ISBN: 978-3-95450-184-7 doi:10.18429/JACoW-IPAC2018-THPML085

INTELLIGENT CONTROLS FOR THE ELECTRON STORAGE RING DELTA

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

Abstract

In recent years, artificial intelligence (AI) has become one of the keywords in the field of controlling, monitoring and optimizing complex particle accelerators. In accelerator controls, one has to deal with a variety of time–dependent parameters, nonlinear dynamics as well as a lot of small, compounding errors. In order to cope with these tasks and to achieve higher performance, particle accelerators require new advanced strategies in controls and feedback systems. Machine learning through (deep) neural networks, genetic algorithms, swarm intelligence and adaptive controls are some of the proposed approaches. Increased computational capability and the availability of large data sets in combination with a better theoretical understanding of new network architectures and training paradigms allow for promising approaches for novel developments. This report aims at illustrating first ideas for possible applications of intelligent controls at the synchrotron radiation source DELTA.

INTRODUCTION

The application of artificial intelligence (AI) methods for accelerator control was already discussed in the late 1980s [1]. At DELTA, a 1.5-GeV synchrotron light source operated by the TU Dortmund University, early ideas of a so–called "cybernetic machine" in the accelerator domain were proposed 1996 in [2]. An example of using genetic algorithms in designing and optimization of transfer line optics are described in [3, 4]. In 2003, a knowledge–based multi–agent expert system was experimentally implemented for automatic control of the transfer line injection efficiency (from booster to storage ring) at DELTA [5]. In 2005, design and comparison of assistive systems based on combinations of evolutionary strategies and neural networks were tested [4, 6]. Unfortunately, all systems did not show significant improvements in practical accelerator operation.

In the light of recent theoretical and practical advances in the field of machine learning and the use of deep neural network–based modeling and controlling techniques, new approaches for the control and monitoring of particle accelerators are emerging. Furthermore, the availability of powerful deep learning programming frameworks like TensorFlow [7], Caffe [8], PyTorch [9], Keras [10] and Matlab [11] allow rapid and optimized implementations of complex algorithms and network architectures. A comprehensive overview of the status quo in these fields is given in [12].

* detlev.schirmer@tu-dortmund.de

CASE STUDIES OF AI AT DELTA

At DELTA, various possible applications of AI–based controls are currently investigated:

Neuronal Network Techniques for Orbit Control

Orbit monitoring and correction is an important task in accelerator controls. At DELTA, SVD–based (singular–value decomposition) orbit correction programs have been successfully used in routine machine operation for many years [13–15] Currently, a new "Cone-Program"–based approach to orbit correction is being evaluated [16]. Another concept applies artificial neural network (ANN) techniques [17, 18]. First prototype studies were carried out with the Matlab programming workbench and corresponding toolboxes [11].

Orbit Drift Compensation: Due to current losses in the superconducting coils, the magnetic field of the superconducting asymmetric wiggler (SAW) decrease over time ($\approx$ 0.5 mT/h) which results in a significant horizontal orbit drift. This drift must be compensated to avoid electron beam losses. A standard SVD–based orbit correction program takes care of this, mainly by adapting the strength of the most effective horizontal corrector magnet ("hk23") which is mounted close to the SAW. Fig. 1 (top and center) shows the time–dependent evolution of the magnetic field strengths (hall probe sensor a, b), in correlation with the steerer strength over one synchrotron user week (four days: from Monday 12:00 h to Friday 12:00 h). The daily dips in the curves result from refreshing the magnetic field of the SAW. All data were extracted from the epicslog database archiver [19] and were averaged over one hour which results in 96 data pairs.

As neural networks are well suited for function fit problems, these data were used to train, by supervised learning, a fully connected feedforward neural network (FFNN with 2 input, 4 hidden and 1 output neuron). Two different kinds of neural nets were investigated on a trial basis: FFNN1, with pure linear transfer functions and backpropagation teaching using the Bayesian Regulation (br) method (green squares) and FFNN2, with tangent–sigmoid transfer functions and backpropagation training using the Levenberg–Marquardt (lm) method (blue squares) [11]. Both nets were trained with randomly selected data sets. To determine the supervised training performance, the average squared difference between net outputs and targets (means squared error (mse)) were calculated. After supervised training of 96 input–output–target data combinations, the neural nets are able to estimate an adequate corrector strength for given magnetic

ISBN: 978-3-95450-184-7 doi:10.18429/JACoW-IPAC2018-THPML085

field strengths, although the nets consist only of seven neurons. FFNN2 generally achieved slightly better results (see Fig. 1, center and bottom). The error is reduced during the week from ± 500 mA (<10%) to less than ± 300 mA (<6%). Even though these are only preliminary results, the accuracy should be sufficient to avoid electron beam losses. Further improvements will be achieved by additional training (more user weeks) and/or with more input–output data correlations (e.g., additional hall probe sensors).

