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DENOISING OF OPTICS MEASUREMENTS USING AUTOENCODER NEURAL NETWORKS

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Abstract

Noise artifacts can appear in optics measurements data due to instrumentation imperfections or uncertainties in the applied analysis methods. A special type of semi-supervised neural networks, autoencoders, are widely applied to denoising tasks in image and signal processing as well as to generative modeling. Recently, an autoencoder-based approach has been developed to improve the quality of phase measurements obtained from harmonic analysis of LHC turn-by-turn data. We discuss the effect of the noise in light of optics corrections, present the results achieved on LHC simulations and demonstrate the potential of the new method by providing a comparison between autoencoder-based reconstruction and LHC measurement data.

MOTIVATION

The presence of noise enforces acquisition of several turn-by-turn measurements for each beam in order to obtain statistically significant computation of the optics functions and uncertainties. Phase advances retrieved through harmonic analysis of turn-by-turn data build a basis for the calculation of other important optics observables [1–4]. Therefore, denoising of phase advance measurements can potentially lead to improvements of overall optics analysis.

Keeping the measurements' noise as low as possible, as well as including most relevant optics observables preferably at all BPMs locations into the correction computation is of a great importance for optics control. In light of recent developments on Machine Learning (ML) methods for optics measurements and corrections [5, 6], further improvements can be achieved through noise reduction and reconstruction of missing data points. Concerning ML-based estimation of quadrupolar gradient errors, reducing the noise in the measurements of optics observables used as input of ML-models highly improves the prediction accuracy. Training regression models to predict all quadrupolar errors in the entire lattice from noisy phase advance data has demonstrated a strong correlation between the noise and the performance of the method. We trained and validated such models by applying different noise factors to the phase advances used as input features. The model performance, described by Mean Absolute Error (MAE) of prediction and explained variance (R^2) decreases significantly with increasing noise factor, as demonstrated in Fig. 1. We also performed a verification of model accuracy using noise-free data for quadrupolar error prediction. The results state that the absence of noise leads to the reduction of relative prediction error for the arc magnets from 30% to 1%, while for the triplet magnets the error reduces less significantly, from 16% to 12%.

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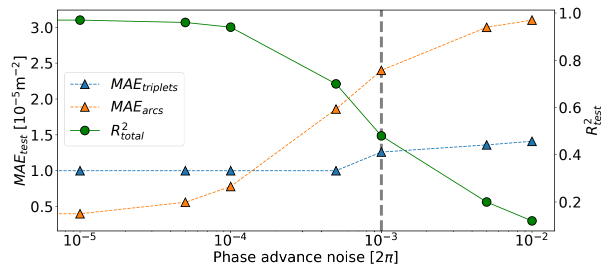

Figure 1: The change in the performance of the model trained for the prediction of arc and triplet magnets depending on phase advance noise. Mean Absolute Error (MAE) and R^2 are typical figures of merit for the performance of supervised regression model and are computed on a test data set. The gray line indicates the currently estimated noise factor for the LHC measurements.

In the following, we provide a brief introduction to Autoencoders, demonstrate how they can be efficiently applied to mitigate the described limitations and discuss achieved results and future steps.

DENOISING AUTOENCODER

Autoencoder is a specific type of a neural network that is trained to reproduce its input in the output layer [7]. The network consists of two parts: a learned encoder function $h = f(x)$ describing a set of hidden layers h and a decoder that produces a reconstruction $r = g(h)$. To perform denoising and data reconstruction, the encoder extracts relevant information from the input by lowering its dimension and filtering the noise. The original input is then reconstructed by the decoder. During the training, the encoder learns to recognize the noise patterns in the input and to keep only the signal relevant for the reconstruction performed by the decoder. Supervised Learning approach can be used when examples of model input and corresponding desired output are available, such that an algorithm can generalize the problem from the given data and produce accurate prediction from unseen input. In order to achieve generalization ability during the training, predictions are made from the incoming input and are then compared to the true corresponding output. For denoising autoencoder, this learning process is described as minimization of a loss function $L(x, g(f(\tilde{x})))$ penalizing $g(f(\tilde{x}))$, where $\tilde{x}$ is the input corrupted by noise and x is original input. Since autoencoder is considered as a special case of a feedforward network, it can utilize the same techniques for training, e.g. gradient descent and backpropagation.

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In order to build training samples, we employ the original simulated and noisy phase advances, as output and input of each sample respectively. The results presented in this work are obtained with an autoencoder implemented using Keras library [8]. It consists of 4 hidden layers and is trained using mean absolute error as loss function, leaky rectified linear unit [9] as activation function in the hidden layers and Adam [10] as optimization algorithm. Figure 2 illustrates the architecture of the applied autoencoder neural network, indicating the number of hidden layers and the number of nodes in each layer. All nodes of each two adjacent layers are fully connected, the connections between the inner nodes are omitted in the illustration only for a clear visualization.

