ISBN: 978-3-95450-227-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2022-TUPOTK061

PROSPECTS TO APPLY MACHINE LEARNING TO OPTIMIZE THE OPERATION OF THE CRYSTAL COLLIMATION SYSTEM AT THE LHC*

M. D'Andrea†, G. Azzopardi, M. Di Castro, E. Matheson,
D. Mirarchi, S. Redaelli, G. Ricci[1], G. Valentino[2],
CERN, European Organization for Nuclear Research, CH-1211 Geneva 23, Switzerland
[1] also at Università degli Studi di Roma "La Sapienza", Roma, 00185 RM, Italy
[2] also at University of Malta, Msida, MSD 2080, Malta

Abstract

Crystal collimation relies on the use of bent crystals to coherently deflect halo particles onto dedicated collimator absorbers. This scheme is planned to be used at the LHC to improve the betatron cleaning efficiency with high-intensity ion beams. Only particles with impinging angles below 2.5 μrad relative to the crystalline planes can be efficiently channeled at the LHC nominal top energy of 7 Z TeV. For this reason, crystals must be kept in optimal alignment with respect to the circulating beam envelope to maximize the efficiency of the channeling process. Given the small angular acceptance, achieving optimal channeling conditions is particularly challenging. Furthermore, the different phases of the LHC operational cycle involve important dynamic changes of the local orbit and optics, requiring an optimized control of position and angle of the crystals relative to the beam. To this end, the possibility to apply machine learning to the alignment of the crystals, in a dedicated setup and in standard operation, is considered. In this paper, possible solutions for automatic adaptation to the changing beam parameters are highlighted and plans for the LHC ion runs starting in 2022 are discussed.

INTRODUCTION

In the context of the intensity upgrade foreseen by the High-Luminosity LHC (HL-LHC) Project [1, 2], collisions with high-intensity ion beams close to the HL-LHC baseline will be delivered already during Run 3 of the LHC [3], starting in 2022. An upgrade of the collimation system is crucial to ensure high-efficiency operation in these demanding conditions, since losses generated by high-intensity ion beams were already close to the quench limits of the superconducting magnets in Run 2 [4–6].

Crystal collimation is an innovative collimation technique that has been extensively studied over the course of Run 2 as a way to improve the cleaning efficiency of the LHC collimation system [7–13]. This concept exploits the property of materials with highly ordered atomic structure to capture charged particles with suitable impact conditions in the potential well generated by neighbouring crystalline planes, a process called *crystal channeling*. Bent crystals can thus be used to efficiently steer beam halo particles by forcing them to follow the curvature of the crystal itself. Since channeled particles oscillate in the relatively empty space between crystalline planes, inelastic interactions with the constituting atoms of the crystal are greatly suppressed, reducing the production of off-momentum particles. After the promising results obtained in first beam tests during Run 2 [14–18], it is planned to use crystal collimation in Run 3 for operation with ion beams, for which a standard secondary collimator can be safely used to intercept the channeled halo [19].

Achieving and maintaining optimal channeling conditions is a crucial element of the setup of a crystal-based collimation system. Only particles whose incident direction is close enough to the direction of the crystalline planes can be caught in the potential well and be efficiently channeled. This process defines an acceptance angle for the channeling phenomenon, which is heavily dependent on the particle energy and changes during dynamical phases of LHC operation, reaching values as low as about 2.5 μrad for energies close to 7 Z TeV. The crystal goniometer assembly is equipped with a high-resolution goniometer with a piezo actuator [20–22] to align its orientation to the beam halo. However, even when achieved, optimal channeling conditions can be easily lost in case of changes in beam dynamics, if the crystal orientation is not promptly and precisely adjusted.

CHALLENGES FOR THE OPERATION OF CRYSTAL COLLIMATORS

The optimal channeling orientation can be identified using Beam Loss Monitors (BLMs) [23, 24] that are ionization chambers placed around the ring to detect secondary showers produced by the interactions of beam particles with machine equipment. In total, around 3500 of these monitors are installed in the LHC. By monitoring losses at the crystal location while it is slowly rotated (a procedure called *angular scan*), a characteristic pattern can be measured when different coherent interactions of beam particles with the crystalline planes become dominant. As can be seen in the top frame of Fig. 1, the optimal channeling orientation corresponds to a minimum in the loss pattern observed at the crystal location during the scan, called *channeling well* (2), due to the decreased probability of inelastic interactions. Given the limited angular range of the region of interest (only a few tens of μrad) and the relatively low reduction factor of local losses for raw data, identifying the optimal channeling orientation online is particularly challenging. Correspondingly, an increase of losses at the location of the secondary collimator used to intercept the channeled halo