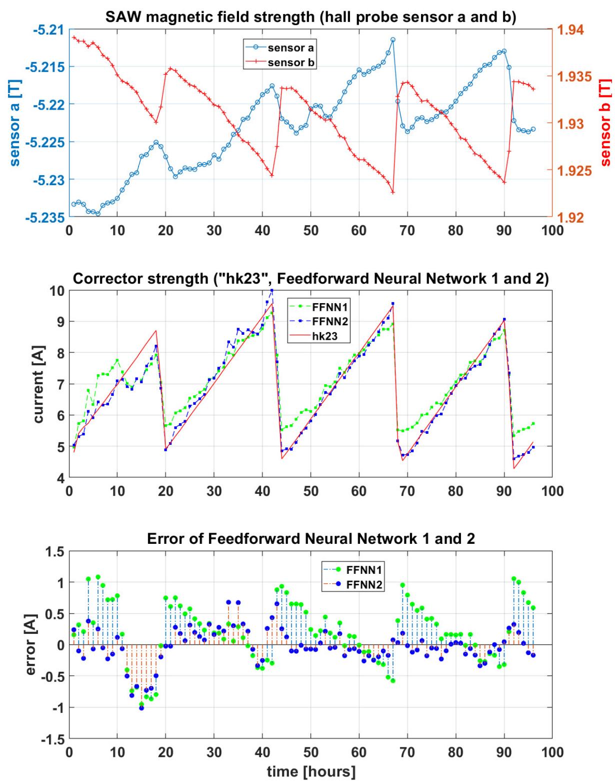

Figure 1: Neural network calculations for orbit drift compensation.

Global (horizontal) Orbit Correction: At first, the neural network topology for the global orbit correction was defined as a classical fully connected three–layer feedforward neural network (FFNN) with 54 input neurons (input layer corresponds to 54 beam position monitors (BPMs)), 54 hidden neurons (hidden layer) and 30 output neurons (output layer corresponds to 30 horizontal steerer magnets). This net was trained with two response matrices (BPM readings for positive and negative single steerer kicks) and 1000 random orbits, generated by randomly distributed steerer kicks (BPM data and corresponding steerer strengths). All training data were generated by a simulated offline model (DELTA lattice version "del008") of the DELTA storage ring using the Accelerator Toolbox [20, 21] integrated in the Matlab framework [11]. The simulated response matrices, the working points and linear optics were crosschecked with real machine data and showed good agreement at a percentage level.The training performance of neural networks depends largely on the availability of large amounts of well–preprocessed training data. Thus, the storage ring offline model is ideally suited as a fast and accurate data source for large sets of training samples.

The result of the FFNN performance function (mse) is shown in Fig. 2. The training data are randomly divided into three kinds of samples [11]: Exclusive training samples (80%) which are presented to the network, whereby the network is adjusted according to its error (blue line), validation samples (10%) which measure network generalization and halt training when generalization stops improving (green line) and testing samples (10%, no effect on training) which provide an independent measure of network performance during training (red line). During training (increasing sample count) the performance improves continuously. After 1000 training samples the mse-value was less than 2×10^{-4}. Different transfer functions (pure linear, logarithmic–sigmoid, tangent–sigmoid) and teaching methods (backpropagation with Levenberg–Marquardt (lm) and Bayesian Regulation (br)) were evaluated. Best results were achieved with the lm–training and the tangent–sigmoid transfer function. As an example, the difference between FFNN–proposed and model–calculated response (steerer strengths for an arbitrary orbit) is shown in Fig.3. The relative mismatch for all steerer magnets is less than 10^{-6}. Even if these simulations give only preliminary estimates, this rather simple approach is showing promising results. However, further investigations must prove its usability in real storage ring operation. First tests are currently being evaluated.

