ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-MOPAB185

HL-LHC LOCAL LINEAR OPTICS CORRECTION AT THE INTERACTION REGIONS

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Abstract

Magnetic imperfections of the HL-LHC inner triplet are expected to generate a significant β-beating. For that reason, improved local optics correction techniques at the low-β insertions is essential to ensure a high luminosity performance in the HL-LHC. In this study, we compare different strategies for local optics correction at the Interaction Regions with respect to their final performance in terms of residual β-beating. Supervised learning techniques are also explored to predict the inner triplet magnetic error contributions.

INTRODUCTION

The performance of the future upgrade of the LHC, the so called HL-LHC, relies on high-gradient Inner Triplet (IT) quadrupoles located close to the different interaction points (IPs). The accurate beam-based correction of lattice imperfections relating to these quadrupoles in the Interaction Regions (IRs) is therefore fundamental [1, 2].

In this paper we summarize the progress made using different techniques related to local correction optics. First, we describe the sorting and pairing strategies to minimize the impact of magnetic errors in the IT magnets. Second, we describe a technique based on supervised learning to predict quadrupole errors in all quadrupoles of the HL-LHC. Then, we briefly show the progress made on the application, for the first time, of the Action-Phase jump correction technique [3] applied to the HL-LHC lattice. Finally, we explore the concept of Reinforcement Learning in the context of local optics correction.

INNER TRIPLET QUADRUPOLE SORTING

The inner triplet is composed of three quadrupoles per IP side, see Fig. 1. Each of these quadrupoles is split in two different parts. A strategy to partially mitigate the impact of magnetic imperfections in the inner triplet is to power in pairs the two units of each triplet magnet. In addition, the different units of Q2 (Q2A and Q2B) are sorted in such a way that the total error introduced is minimised.

In general, the error associated to the quadrupole gradient can be decomposed into three main contributions: an error associated with the magnetic gradient itself and two errors associated with the magnetic measurements, the random and the systematic errors.

Although the random errors can be estimated through dedicated measurements, the determination of the systematic component remains more challenging. We will see later

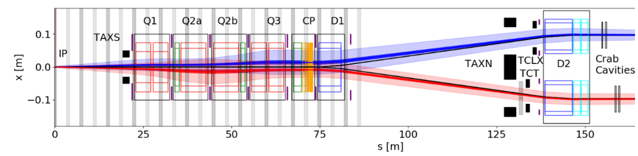

Figure 1: Sketch of the inner triplet region.

that this component can be predicted by applying supervised learning techniques to optics measurements around the ring. The corresponding errors introduced in simulations in the inner triplet quadrupoles are summarized in Table 1. The gradient and measurement errors follow a Gaussian distribution cut at 3σ while the systematic errors follow a uniform distribution.

Table 1: Errors (in $[10^{-4}]$ Units) and A/B Units Sorting and Pairing Possibilities of the Inner Triplet Magnets

Magnet	Grad.	Meas.	Syst.	Sorting	Pairing
Q1/Q3	50	2	10	No	Yes
Q2	50	2	10	Yes	Yes

SUPERVISED LEARNING FOR QUADRUPOLE ERROR PREDICTION

The magnetic errors on the triplet quadrupoles are one of the main sources of β-beating not only in the IRs but also around the whole ring. Being able to determine the magnetic error is important to perform a better correction. In a similar way that was done in the LHC [4, 5], we have trained a regression model to predict the magnetic error of all ring quadrupoles including the error of the inner triplet quadrupoles.

Data Generation

In order to generate the data required to train the model, 80000 different machines have been simulated using MADX, each following a random distribution of the magnetic errors in the quadrupoles following the values shown in Table 1. From each of the seeds the corresponding values of the quadrupoles errors have been recorded and introduced as target values as well as the values of the β-functions at BPMs closest to the different IP, the phase advance difference from the ideal model all around the ring and the normalized dispersion which are used as features to train the regression model. This is a simplified model and no noise corresponding to the actual measurement data was included.

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Regression Model

The supervised learning has been carried out on a Ridge linear model as regression method. Other algorithms have been explored, such like Random Forest, but the resulting performance did not surpass the performance of simpler models in addition to a significant increase of required training time. Hyperparameters have been optimized using a grid scan and we used cross-validation to ensure that the model is robust enough to make accurate enough prediction on the test set. The final scores of the trained model on the training set and the test set are shown in Table 2. These results are quite good although there is still room for improvement.

