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MACHINE LEARNING APPLIED TO AUTOMATED TUNES CONTROL AT THE 1.5 GeV SYNCHROTRON LIGHT SOURCE DELTA

D. Schirmer*, Center for Synchrotron Radiation (DELTA), TU Dortmund University, Germany

Abstract

Monitoring the storage ring betatron tunes is an important task for stable machine operation. For this purpose classical, shallow (non-deep), feed-forward neural networks (NNs) were trained with experimental machine data as well as with simulated data based on a detailed lattice model of the DELTA storage ring. Comparable tune correction accuracies were obtained with both data sources, both in real machine operation and for the simulated storage ring model.

INTRODUCTION

DELTA is a 1.5-GeV electron storage ring facility operated by the TU Dortmund University producing synchrotron radiation ranging from THz to the hard x-ray regime [1, 2]. Due to thermal orbit motion and magnetic current-dependent field changes, the tunes may vary during machine operation. Therefore, automatic tunes correction is an essential task especially for the DELTA storage ring, as otherwise sudden beam losses can occur.

To provide a precise, reliable and fast tune reading, the complete measurement setup was renewed in 2006 [3]. It is based on broadband beam excitation with an diagonal kicker magnet (kick in both x,y-planes at once) and measurement of the relaxation betatron oscillations turn-by-turn. The betatron frequency detection utilized a classical numeric approach applying fast Fourier transform and Levenberg-Marquardt algorithms for data fitting. Thus, a tune measuring accuracy of better than $2 \cdot 10^{-5}$ can be achieved [3].

A PID-tune feedback loop based on this measurement compensates for tune shifts. This method is regularly in use since many years as the standard tune control method at the DELTA storage ring.

MACHINE LEARNING APPROACH

Simulation Results

An alternative approach is the application of machine learning (ML) methods. For this purpose, simulations were initially executed to identify if there exists a ML-trainable correlation between quadrupole strength variations and corresponding tune shifts. A detailed lattice model of the DELTA storage ring served as the basis for x,y-coupled linear optics and tunes (Q_x, Q_y) computations within the Accelerator Toolbox (AT) framework [4, 5]. The lattice contains all main accelerator components including all insertion devices (IDs) such as the superconducting asymmetrical wiggler magnet (SAW) [6]. It is mainly composed of a sequence of so-called triplet unit cells arranged in the arcs of the racetrack-shaped storage ring [7]. In order to minimize optics variations in the straight sections, exclusively 7 quadrupole families installed in these unit cells are used for tunes control. Thus, a total of 3 horizontally and 4 vertically focusing quadrupole families can be operated independently by dedicated power supplies.

For simulations, the strengths of these quadrupole families were randomized, uniformly distributed within four interval limits (±0.1%, ±0.5%, ±1%, ±2%), whereby these limits have also been uniformly randomized. This leads to Gaussian-like distributions without outliers beyond the interval limits and thus avoids the risk of beam losses in the later application on real machine operation. For each set of limits, 3000 related tunes were computed via the AT-framework (see Fig. 1).

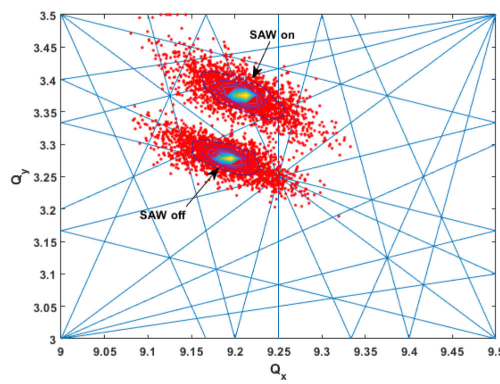

Figure 1: Distribution of 3000 tune calculations for quadrupole settings randomly varied by ±1% for two cases, with SAW switched on and off, respectively. The tune is vertically shifted due to strong edge focusing effects of the SAW.

With the results of overall 12000 simulations, classical 3-layer, fully connected feed-forward neural networks (NNs) were trained (see Fig. 2). They consists of 2 input neurons (tune shifts: ΔQ_x, ΔQ_y), neurons in one hidden layer (optimal quantity determined by trial and error) and 7 output neurons (quadrupole strength variations: ΔK). The nonlinear hyperbolic tangent serves as the network transfer function between the input and hidden layer and a linear transfer function was applied between the hidden and output layer. The NNs were subjected to supervised training with a variety of training methods [8–11]. Best results were achieved with a conjugate gradient backpropagation with Polak-Ribiére updates [9]. Corresponding learning curves are shown in Fig. 3(a) as an example. The learning performance is rated by the mean square error (mse) of the NN output: mse $= 1/P \sum_{p=1}^{P} 1/N \sum_{n=1}^{N} (o_{pn} - t_{pn})^2$. It sums up the square difference between all target (t) and NN output (o)

* detlev.schirmer@tu-dortmund.de

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neurons (N) for all training patterns (P). With increasing number of 'full' batchsize backpropagation iterations (80% of all data pairs P) the mse of the network was reduced by more than two orders of magnitude. The validation learning curve (green line) demonstrates that the NNs can be trained by simulated data and they are able to generalized the correlation between tune shifts and quadrupole strength variations. The training regression coefficient is calculated to $R = 0.65$.