* Work supported by the HL-LHC Project
† marco.dandrea@cern.ch

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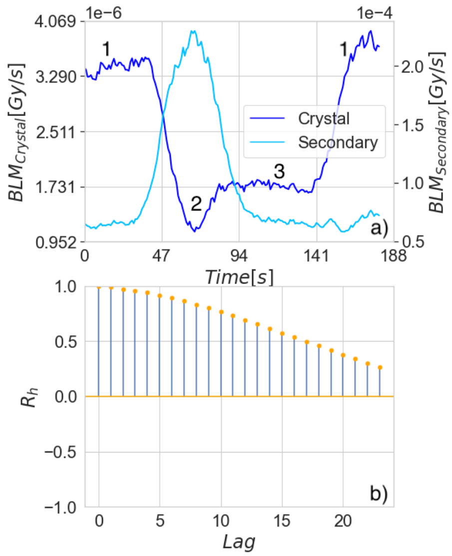

Figure 1: a) Raw BLM signal in which the channeling pattern and the increase of losses on the corresponding secondary collimator can be identified. b) Autocorrelation of the crystal signal showing positive values for all lags.

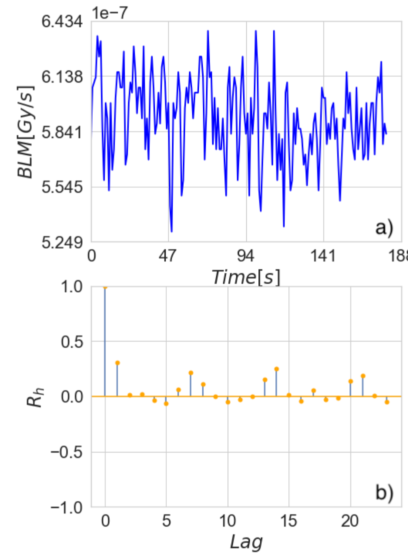

Figure 2: a) Raw BLM signal in which the channeling pattern cannot be identified and its b) autocorrelation. The signal shows a weak autocorrelation for all lags.

can be observed. On one side of the channeling well, a *volume reflection plateau* (3), where particles bounce off of the crystalline planes instead of being channeled and losses are slightly higher, can be seen. Two *amorphous plateaus* (1), where the orientation is so far away from optimal channeling that the crystal behaves like a standard collimator, are visible at the edges of the scan.

Three tasks, distinguished by progressively smaller angular range and applied in different scenarios, have been identified for the operation of crystal collimators:

- **Task 1**: Angular scan in the full angular range of the goniometer. This is performed to find the optimal channeling orientation of a crystal collimator in the initial setup after the installation in the machine, or if the reference orientation of the goniometer was lost. This first setup step is particularly difficult as this characteristic pattern spans only a few tens of μrad, while the rotational range of the goniometer is of 20 mrad.
- **Task 2**: Short angular scan (i.e. only around the channeling well). This procedure is done to verify the optimal orientation found in previous measurements and features a much smaller range (a few μrad), requiring a more detailed analysis of BLM patterns. This is important to check fill-to-fill variations and assess the long-term stability of the system, which was never tested to the extent of the planned operational use.
- **Task 3**: Continuous monitoring of losses while the crystal is kept in channeling. The aim of this task is to recognize if the optimal orientation is being lost not only because the crystal is moving, but also because of changes in the beam dynamics. Being able to adapt and compensate these changes is important to ensure stable performance of crystal collimation during operation.

The possibility to use machine learning to achieve and continuously monitor channeling conditions by recognizing these loss patterns has been explored, to potentially automatize the process while making it less dependent on human inputs and less error-prone. This work started by tackling task 1 as a first step. While preliminary results show that the machine learning model developed in [25] can be used to classify the signal increase at the secondary collimator, as the profile is similar to that of a collimator spike, an entirely new model needed to be developed to recognize the peculiar shape of the channeling well. The algorithm design and results are presented.

MACHINE LEARNING MODEL FOR CHANNELING WELL CLASSIFICATION

The limited dataset used in this initial work consists of about 150 sets of 1 Hz BLM signals gathered during machine development studies with proton and Pb ion beams in 2018. The segmented BLM signals have been evenly distributed into two classes in the following way: 63 signals belonging to the channeling class (Fig. 1) and 83 signals belonging to the non-channeling class (Fig. 2). In Fig. 1 a BLM signal profile with the characteristic pattern of channeling conditions and the three sections of the full angular scan are shown. The first analysis performed, in order to exploit the differences between the signals of the two classes under study, has been the autocorrelation analysis. The autocorrelation represents the degree of similarity between a signal and a lagged version of itself over successive time intervals [26]. Low correlation could be a symptom of randomness in the signals, while strong positive autocorrelation is symptom of high predictability. Therefore, this analysis was adopted because it allows to visually verify randomness differences in the signals of the channeling and non-channeling classes.