Table 2: Score and Mean Absolute Error (MAE) of the Train and Test Sets

Set	R^2 score	MAE [10^{-6}m^{-1}]
Train	0.89	3.3
Test	0.85	3.8

Quadrupole Error Prediction

The trained model has been used to predict the magnetic errors of the HL-LHC lattice v1.3 with $\beta^* = 30$ cm. As a particular case to evaluate the predictive power of the trained model. We can take the particular case of the prediction of the relative magnetic errors in the inner triplet magnets. In Fig. 2, the error in the prediction of the magnetic error of Q2 is shown as a function of the actual magnetic error. In this case, the mean absolute error (MAE) between the predicted value and the true value is around 2.9×10^{-4} while the initial distribution is centered around 7×10^{-4}, showing that this technique improves by more than a factor 2 the quadrupolar strength uncertainty.

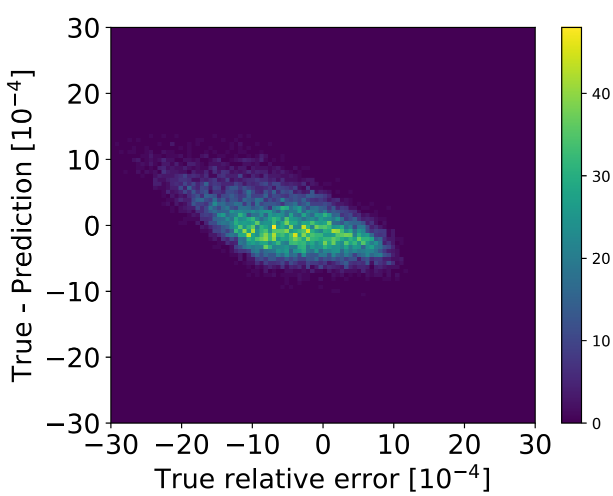

Figure 2: Density plot of the difference between IT quadrupole magnet error predicted from model and true relative error as a function of the true relative error for different Q2 quadrupoles.

Systematic Error Prediction

The systematic component of the magnetic error is unknown. At the same time, this component represents a significant fraction of the total error and hence, it has a significant influence on the resulting β-beating. Therefore, being able to use the regression model to predict the value of the systematic error would help with the posterior correction. Assuming that all magnets of the same type (i.e. the quadrupole magnets of the inner triplet) have the same systematic error component, we can estimate its value by averaging the total magnetic error, $(\Delta K/K)_{\text{syst}} \sim \langle \Delta K/K \rangle$. We have shown that we are able to predict the total magnetic error. Therefore, it is easy to extract the systematic part. In Fig. 3 the systematic error reconstructed from the predictive model and the actual systematic error for the IT quadrupoles are compared. We can see that, as expected, since the quadrupole error prediction is accurate enough, the regression model is able to accurately predict the systematic component with a MAE of $0.15 \cdot 10^{-4}$. In such a way, a first iteration of the optics correction could focus on the systematic component leaving the random components to the second iteration.

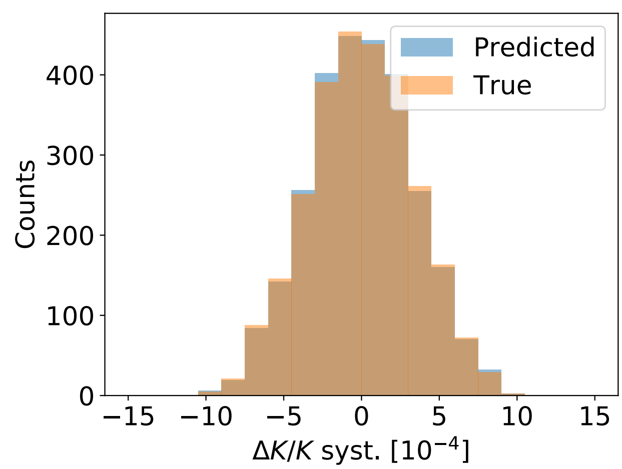

Figure 3: Histogram comparing the systematic error in the IT predicted from the model and the true value.

ACTION-PHASE JUMP

The Action-Phase Jump (APJ) technique for optics correction has shown a comparable or even superior performance to classical Segment-by-Segment (SbS) technique for correcting local optics in the IRs. These results obtained in the LHC make of APJ a promising technique also for the optics correction of the future HL-LHC. Following the same simulation principles described in [6], APJ has been used to correct the local optics in IR1 for the HL-LHC optics v1.3 with $\beta^* = 30$ cm. In Figs. 4 and 5 the residual β-beating after correction is shown for the full ring and the IR1 region respectively. In Table 3 the numerical results of the correction are shown. The residual β-beating around the ring is in all cases below 2% with the maximum never reaching above 2.5%.

