15th International Particle Accelerator Conference,Nashville, TN JACoW Publishing
ISBN: 978-3-95450-247-9 ISSN: 2673-5490 doi: 10.18429/JACoW-IPAC2024-TUPS42

# REAL TIME CRYSTAL COLLIMATION MONITORING AT THE CERN LARGE HADRON COLLIDER*

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*Abstract*

At the CERN Large Hadron Collider (LHC), bent crystals play a crucial role in efficiently redirecting ion-beam halo particles toward secondary collimators used for absorption. This innovative method leverages millimeter-sized crystals to achieve deflection equivalent to a magnetic field of hundreds of Tesla at LHC's highest energies. This advancement significantly enhances the machine's cleaning performance. Nevertheless, ensuring the ongoing effectiveness of this process requires maintaining optimal angular alignment of the crystals against the circulating beam. This study aims to improve the monitoring of crystal collimation to provide a tool that detects deviations from the optimal channeling orientation during beam operation. These deviations may arise not only from crystal movements but also from fluctuations in beam dynamics. The ability to adapt and compensate for these changes is crucial for ensuring consistent and stable performance of crystal collimation during LHC operations. To achieve this, a feed-forward neural network (FNN) was trained using data simulated with the SixTrack-FLUKA Coupling reproducing the pattern of losses obtained during the 2023 ion run. The findings reveal that while the network can learn from the dataset, it lacks the ability to supervise the crystal devices effectively. Thus, it underscores the challenge of accurately classifying when the crystal is optimally aligned with the circulating beam during operation.

## INTRODUCTION

The crystal collimation technique, a new approach extensively investigated for deployment as part of the High-Luminosity Large Hadron Collider (HL-LHC) upgrade [1], aims to enhance the ion-beam cleaning efficiency of the LHC collimation system [2–8]. This method leverages the unique property of materials with highly organized atomic structures to capture charged particles under appropriate impact conditions within the potential well formed by adjacent crystalline planes, a phenomenon known as *planar channeling*. Utilizing bent crystals, this technique efficiently redirects beam halo particles by forcing them to follow the curvature of the crystal [5].

Achieving and maintaining the optimal channeling conditions in a reliable way is crucial for the efficient deployment of a crystal-based collimation system at the LHC. The particles to be channeled must closely align with the orientation of the crystalline planes to be effectively captured within the potential well. This defines the acceptance angle for the channelling phenomenon, and is known as the critical angle. At energies approaching 7 $Z$ TeV, the critical angle is only around 2.5 μrad [7]. To address this challenge, the crystal goniometer assembly incorporates a high-resolution goniometer equipped with a piezo actuator [9–11] to align the crystal orientation with the beam halo. However, changing beam and environmental conditions imply the need for continual adjustment of the crystal orientation to ensure that the channeling condition is maintained.

This study introduces a Feed-forward Neural Network (FNN) deep learning model designed to enhance the classification of the crystal's state during operation. Its purpose is to streamline the utilization of these devices by monitoring potential deviations from the optimal channeling orientation, which could diminish the cleaning efficiency of the crystal collimation scheme.

## CRYSTAL COLLIMATION AND PROBLEM FORMULATION

As outlined in [12], the HL-LHC upgrade includes the implementation of crystal collimation for ion beams, a technique employing bent crystals to coherently manipulate halo particles, directing them towards a single absorber in either the vertical or horizontal plane through planar channeling. Ideally, only one crystal per beam and per plane is required, along with an absorber to capture channeled particles [5]. Attaining optimal performance using this novel collimation technique necessitates precise angular alignment of the crystals with the beam envelope. Determining the appropriate channeling orientation and maintaining it are highly challenging tasks. A method to find the channeling orientation has already been addressed in [13]. This study will focus on the second task: maintaining the optimal channeling orientation position during operation with high-intensity beams.