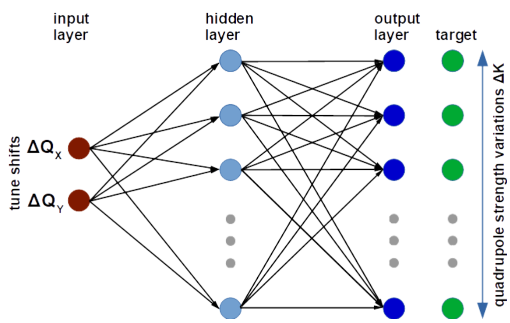

Figure 2: Three-layered (input/hidden/output) NN topology to be trained for the automated tunes control.

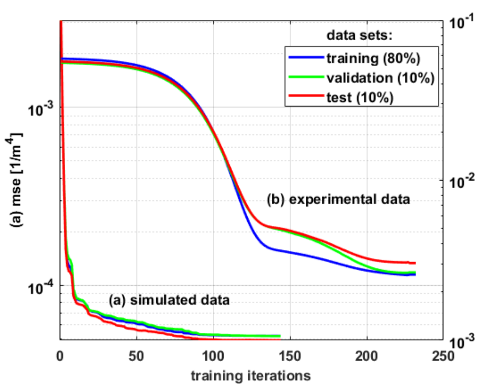

Figure 3: Training performance of different data sets determined by the mean square error (mse). The trainings were performed with a batch size of 12000 simulated (a) and about 600 experimental (b) data with different backpropagation learning algorithms [8–11].

Subsequently, the NNs were verified with the accelerator model. Figure 4 shows the tune matching for an arbitrary goal tune as an example. The initial tunes were defined by the SAW status (switched on/off). In both cases the desired goal tune was reached iteratively. The number of steps is adjustable. In principle, smaller demanded tune shifts (< 0.01) can be performed in larger steps (less iterations). The step size resolution essentially depends on the related data quantity of corresponding step widths during NN training.

Application in Real Machine Operation

On the basis of the simulation studies described above, corresponding experimental data were recorded during real storage ring operation. Again, only the current set values of the quadrupole families in the arcs were randomly changed

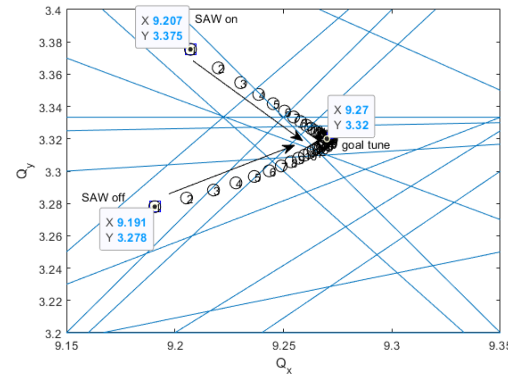

Figure 4: Example for verification of NNs trained by simulated data and applied to the simulated storage ring model. The desired goal tune was reached in iterative steps from different start values, SAW switched on and off, respectively.

and subsequently the associated tunes were measured with an accuracy of better than $1 \cdot 10^{-4}$ [3]. To minimize the probability of beam losses due to, e.g., large tune jumps, the variation interval of the quadrupole settings was limited to ±0.5% for each power supply family. During a machine run of about 2 hours, more than 600 data pairs were recorded.

The NN layout described above (see Fig. 2) could also be used to successfully train with these measured experimental data (see Fig. 3(b)) [8–11]. Because the measured data are more noisy than data from simulations, the regression coefficient is reduced to $R = 0.45$.

Neural Network Validations

Although the regression correlation is smaller in comparison to simulation calculations, these trained NNs were still tested to determine quadrupole changes for desired tune shifts in real machine operation. Figure 5 demonstrates two successful examples for storage ring tune controls, with the SAW switched off and on, respectively.

In general, NNs were able to calculate the correct quadrupole settings to reach the desired target tunes in just a few steps. But since the quadrupol power supplies cannot be controlled synchronously in real time, the new quadrupole set values must be approached in smaller steps. After each single step, the tune was determined again (see numbered actual tunes in Fig. 5) and the NNs predicted the next step until the desired goal tune was reached iteratively. Nevertheless, this method is not always successful either, since, as with the standard PID method, harmful resonances can be crossed, as indicated by the resonance lines in the $Q_{x,y}$-tune diagrams. In the shown examples, the goal tunes were reached in 10 respectively 50 steps with an absolute error of less than $4 \cdot 10^{-3}$. The step size depends on the demanded total tune shift and the quadrupole variation limits during training. Returning from the goal tune to the initial start tunes was also possible analogously.