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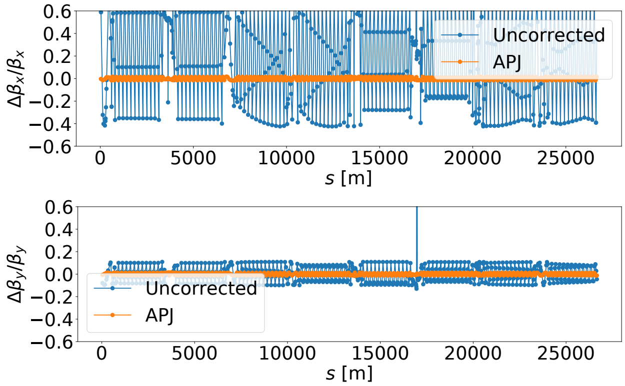

Figure 4: Residual β-beating around the ring for B1 after applying APJ correction.

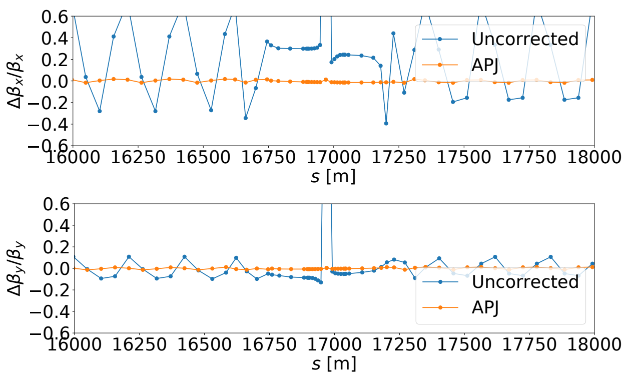

Figure 5: Residual β-beating in IR1 for B1 after applying APJ correction.

Table 3: Results of the Correction Using APJ Technique

	RMS($\Delta\beta/\beta_{x/y}$) [%]	**Max($\Delta\beta/\beta_{x/y}$) [%]**
B1	1.2/0.95	1.7/1.3
B2	1.2/1.7	1.6/2.4

In the future, the plan is to run simulations using nominal collision optics with $\beta^* = 15$ cm.

REINFORCEMENT LEARNING FOR OPTICS CORRECTION

A different approach based on RL techniques has also been considered. Recent advances in RL applications in accelerators operation have been studied [7]. The idea is to train an agent that will perform a series of actions that tries to correct linear optics in the IRs. The reward is based on the rms beta-beating obtained after each agent's action as it is shown in the algorithm layout in Fig 6.

Surrogate LHC Model as Environment

The LHC model represents the environment where the agent carries out its actions and the one that delivers the reward as a response to the agent's actions. A surrogate model has been trained with the aim to reduce the CPU time that otherwise would be required if running MADX at each iteration of the training. The training of the surrogate model profits from the data already generated for the prediction of magnetic error in quadrupoles. In this case, however, inputs and outputs are swapped. The idea is that, in this case, each machine configuration (given by a set of quadrupole errors) leads to a particular set of β-beating values. After the training of the Ridge model, the scores obtained are 0.95 for both the train and test data sets. The MAE obtained in the prediction of the value of β-function in the whole ring is of 9.6 meters. Therefore, we conclude that this surrogate model might be used as a reliable enough environment in the RL algorithm.

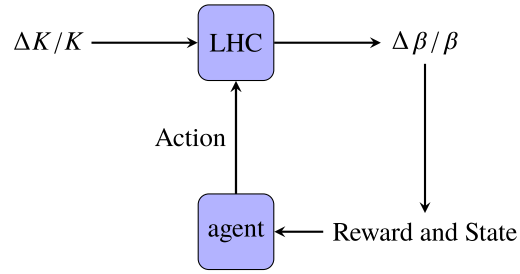

Figure 6: Scheme of the Reinforcement Learning algorithm for optics correction.

Agent, Policy and Reward

The reward is based on the value of the β-beating computed after each agent's action. If the action tends to reduce the β-beating then the reward is positive while if the β-beating is increased after the action the reward is negative. The agent is expected to be a simple feed-forward neural network that performs the different actions based on quadrupole corrector following a given policy π which will be determined using Q-learning.

CONCLUSIONS AND FUTURE PROSPECTS

Different techniques for local optics corrections in the LHC IRs have been considered. A regression model has been trained in order to successfully predict quadrupole magnetic errors using β-function and phase advance as features achieving an R^2 score of 0.85 in the test sample. From the same analysis, we have demonstrated that the systematic error component can be estimated from the predicted errors. Action-Phase Jump techniques show promising results on the correction of the local optics in IR1. These results will be compared to SbS techniques.

The first steps towards a reinforcement learning model for optics correction have been carried out. A HL-LHC surrogate model has been created and the first ideas for the policy of the agent have been explored.

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