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MACHINE LEARNING PROJECTS AT THE 1.5–GEV SYNCHROTON LIGHT SOURCE DELTA

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Abstract

In recent years, several machine learning (ML) based projects have been developed to support automated monitoring and operation of the DELTA electron storage ring facility. This includes self-regulating global and local orbit correction of the stored electron beam, betatron tune feedback as well as electron transfer rate (injection) optimization. Furthermore, the implementation for a ML-based chromaticity control is currently prepared. Some of these processes were initially simulated and then successfully transferred to real machine operation. This report provides an overview of the current status of these projects.

INTRODUCTION

DELTA is a 1.5–GeV electron storage ring facility operated by the TU Dortmund University as a synchroton light source [1] and as a facility for ultrashort pulses in the VUV and THz regime [2, 3]. Due to thermal orbit movements and magnetic field changes caused by different insertion device setups, the beam orbit and the betatron tunes may vary during storage ring operation. Therefore, autonomous local and global beam position corrections as well as self-adjusting tunes controls are important tasks, as otherwise sudden beam losses can occur. For this purpose, conventional, fully connected, shallow feed-forward neural networks (NNs) were investigated and have been successfully implemented. Both machine learning (ML) based controls were first simulated and tested on a detailed storage ring model within the Accelerator Toolbox (AT, [4, 5]) framework and were then successfully applied during real accelerator operation.

So far, the storage ring chromaticity values have been adjusted empirically based on experience. Setting of new values can only be done by time-consuming trial and error. For this reason, a ML-based algorithm for automated chromaticity adjustment is currently being prepared, very similar to the already implemented ML-based betatron tunes control. Classical, non-deep NNs are also used in this case.

At present, the electron transfer efficiency from the booster synchrotron to the storage ring is being optimized with the help of ML techniques, too. Here, NNs as well as Gaussian process regression (GPR) methods are explored.

ORBIT CORRECTION

Extensive studies for a ML-based orbit correction (OC) at the storage ring DELTA started already in 2017. Therefore, initially only the horizontal beam positions were disturbed by horizontally deflection corrector magnets (steerer) and the corresponding data pairs (orbit/steerer changes) were used as training data for supervised learning of fully connected neural NNs. First simulations have shown that already three-layered neural networks were able to learn correlations between beam position deviations and steerer strength changes. The application of such trained networks on the real storage ring results in similarly good beam position correction quality compared to conventional OC methods like SVD-based (singular value decomposition [6]) programs, however, with significantly fewer correction steps [7]. Subsequently, the ML algorithm was extended to both accelerator planes (x/y-coupled orbit), including weighted beam position monitor (BPM) signals. Thus, exposed positions in the DELTA storage ring (e.g., injection region, synchrotron radiation source points) can now be adequately considered in the ML-based OC.

In comparison with a more advanced numerical OC approach (qp-cone [8, 9]), the ML-based version results also in similar correction performance, which is scored by the weighted rms orbit error summed for both planes. On average the ML method still required fewer OC steps in this benchmark.

Exemplarity, some benchmark results are depicted in Fig. 1 (ML-based) and Fig. 2 (conventional). Even beam position deviations provoked by perturbations which were not applied during the training (e-j) could also be compensated equally. In all cases, after each provoked orbit disturbance, the residual weighted orbit error, as a measure for the OC