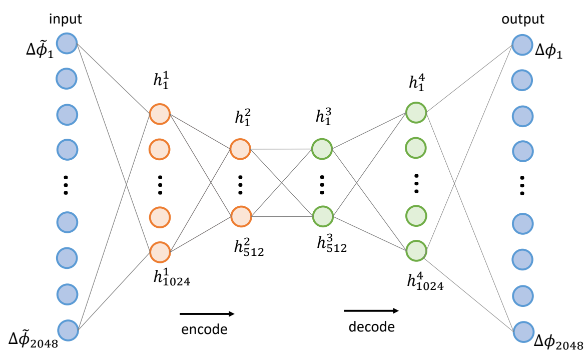

Figure 2: The architecture of autoencoder network used for the denoising and reconstruction of simulated noisy phase advance deviations $\Delta\tilde{\phi}$, to produce original values $\Delta\phi$. Input and output layers consist of 2048 nodes corresponding to the total number of BPMs in both beams, horizontal and vertical planes.

DATA GENERATION

In order to apply this approach to denoising and reconstruction of phase advances, autoencoder network is trained using phase advance deviations from the nominal model simulated with different distributions of realistic magnet errors. Introducing random magnet errors allows to generate a large set of training data, consisting of realistic LHC optics corresponding to the expected optics errors. In this study, the simulations are performed using the settings of $\beta^* = 40$ cm optics.

The input contains phase advance deviations from the nominal model simulated at every BPM, given the noise. This noise of the phase advance measurement is estimated to be $10^{-3} \times 2\pi$ in a BPM with $\beta = 171$ m and it is scaled with the $1/\sqrt{\beta}$ at the rest of locations. This estimation is generally valid for both beams in horizontal and vertical planes. In addition, we replace 10% of input values with zeros in order to simulate the presence of faulty BPMs which measurements are not available in the optics analysis data. The corresponding output contains the full set of noise-free phase advance deviations from design, including the values at simulated faulty BPMs. In total, 10000 samples including 2048 input features and 2048 output targets in each sample are generated and divided into training and test sets, 80% and 20% respectively.

RESULTS

First, we validate the trained autoencoder on a set of 100 LHC simulations, generated independently from training data using $\beta^* = 40$ cm optics. The predicted sets of phase advance deviations are compared to the ground truth simulations. By this means, both objectives to be achieved by applying the autoencoder can be verified. The residual error of prediction at the location of available BPMs is compared to the simulated noise, quantifying the noise reduction in the autoencoder-processed data. The reconstruction of simulated faulty BPMs is verified against the agreement with original simulated values at these BPMs.

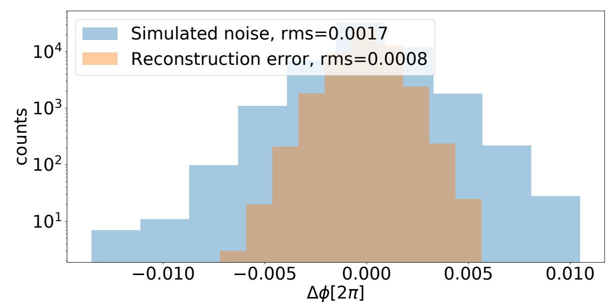

Figure 3: Comparison between the noise added to original simulation of phase advance deviations in beam 1, horizontal plane to the reconstruction error (the difference between true simulated phase advance deviations and corresponding predicted values) of autoencoder's prediction, performed on 100 LHC simulations.

Processing the phase advance data with autoencoder allows to reduce the noise added to simulated phase advances by a factor of 2 as demonstrated in Fig. 3. The rms error of prediction w.r.t. to original simulated phase advance deviations obtained from 100 validation samples, for both beams, horizontal and vertical planes is 5%.

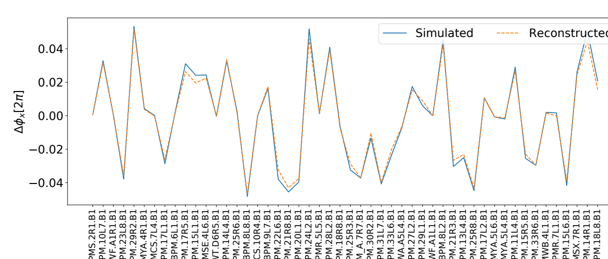

Figure 4: Example of reconstructing the phase advance deviations at the locations of simulated missing BPMs in horizontal plane, beam 1 using autoencoder neural network.

