every newly injected batch of bunches. The UCAP node makes the model's prediction available for both on-line display and off-line analysis. Finally, a Graphical User Interface (GUI) has been developed to visualize the predicted beam parameter values for each injected bunch, supporting the efficient diagnosis of beam quality issues.

CONCLUSION

This paper presents a comprehensive ML approach to longitudinal beam diagnostics. The successful validation against established methods such as orbit, BQM, and voltage calibration underlines the reliability of the ML model predictions. Notably, the short execution time of the model enables on-line usage with multi-bunch beams. With the integration to CERN's MLP, the implementation of a UCAP node and a GUI front-end, the deployment of the model in the CCC has been streamlined. The new system also facilitates operators to swiftly diagnose and address beam quality concerns.

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