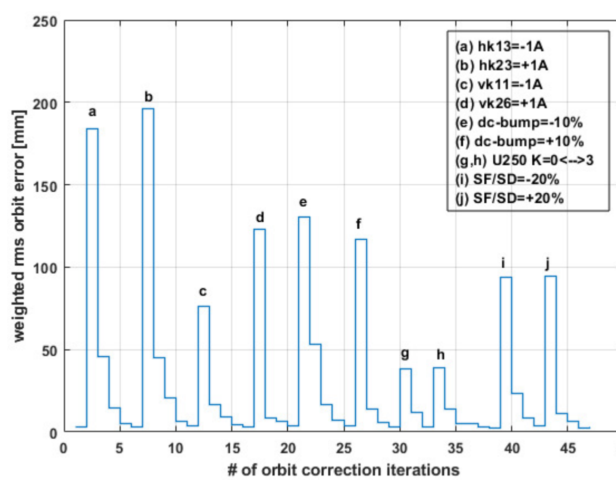

Figure 1: Individual correction steps for different scenarios of orbit deviations (a-j) performed with the ML-based OC program. In comparison to Fig. 2, similar final residual orbit qualities, scored by the weighted rms orbit error, are achieved in significantly fewer iterations.

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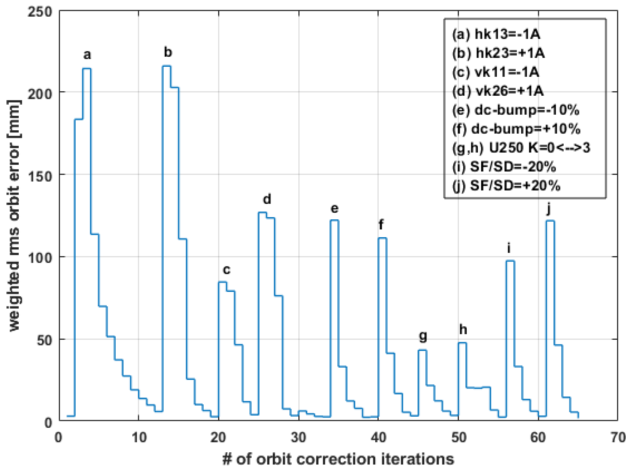

Figure 2: Number of orbit correction iterations to compensate the same orbit disturbing sources (a-j) as indicated in Fig. 1 performed with a qp-cone-based conventional orbit correction program [8, 9].

performance, converged to less than 3 mm. Further details of the ML-based orbit correction procedure are documented in [7, 10].

BETATRON TUNE CONTROL

To obtain appropriate data for NN training, the set values of seven independent quadrupole families located in the storage ring arcs were randomly changed and subsequently the associated tune shifts were recorded. Three-layered NNs were trained with experimental machine data as well as with simulated data based on a detailed lattice model of the storage ring [11]. Thereby, for supervised learning a variety of different gradient backpropagation methods were tested [12].

With both data sources, comparable tune correction accuracies were achieved, both, in real machine operation and for the simulated storage ring model. In addition, it was also possible to perform tunes control 'crosswise', i.e., control of the real storage ring with NNs only trained by simulated model data; and vice versa, NNs only trained with real machine data and then applied to the simulation model. In all cases, the desired tune matching was successful.

In contrast to conventional PID control methods [13], trained NNs are able to approach the desired target tunes in fewer steps, which could enable a more controlled scanning in the tune diagram. Since the DELTA quadrupole power supplies lack the feature to drive synchronously in real-time, an iterative procedure for the NN-based tune control loop must necessarily be applied. Figure 3 depicts typical ML-based tune matching examples. Further examples and a more detailed description can be found in [12].

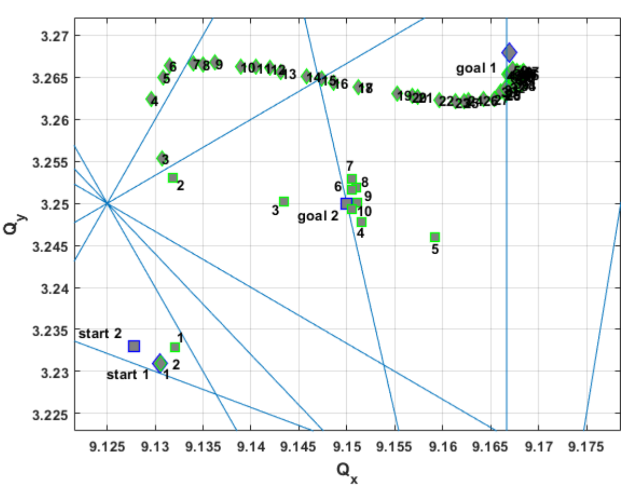

Figure 3: Validation of NNs trained with experimental data and applied to real machine operation. Two experiments demonstrate tune matching from start to goal tunes without beam losses. In the first experiment, 10 steps were performed (superconducting wiggler magnet switched on, rectangular markers) and in the second test 50 steps were executed (superconducting wiggler magnet switched off, diamond markers) [12].