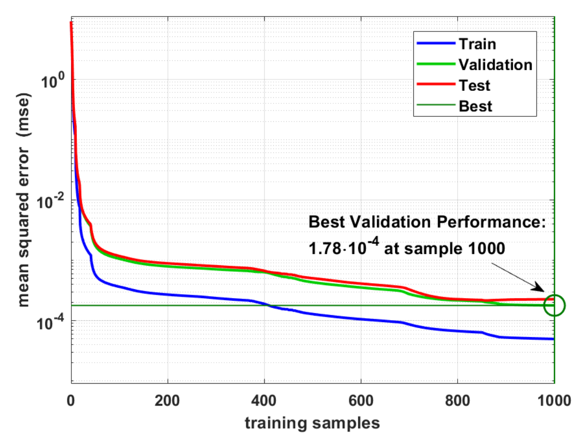

Figure 2: Neural network training performance (mse) for global orbit correction.

PID–Based and Adaptive Neuro–Fuzzy Controls

In some areas of the DELTA control system, conventional PID controllers are implemented. For example, the cavity power control of the DELTA RF–system as well as the water temperature control of the injection coolers (buncher, linac structures) and the booster/storage ring cavities are controlled in this manner. A water cooling system for the new EU–type cavity was developed in–house and is currently

ISBN: 978-3-95450-184-7 doi:10.18429/JACoW-IPAC2018-THPML085

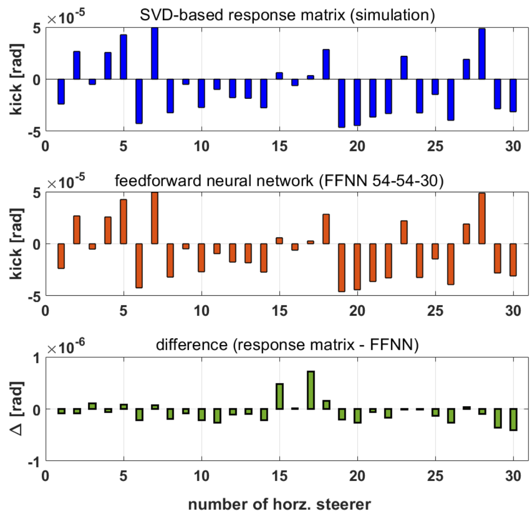

Figure 3: Comparison of neural network and SVD–based offline model calculations.

commissioned. Sensor and actuator data exchange is provided by a WAGO–I/O–system [19], whereby the high–level control is also performed by a traditional EPICS record–based PID algorithm [22]. In most cases, conventional controllers such as the PID algorithms fulfill the requirements. Although they have the advantage of being conceptually very simple, robust and fast, they have several important limitations as the number of parameters to control increases. Here, adaptive controls could offer alternative approaches. For example, neuro–adaptive–fuzzy controllers have the advantage of being able to dynamically adapt to non–linearly changed boundary conditions (e.g., long–term changes in ambient air temperature or variations of water temperature supplied by the cooling tower system, etc.). In contrast to that, PID parameters require frequent manual recalibrations. Fuzzy logic systems could also be identified as a good initial candidate for the application of neural network-based control methods.

To study this, the water cooling system for the EU–type cavity was schematically modeled in the Matlab/Simulink software framework [11]. The schematics of the control loop is shown in Fig. 4. The goal is to keep the water outlet temperature constant at a level of 33 degrees within ±0.5 degrees. The water is heated by the cavity body depending on the supplied RF power (max. 75 kW). A PT1000 sensor measures the water temperature directly after the cavity water outlet. A valve regulates the cold water supply provided by a heat exchanger [22]. Conventional PID controllers follow an arbitrary step function heating curve with typical control over– and undershoots (see Fig. 5, red curve). The response behaviour can significantly be improved by a fuzzy logic controller (see Fig. 5, blue curve). Here, a set of five fuzzy rules (for the water temperature and valve position, respectively) with Gaussian membership functions were implemented as a first simulation test.