Finally, it was examined whether it is also possible to perform tunes control of the real storage ring with NNs only trained by simulated model data; and vice versa, NNs

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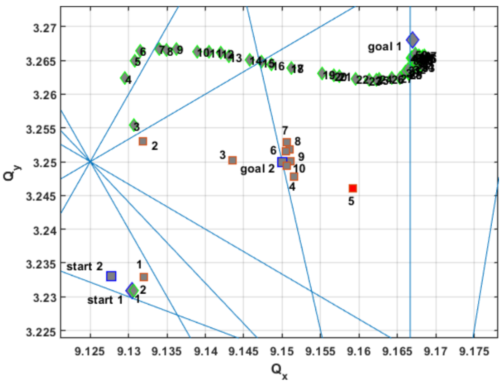

Figure 5: Validations of NNs trained with experimental data and applied to real machine operation. Two experiments demonstrate tune matching from start to goal tunes without beam losses. In the first experiment, 10 steps were performed (SAW switched on, red rectangular markers) and in the second test 50 steps were executed (SAW switched off, green diamond markers).

only trained with real machine data and then applied to the simulation model. This should be possible as long as the relationship between quadrupole variation and tune change in the linear storage ring model is similar to that of the real machine. Here, the correct conversions of model simulation parameters to real magnet power supply current settings and vice versa is an important task. The corresponding recalculations were performed by a Matlab version of the conversion program "i2k" [6, 8, 12]. The program also takes non-linear magnetic saturation and cross-talk effects of the combined function magnets into account [12]. Figure 6 illustrates a typical tune matching application as an example. It is comparable to the validation shown in Fig. 5, which has been obtained with real machine data exclusively. This example demonstrates, for the first time at the DELTA storage ring, that NNs trained by simulated model data can also be used for controlling real machine processes. In an analogous manner, it was also possible to use NNs trained by measured data to perform tune control on the simulated storage ring model (see Fig. 7). This result corresponds to the verification example shown in Fig. 4. As previously indicated, the step sizes can be adjusted within certain limits essentially determined only by the value range of training data.

So far, only difference data ($\Delta Q_{x,y}$ and $\Delta K_{QF,QD}$) with small changes (approx. 1%) were used for NN training. As long as the correlation of these relative changes (gradients) is similar for a wide range of optics settings (i.e., absolute tunes), this ML technique is applicable in a wide tune workspace of the DELTA storage ring, without having to retrain the NN.

SUMMARY AND OUTLOOK

At the electron storage ring DELTA, it could be shown that trained NNs can also be used for automated tunes adjustment. The network training was carried out with data recorded

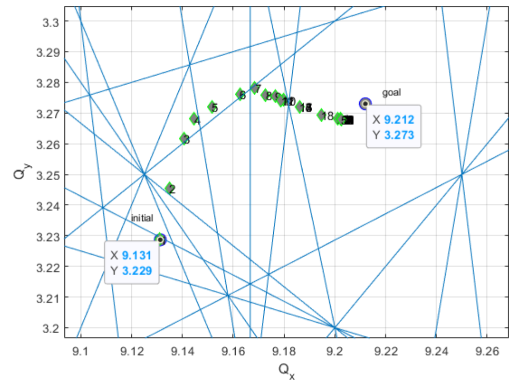

Figure 6: Example for the validation of NNs trained by simulation data and applied in real accelerator operation. The desired goal tune was gradually approached in 50 steps.

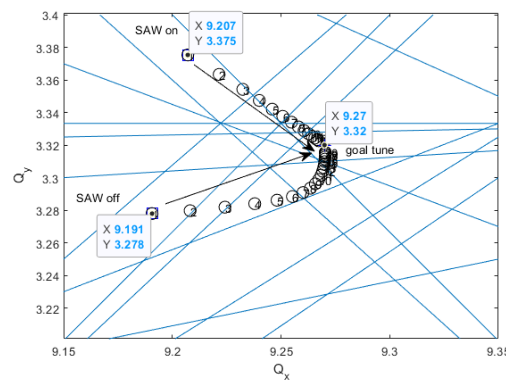

Figure 7: Example for the verification of NNs trained by real machine data. The goal tune was reached in 25 iterations. NNs were applied to the simulation model with SAW switched on and off, respectively (compare to Fig. 4).

during real machine operation as well as with simulation data based on an accelerator model. With both data sources, comparable tune controlling accuracies were achieved in real machine operation.

In principle, the ML method presented in this article can also be transferred to other accelerator optimization tasks. Varying the sextupole strengths and measuring corresponding chromaticity changes is one example. NN trained by such data can be applied to adjust desired chromaticities. A similar method could also be applied to the adjustment of beam coupling and the associated beam size [13]. For this purpose, one would have to vary the strengths of skew quadrupoles and determine the related coupling change.

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