CHROMATICITY CONTROL

Similar to the ML-based tune control, the procedure can likewise be transferred to an automatic ML-based chromaticity control. At the DELTA storage ring, the chromaticity values are manually adjusted using 15 independent sextupole power supply circuits. However, to account for the symmetry of the optics, these circuits are grouped into 7 sextupole families during standard machine operation.

To acquire suitable ML training data, first, the sextupole strengths are scanned systematically for single and then randomly varied for all families. For each strength change, the associated chromaticity shifts are measured. Figure 4 visualizes corresponding simulation results for a DELTA storage ring model. With these data pairs (strength varia-

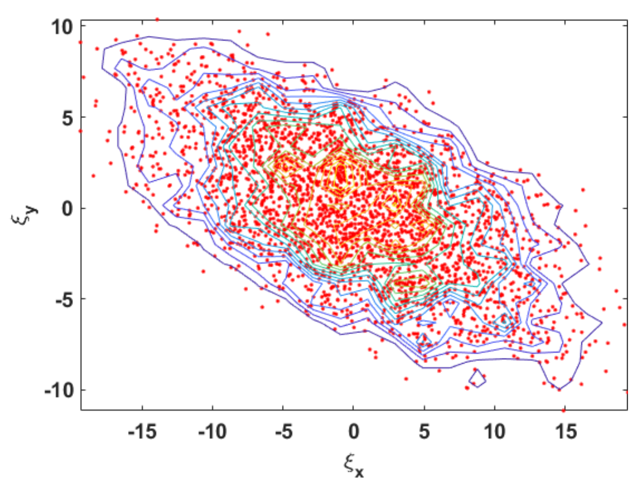

Figure 4: Distribution of 3000 chromaticity shifts invoked by uniformly randomized strength variations of seven independent sextupole families. The data are obtained by AT optics calculations based on a Delta storage ring model and are used for supervised training of NNs.

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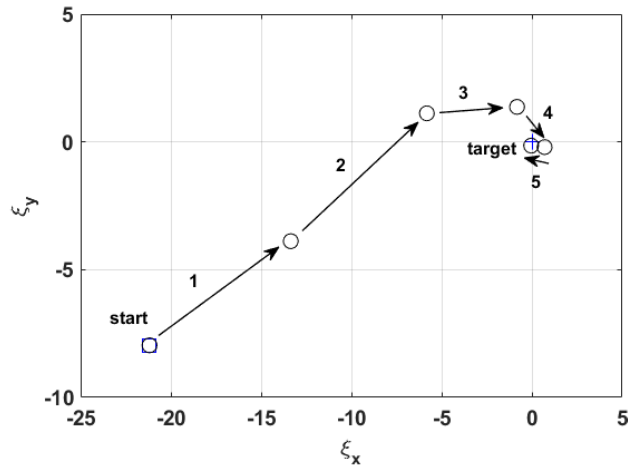

Figure 5: Example for verification of NNs trained by simulated data (see Fig. 4) and applied to the DELTA storage ring model. The desired target values for compensated chromaticity (goal: $\xi_x = \xi_y = 0$) were reached in iterative steps starting at the setting for natural chromaticity ($\xi_x = -21$, $\xi_y = -8$, sextupoles switched off).