The ideal channeling orientation can be monitored using Beam Loss Monitors (BLMs) [14, 15] positioned at the location of the collimators. These monitors are designed to detect beam losses by measuring the ionization generated when beam particles interact with their gas volume, producing a signal measurable in units of Gy/s. With the use of BLMs it is possible to monitor the various orientation states of the crystal: (1) *amorphous*, where the orientation deviates significantly from optimal channeling, causing the crystal to

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behave like a typical amorphous scatterer; (2) *channeling*, characterized by particles being trapped between the crystalline planes, resulting in reduced inelastic interaction rates and increased losses at the secondary collimator intercepting the channeled particles; (3) *volume reflection*, wherein particles bounce off the crystalline planes rather than being channeled, with slightly higher losses occurring at the crystal location and lower losses at the absorber collimator location. Each orientation shows characteristic loss patterns that can be used to identify the state of the crystal. As an example the loss pattern in Fig. 1 shows the BLM signals in the transverse collimation region of the LHC (IR7) when the crystal is in its channeling orientation. In this case the highest peak occurs at the secondary collimator intercepting the channeled halo.

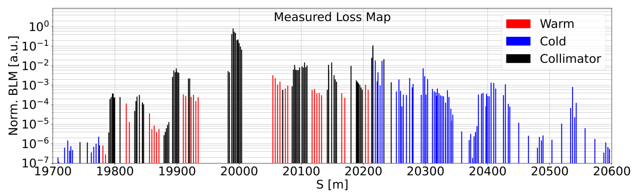


Figure 1: Beam Loss monitor loss pattern for the horizontal plane of Beam 1 with the crystal collimation system in its channeling orientation.

Numerous tests were conducted at the LHC to comprehensively characterize crystal-assisted collimation before deployment in operation. However, all these tests were conducted during Machine Development studies, over short durations and with low beam intensities. During the first operational deployment of crystal-assisted collimation with high-intensity beams in the 2023 Pb run [16], significant stability issues were observed with the devices, posing challenges in maintaining channeling during the run. All four devices (one per beam per transverse plane) were affected, but this study primarily concentrates on the horizontal device of Beam 1, as it exhibited sufficient persistent losses to enable continuous monitoring of the crystal orientation.

Figure 2 illustrates the angle adjustment required to maintain the optimal channeling orientation over time. It can be seen that the crystal positioned on Beam 1 in the horizontal plane during flat top (period at which the LHC is at its maximal energy) exhibited noticeable fluctuations from the initial optimal alignment. The initial optimal channeling orientation was determined during commissioning with low-intensity beams and the deviation from this reference value was calculated using a tool [18] designed to optimize angular orientation. These observations led to the conclusion that real-time monitoring and classification of the crystal state during operation are necessary.

## DATASET

The data utilized in this study makes use of the losses expected at different locations of the accelerator simulated using coupling of the SixTrack and FLUKA codes [19–

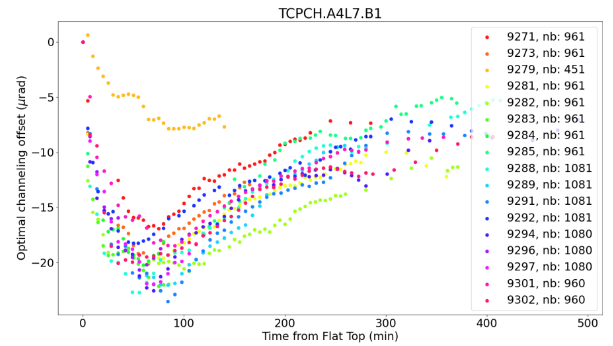


Figure 2: Offset from the initial optimal channeling orientation as a function of time at flat top, from Ref. [17].

25]. FLUKA is a widely employed Monte Carlo simulation software package for particle transport and interactions with matter that enables particle behaviour to be to accurately modelled as they interact with various materials. SixTrack allows the 6D symplectic multi-turn magnetic tracking of particles. Leveraging these tools, we successfully simulated the beam's interaction with the crystal at varying energies. The scenario used in these simulations is that of the LHC during the 2023 ion run. An initial distribution of $1 \times 10^6$ Pb ions in a pencil beam that impacts the crystal at a depth of 1 μrad [26] was setup. The resulting particles were then tracked until they hit the aperture or were absorbed by a collimator.