Reconstruction of missing measurements from faulty BPMs is validated by omitting 10% of values in the input of

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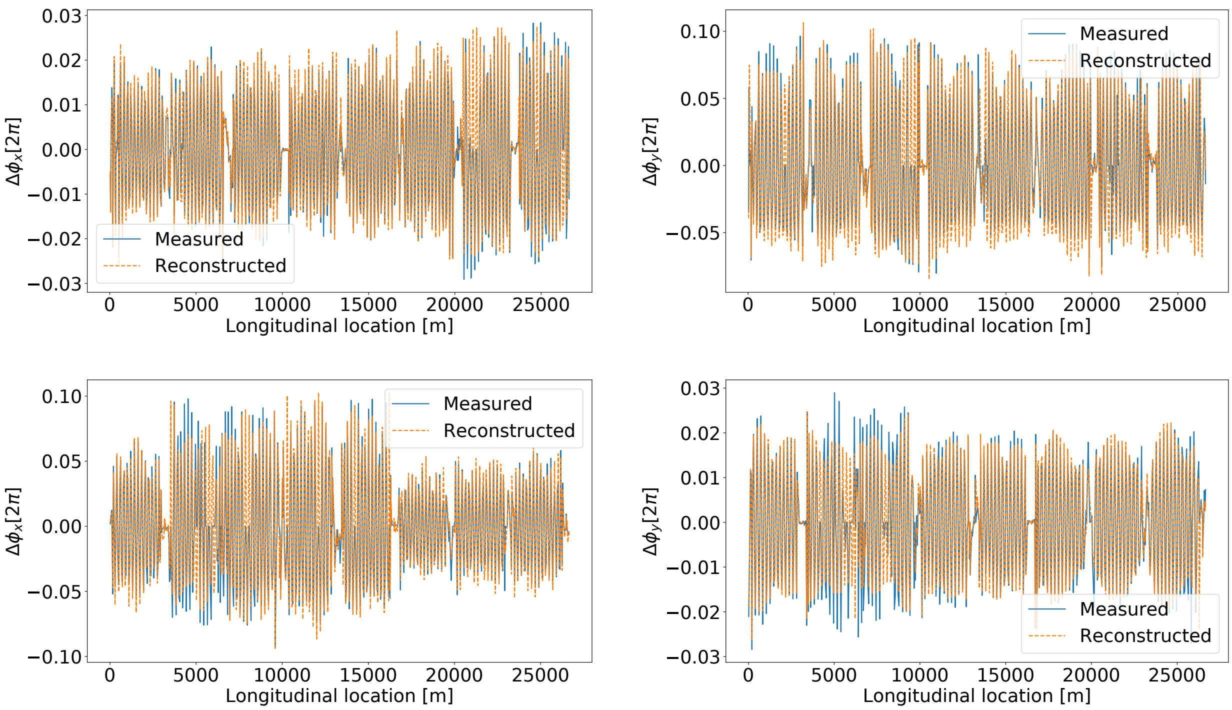

Figure 5: Comparison between LHC measurements and autoencoder's reconstruction in horizontal and vertical plane for beam 1 (right) and beam 2 (left). The optics analysis provides phase advances at the locations of well-functioning BPMs only. Zeroes in the measurements indicate the locations of faulty BPMs where the measurements are not available and are to be potentially replaced by autoencoder-reconstruction.

the autoencoder, simulating the absence of measurements from faulty BPMs. An illustrative example of comparison between autoencoder prediction at the location of discarded data points and corresponding original true simulated values is shown in Fig. 4 demonstrating a very good agreement. The relative error of prediction in the shown example is 8%.

The approach for phase advance reconstruction using the autoencoder is also tested on measurements data from LHC commissioning in 2016, for $\beta^* = 40$ cm. Unlike in simulations, here the true values of missing data points, as well as noise-free calculations of phase advance deviations are unknown. Hence, the full set of computed phase advance deviations from ideal optics, instead of the values at the locations of faulty BPMs only, is compared to the autoencoder output in order to assert the reliability of prediction.

Figure 5 demonstrates the comparison between the measured phase advance deviations and autoencoder-based reconstruction. In total, for both beams and horizontal plane, the phase deviations in the measurements at the location of well-functioning BPMs and the corresponding reconstruction agree to 88%. The good agreement between measurement and prediction, together with the results obtained from a large number of from simulations, confirm that this approach can produce reliable reconstruction of phase advance measurements, reducing the noise.

CONCLUSION

Initially, the application of autoencoder neural network has been found to be a promising solution for denoising, improving the quality of phase advance data which are essential for overall optics analysis. A possible future step of the presented study is to employ the denoised phase advance data into the computation of β-function, aiming to reduce the uncertainty of its calculation from phase. Alternatively, future work can be related to the application of denoising autoencoder directly to turn-by-turn data, before performing harmonic analysis.

The main advantage of applying an autoencoder neural network is the possibility to combine two different objectives using one ML technique, namely the reconstruction of missing data and measurements denoising. As shown on simulations, the noise can be reduced by a factor of 2, as demonstrated by comparing the simulated realistic noise in the phase advance measurements against the error of autoencoder's reconstruction. Moreover, an accurate reconstruction of the full set of phase advances has been demonstrated on LHC measurements data, promising successful application of the proposed denoising technique to optics analysis data.

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