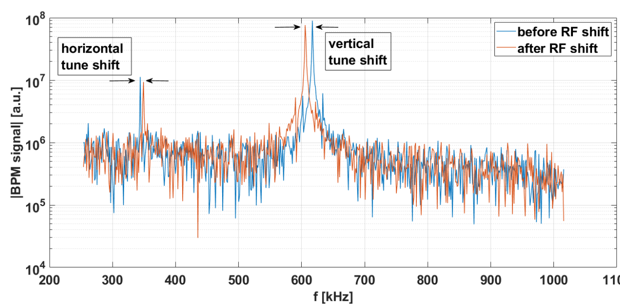

Figure 6: FFT beam spectrum from turn-by-turn orbit data recorded at a dedicated 'fast' BPM (blue) and after (red) a cavity radiofrequency (RF) variation of 5 kHz. The horizontal and vertical chromaticities are calculated by determining the betatron tune peak shifts induced by the cavity RF variation.

tions and chromaticity shifts), 'chromaticity-models' will be trained, which later could serve to adjust and control the chromaticity values automatically during real machine operation. Figure 5 illustrates an example for simulated chromaticity matching performed with a 3-layered NN which has been trained by conjugate gradient backpropagation using the data depicted in Fig. 4. The natural chromaticity ($\xi_x = -21$, $\xi_y = -8$) which occurs with all sextupole switched off (start) can be adjusted to full chromaticity compensated values ($\xi_x = \xi_y = 0$) by the ML-based control loop. The step size (number of iterations) is adjustable and depends mainly on the granularity of the trainings data.

For chromaticity determination in real ring operation, the cavity radiofrequency (RF) must be shifted and then the tune shifts ΔQ is determined via an FFT spectrum from turn-by-turn orbit data at a dedicated 'fast' BPM (see Fig. 6 as an example). With $\Delta Q = \xi \cdot \Delta p/p$ follows for the chromaticity $\xi = \Delta Q \cdot p/\Delta p = -\alpha_c h \Delta f_\beta / \Delta f_{\mathrm{RF}}$. Δf_{RF} corresponds to changes of the cavity radiofrequency, Δf_β is the measured betatron frequency shift, h is the harmonic number and the momentum compaction factor $\alpha_c = (\Delta L/L)/(\Delta p/p)$ relates the relative orbit path length change $\Delta L/L$ to the relative momentum change $\Delta p/p$. Work on this project has just started in the framework of a master's thesis.

INJECTION OPTIMIZATION

Already in 2005, first attempts were made to optimize the electron transfer rate (injection efficiency) from the booster synchrotron to the storage ring by a combination of genetic algorithms and neural networks [14, 15]. Currently, this idea is being resumed but now with an expanded number of parameters and with a significantly enlarged database for ML-based training. In addition to the strength settings of the transfer line magnets, the injection elements of the storage ring (e.g., kicker magnets, magnets of a static injection bump) as well as the trigger timings of all pulsed transfer line and injection magnets are now taken into account, too.

In total, currently up to 30 different parameters can be varied systematically or randomly. For each individual injection parameter variation, the corresponding change of the injection efficiency is measured simultaneously. In this way, several thousand pairs of experimental data sets were generated which served as inputs for various machine learning techniques. So far, classical feed-forward neural networks (NNs) and Gaussian process regression (GPR) methods were used for modeling [16, 17]. First training results are shown in Fig. 7 (GPR-based) and Fig. 8 (NN-based). They show the trained model predictions of the injection efficiencies as a function of approx. 750 measured transfer efficiencies.