The simulation involves the crystal interacting with the beam under three distinct conditions: channeling, volume reflection, and amorphous configurations. As depicted by the green bars in Fig. 3, when the crystal (TCPCH.A4L7.B1) is in channeling, the device absorbs minimal energy. This is because the particles channeled through the lattice planes encounter fewer interactions with atomic nuclei in the crystal. On the other hand, the energy absorbed by the secondary collimator (TCSPM.B4L7.B1) is notably higher because it intercepts the particles channeled by the crystal. For a crystal in amorphous conditions (red bars in Fig. 3), the energy absorbed by the crystal exceeds the energy observed by the secondary collimator as it behaves like a standard scatterer, with the beam interacting with the crystal material. Consequently, the energy absorbed by the secondary collimator decreases. In the case of volume reflection (blue bars), the loss pattern resembles that of the amorphous case, with the notable addition of a concentration of energy deposited near the crystal and the TCSPM.6R7.B1 collimator.

Feed-forward Neural Networks (FNNs), due to their shallow architecture, require a substantial volume of diverse data to effectively discern intricate patterns. To mitigate the computational cost of extensive simulations, the dataset underwent enlargement, augmenting the number of examples available for network learning, thus bolstering its generalization and robustness. Furthermore, data augmentation served to mitigate overfitting during training, a prevalent issue in FNNs, by imposing regularization through exposure

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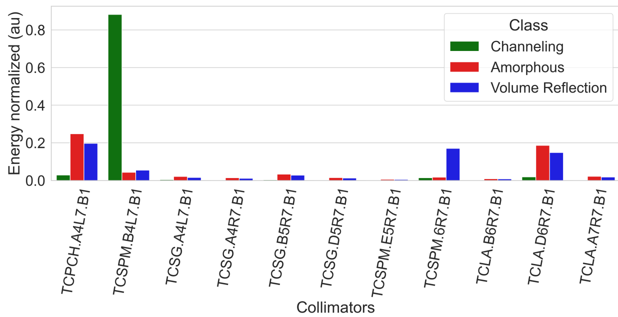


Figure 3: Absorbed energy distribution of impacting particles normalized to the total energy loss observed on various collimators when the horizontal crystal experiences channeling, amorphous, or volume reflection conditions on Beam 1.

to diverse instances of the dataset. In essence, dataset enlargement amplifies the efficacy and dependability of FNN models by infusing the training data with a set of varied samples.

The process of enlarging the dataset involved several key steps. Initially, the standard deviation of the noise to be added to the dataset is determined using a factor derived from the minimum value present in the original dataset. Subsequently, random noise, characterized by the previously calculated standard deviation, is added to the dataset. This noise is sampled from a normal distribution centred at 0 with the determined standard deviation. This method ensures the generation of an expanded and diversified dataset while preserving the underlying patterns of the data classes, thereby facilitating the training of the FNN. The augmented dataset was divided into a test set, comprising 20% of the original dataset (300 samples), and the enlarged training set containing the remaining portion (1200 samples).

## THE MODEL

The model used in this work is a feed-forward neural network that takes as input the normalized energy in 11 different collimators located in IR7. The FNN is forced to discern complex patterns within the dataset that correspond to the three states of the crystal. The FNN described in this paper utilizes the Adam optimizer for training. The architecture consists of three dense layers. The first has 16 units and incorporates a dropout rate of 0.1 to prevent overfitting. Following this, the second dense layer contains 80 units and employs a dropout rate of 0.5. Finally, the third dense layer consists of 176 units with a dropout rate of 0.5. These dropout layers aid in regularizing the model and reducing the likelihood of overfitting by randomly dropping a fraction of connections during training. The optimal architecture of the feed-forward neural network was determined through a systematic search process, specifically employing random search methodology, to ensure robust performance and generalization capability. As depicted in Fig. 4, during training the model exhibits a narrowing gap between the training and validation loss. Where the training loss measures how well the performs on the training data during the training phase, while the test loss, evaluates the model's performance on data that it has not seen during training. The convergence observed suggests that the model has learned pertinent patterns from the training dataset without overfitting.