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The vertical axis of the autocorrelation plot is given by:

$$R_h = \frac{C_h}{C_0} \tag{1}$$

where C_h is the autocovariance function:

$$C_h = \frac{1}{N}\sum_{t=1}^{N-h}(Y_t - \overline{Y})(Y_{t+h} - \overline{Y}) \tag{2}$$

and C_0 is the variance function [27]:

$$C_0 = \frac{\sum_{t=1}^{N}(Y_t - \overline{Y})^2}{N}. \tag{3}$$

As it can be seen in the lower frame of Fig. 1, the raw BLM signal belonging to the channeling class shows an autocorrelation that starts at value 1 and slowly declines, which is the signature of "strong autocorrelation". In Fig. 2, on the other hand, a pattern cannot be seen as the autocorrelation is always under 0.5 for all lags and the signal is mostly random. Therefore from this analysis it was possible to identify differences between the signals belonging to the classes under study. This difference can be exploited by a machine learning algorithm to distinguish and classify signals.

Table 1: Network Architecture Layers and Parameters

Layer	Output Shape
1D CNN	(None, 430, 64)
Batch Normalization	(None, 430, 64)
ReLu	(None, 430, 64)
Dropout	(None, 430, 64)
Global Average Pooling	(None, 64)
Dense	(None, 1)

The structure of the convolutional neural network (CNN) listed in Table 1, originally proposed in [28], was developed with the use of the deep learning library Keras [29] with TensorFlow [30] for the backend and it has been adapted to the problem under study. Before feeding the data into the first CNN layer a Z-Score normalization at each signal is applied, such that they have the properties of a standard normal distribution with mean $\mu = 0$ and standard deviation $\sigma = 1$ [31]. The developed model consists of a 1D convolutional layer followed by a batch normalization layer, a rectified linear unit activation function and a dropout layer (with a 0.2 frequency rate) adopted to reduce overfitting. The aforementioned structure is repeated three times and is closed by a 1D global average pooling layer and a dense layer with one neuron with a sigmoid activation function. The choice of the latter allows to output a probability, precisely the probability that the time series analyzed shows a pattern compatible with channeling.

The evaluation metric adopted in this work is the precision, i.e. the ratio between true positives and the sum of true positives and false positives:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}. \tag{4}$$

A true positive is a BLM signal that presents the channeling pattern correctly classified by the model, while a false positive is a time series that represents a spurious signal misclassified by the model. This was chosen among the available evaluation metrics because false detection of a collimator under channeling conditions is more harmful than not detecting channeling conditions.

In this first exploratory study, the proposed model has been trained by using 80% of the randomly shuffled dataset and has been tested on the remaining 20%. An Adam optimizer was used to accelerate the gradient descent process and the loss function utilized was the binary cross-entropy. Furthermore, the early stopping technique with a patience parameter of 50 was adopted in order to prevent overfitting. The CNN achieved a precision of 96.15% on unseen BLM signals with proton and ion beams. This is a promising result considering the limited dataset, and indicates that convolutional neural networks can be applied to tackle task 1.

CONCLUSIONS AND OUTLOOK

The precise alignment of crystal collimators is a fundamental aspect of their use to improve the cleaning performance of the LHC collimation system, given the challenges posed by the small angular acceptance of the channeling process. In preparation for the use of crystal collimation in the 2022 Pb ion run at the LHC, advanced control algorithms were explored to achieve and continuously maintain optimal channeling orientation during extended operation, identifying in particular three separate tasks: full angular scan, short angular scan and continuous monitoring. In this work, the possibility to apply machine learning techniques to these operational scenarios was considered, tackling task 1 as a starting point. Following a detailed analysis of BLM signals collected during 2018 machine development activities, a new deep learning framework that makes use of convolutional neural network was proposed to classify the signals and identify the signature of an optimal channeling orientation. Despite the limited dataset, the developed model has shown excellent results in terms of precision and demonstrated reliability in the application of machine learning to task 1. A further step is to improve model confidence by using a larger dataset. This work will then be expanded in future studies in order to address the two remaining tasks, possibly by exploiting further the spike detection model already developed in [25], implementing the analysis of higher frequency BLM signals for more granularity, and classifying additional BLM signals other than those at the crystal and at the secondary collimator. Machine development activities are planned to take place during Run 3 of the LHC to deploy and test these models.

ACKNOWLEDGEMENTS

Data analyzed in this work were gathered during crystal collimation activities at the LHC supported by the HL-LHC Project, using crystals characterized by the UA9 collaboration and manufactured by INFN-Ferrara and PNPI.

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