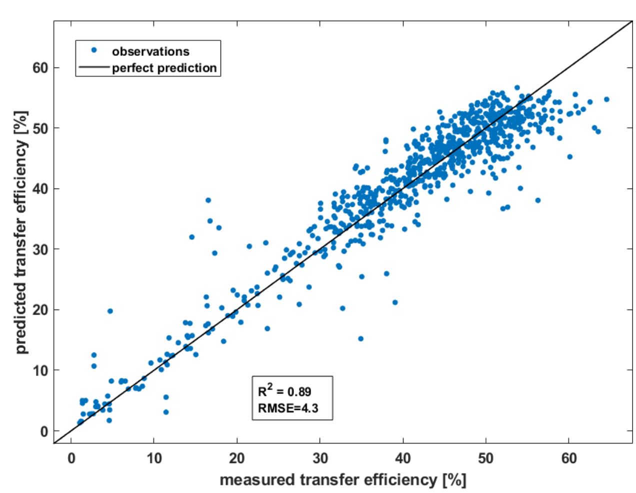

Figure 7: Injection efficiencies predicted by a Gaussian process regression (GPR) model versus measured efficiencies. The machine learning was performed with approx. 750 measured data sets. The GPR applied the nonisotropic exponential kernel function for model adaption [16]. The fit results in a correlation coefficient of $R^2 = 0.89$ and a root mean squared value (RMSE) of 4.3.

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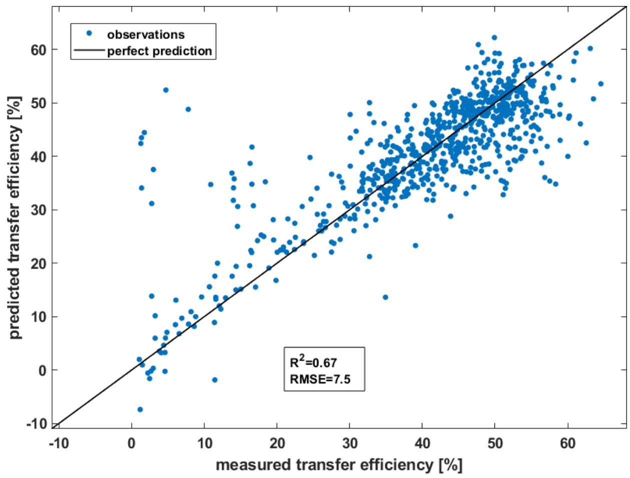

Figure 8: Injection efficiencies predicted by a model based on a narrow neural network (NN) versus measured efficiencies. The machine learning was performed with the same 750 data sets as used for GPR-based modelling. The NN is composed of three fully connected ReLU-layers (28/10/1) [16]. The fit results in a correlation coefficient of $R^2 = 0.67$ and a root mean squared value (RMSE) of 7.5.

The plots were obtained applying the k-fold cross validation method. Therefore, the training data sets were randomly shuffled and then divided into k partitions. For each training-validation iteration a different partition for validation was used. The remaining data was applied for testing. Thus, each data partition was used once for validation and $k - 1$ times for training.

Both ML methods find clear correlations, whereby the GPR-trained model results in a significantly larger correlation coefficient R and thus seemed to be more suitable for transfer rate modeling. The next step is to apply these models to keep the injection efficiency at a high level in an automated way using an optimization algorithm (e.g. BFGS [18] or Bayesian optimization [19]) without the need for operator interventions [20]. These studies are currently being continued.

SUMMARY

ML-based techniques are increasingly replacing conventional optimization methods in the fields of particle accelerator controls. At the electron storage ring facility DELTA, it was demonstrated that specially designed and trained neural networks are suitable for a variety of control tasks. Supervised training of the NNs was performed with data recorded during real machine operation and with simulation data based on accelerator models. Compared to classical numerical methods, it was shown that the different ML-based applications could achieve comparable correction accuracies. In contrast to conventional numerical methods, neural networks are in principle able to converge to the desired target values in fewer iterations, resulting in a faster correction convergence behaviour. Inspired by a variety of ML-supported applications in other scientific fields, additional use cases in the domain of accelerator controls are being evaluated. First ideas for a neuro-fuzzy feedback loop, e.g., for the water cooling system of the new EU-type RF cavity installed at the DELTA storage ring, have already been discussed [7]. It is planned to migrate all ML-based programs to a dedicated GPU-based ML server which provides a powerful hardware platform and a more user friendly ML framework (ML workflow) for future, more sophisticated ML applications.

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