Although the model demonstrated good performance during training, achieving a low validation loss, it failed to generalize effectively when presented with unseen BLM data logged during ion runs. This limitation may stem from the utilization of a model trained on simulated data for classifying real-world data, emphasizing the critical need to bridge the gap between simulated and actual operational environments.

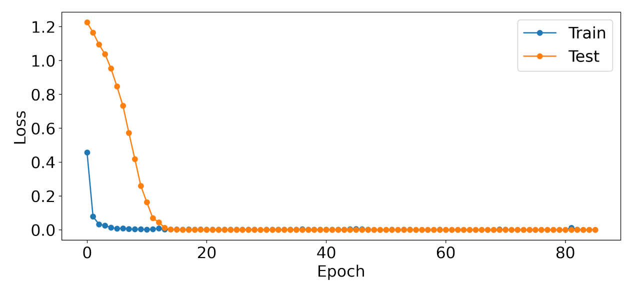


Figure 4: Loss Curves for training and test sets. The plot depicts the progressive reduction of test loss, aligning closely with the train loss curve, signifying effective learning of the model.

## CONCLUSIONS

In this study, we aimed to enhance the monitoring and classification of crystal collimator states during operation at the CERN Large Hadron Collider (LHC). Our efforts focused on developing a Feed-forward Neural Network (FNN) model to detect deviations from the optimal channeling orientation of crystals during LHC operations. We trained the model using simulated data generated by coupling the SixTrack and FLUKA simulation codes, with the aim of replicating conditions observed during the 2023 ion run.

Despite the promising performance of the FNN during training, it failed to effectively generalize when presented with unseen Beam Loss Monitor (BLM) data collected during ion operations. This limitation underscores the challenge of bridging the gap between simulated and real-world operational environments. Further efforts are needed to improve the model's ability to classify crystal states accurately during actual LHC operation.

Our study highlights the complexity of integrating advanced machine learning techniques into practical operational contexts, particularly in high-energy physics environments like the LHC. Future research directions may involve refining the FNN architecture, incorporating losses observed in other locations of the accelerator as inputs, and exploring alternative training methodologies to enhance the model's performance in real-world scenarios.

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# REFERENCES


[1] S. Redaelli *et al.*, "Chapter 5: Collimation system", *CERN Yellow Rep. Monogr.* vol. 10, pp. 87–114, 2020. doi:10.23731/CYRM-2020-0010.87

[2] W. Scandale and A. Taratin, "Channeling and volume reflection of high-energy charged particles in short bent crystals. Crystal assisted collimation of the accelerator beam halo", *Phys. Rep.*, vol. 815, pp. 1–107, 2019. doi:10.1016/j.physrep.2019.04.003

[3] W. Scandale *et al.*, "Observation of channeling for 6500 GeV/c protons in the crystal assisted collimation setup for LHC", *Phys. Lett. B*, vol. 758, p. 129, 2016. doi:10.1016/j.physletb.2016.05.004

[4] V. Previtali, "Performance evaluation of a crystal-enhanced collimation system for the LHC", Ph.D. thesis, EPFL, Lausanne, Switzerland, 2010. CERN-THESIS-2010-133.

[5] D. Mirarchi, "Crystal collimation for LHC", Ph.D. thesis, Imperial College London, UK, 2015. CERN-THESIS-2015-099.

[6] R. Rossi, "Experimental assessment of crystal collimation at the Large Hadron Collider", Ph.D. thesis, Università degli Studi di Roma "La Sapienza", Italy, 2017. CERN-THESIS-2017-424.

[7] M. D'Andrea, "Applications of crystal collimation to the CERN Large Hadron Collider (LHC) and its High-Luminosity upgrade project (HL-LHC)", Ph.D. thesis, Università degli Studi di Padova, Italy, 2021. CERN-THESIS-2021-022.

[8] S. Redaelli *et al.*, "First observation of ion beam channeling in bent crystals at multi-TeV energies", *Eur. Phys. J. C*, vol. 81, no. 2, p. 142, 2021. doi:10.1140/epjc/s10052-021-08927-x

[9] S. Montesano *et al.*, "Installation of the LUA9 Equipment in IR7 of the LHC", Rep. LHC-TEC-EC-0001. CERN, Geneva, Switzerland, 2014.

[10] S. Redaelli, A. Masi, D. Mirarchi, S. Montesano, and R. Rossi, "Installation in IR7 of Primary Crystal Collimators (TCPC) on Beam 2", Rep. LHC-TC-EC-0008. CERN, Geneva, Switzerland, 2016.

[11] M. Di Castro, R. Bruce, and S. Redaelli, "Upgrade of the Crystal Collimation IR7 YETS 2022", Rep. LHC-TC-EC-0020. CERN, Geneva, Switzerland, 2022.

[12] S. Redaelli, R. Bruce, A. Lechner, and A. Mereghetti, "Chapter 5: Collimation system", in *High-Luminosity Large Hadron Collider (HL-LHC): Technical design report*, pp. 87–114. doi:10.23731/CYRM-2020-0010

[13] M. D'Andrea *et al.*, "Prospects to apply machine learning to optimize the operation of the crystal collimation system at the LHC", in *Proc. IPAC'22*, pp. 1362–1365. doi:10.18429/JACoW-IPAC2022-TUPOTK061

[14] B. Dehning *et al.*, "The LHC Beam Loss Measurement System", in *Proc. PAC'07*, Albuquerque, NM, USA, Jun. 2007, paper FRPMN071, pp. 4192–4194.

[15] A. A. Garcia, B. Dehning, G. Ferioli, and E. Gschwendtner Geneva, "LHC Beam Loss Monitors", in *Proc. DIPAC'01*, Grenoble, France, May 2001, paper PM14.

[16] S. Redaelli, "Crystal collimation of heavy-ion beams", presented at IPAC'24, Nashville, TN, USA, May 2024, this conference.

[17] D. Mirarchi, "Stability of crystal channeling during the ion run", in *Collimation Upgrade Specification Meeting n. 169*. https://indico.cern.ch/event/1367172/.

[18] D. Mirarchi *et al.*, "Operational handling of Crystal collimation at the LHC", in *Proc. IPAC'23*, Venice, Italy, May 2023, pp. 559–562. doi:10.18429/JACoW-IPAC2023-MOPL022

[19] C. Ahdida *et al.*, "New Capabilities of the FLUKA Multi-Purpose Code", *Front. Phys.*, vol. 9, 2022. doi:10.3389/fphy.2021.788253

[20] G. Battistoni *et al.*, "Annals of Nuclear Energy", *Front. Phys.*, vol. 82, pp. 10–18, 2015.

[21] E. Skordis *et al.*, "FLUKA coupling to Sixtrack" , in *Proc. of the ICFA Mini-Workshop on Tracking for Collimation*, pp. 17–25. https://cds.cern.ch/record/2694313

[22] P. D. Hermes *et al.*, "Simulation of Heavy-Ion Beam Losses with the SixTrack-FLUKA Active Coupling", in *Proc. IPAC'16*, Busan, Korea, May 2016, pp. 2490–2493. doi:10.18429/JACoW-IPAC2016-WEPMW029

[23] A. Mereghetti *et al.*, "SixTrack-Fluka Active Coupling for the Upgrade of the SPS Scrapers", in *Proc. IPAC'13*, Shanghai, China, May 2013, paper WEPEA064, pp. 2657–2659. https://jacow.org/IPAC2013/papers/WEPEA064.pdf

[24] R. Cai *et al.*, "Simulation framework and measurements of crystal collimation of proton beams at the Large Hadron Collider", in *Nucl. Instrum. Methods Phys. Res., Sect. A*, vol. 1060, p. 169038, 2023. doi:10.1016/j.nima.2023.169038

[25] R. De Maria *et al.*, "SixTrack Version 5: Status and New Developments", in *Proc. IPAC'19*, Melbourne, Australia, May 2019, pp. 3200–3203. doi:10.18429/JACoW-IPAC2019-WEPTS043

[26] R. Bruce *et al.*, "Simulations and measurements of beam loss patterns at the CERN Large Hadron Collider", *Phys. Rev. Spec. Top. Accel. Beams*, vol. 17, p. 081004, 2014. doi:10.1103/PhysRevSTAB.17.081004