As soon as measured data are available, the controller will be extended by an adaptive neuro–fuzzy learning sys-

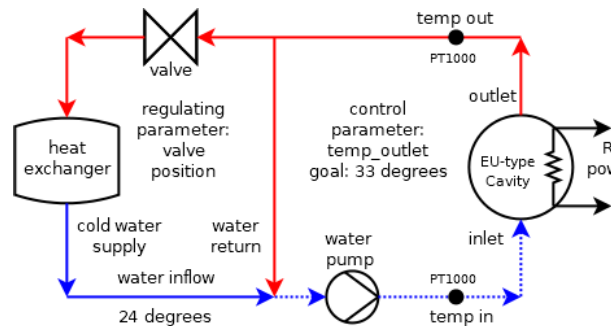

Figure 4: Water temperature control loop for the EU–type cavity.

tem. This system provides a method for the fuzzy modeling procedure to learn information about data sets in order to compute the membership function parameters that best allow the associated fuzzy interference system to track the measured input/output data. This learning method works very similar to that of neural networks [11].

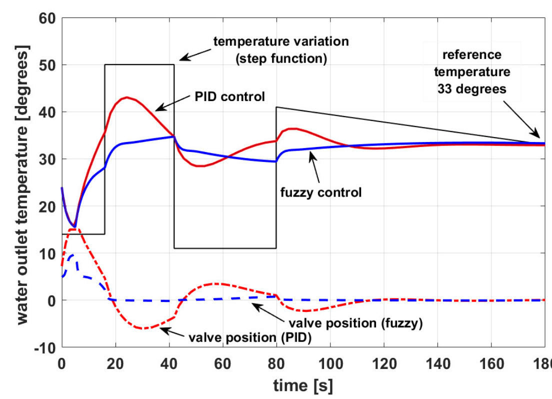

Figure 5: Comparison of PID and fuzzy control simulations.

SUMMARY AND OUTLOOK

Machine learning offers new, powerful and flexible solutions in many areas of accelerator controls. At DELTA, various applications are in the evaluation phase with promising intermediate results. The usability in real machine operation is currently being tested.

Computing performance is often a significant issue when training a machine learning model, especially for multilayered (deep) neural networks with millions of neurons. Therefore, high–performing hardware components such as special graphics or tensor processor units with optimized software features (e.g., parallel and distributed processing) will be necessary in the future. This could open up further demanding application possibilities [23].

ACKNOWLEDGEMENT

It is a pleasure to acknowledge the permanent support by the TU Dortmund and other research institutes. In particular I would like to thank the EPICS community for permanent support and the whole DELTA team for inspiring and constructive discussions.

ISBN: 978-3-95450-184-7 doi:10.18429/JACoW-IPAC2018-THPML085

REFERENCES

[1] D. P. Weygland, "Artificial Intelligence and Accelerator Control", in *Proc. PAC'87*, Washington, DC, USA, pp. 564–566.

[2] C. Biermann, E. Wildner and A. Lüdeke, "A cybernetic machine for controlling and optimizing accelerator processes", DELTA, Internal Report, 1996, unpublished.

[3] D. Schirmer *et al.*, in *Proc. PAC'95/HEACC'95*, Dallas, USA, pp. 1879–1881.

[4] D. Schirmer *et al.*, "Electron Transport Line Optimization Using Neural Networks and Genetic Algorithms", in *Proc. EPAC'06*, Edinburgh, Scotland, pp. 1948–1950.

[5] E. Zimoch, "Entwicklung und Einsatz eines intelligenten Agentensystems zur Optimierung der Injektion in den Speicherring der Synchrotronstrahlungsquelle DELTA", dissertation, Phys. Dept., TU Dortmund, Germany, 2003.

[6] T. Buening, D. Mueller, "Entwurf und Vergleich unterstützender Systeme zur Verbesserung der Injektionseffizienz von DELTA, basierend auf Evolutionsstrategien und neuronalen Netzen", diploma thesis, Phys. Dept., Computer Science Dept., TU Dortmund, Germany, 2005.

[7] TensorFlow, `https://www.tensorflow.org/`

[8] Caffe, `http://caffe.berkeleyvision.org/`

[9] PyTorch, `http://pytorch.org/`

[10] Keras, `https://keras.io/`

[11] MATLAB/SIMULINK and Neural Network, Fuzzy Logic, Genetic Algorithm Toolboxes, Release 2017b, The MathWorks, Inc., Natick, Massachusetts, United States.

[12] A. L. Edelen, "Neural Networks for Modeling and Control of Particle Accelerators", FERMILAB-PUB-16-121-AD, 2016.

[13] D. Zimoch, "Implementierung eines Orbitkorrektursystems an der Synchrotronstrahlungsquelle DELTA", dissertation, Phys. Dept., TU Dortmund, Germany, 2002.

[14] B. Keil, "A Unified Distributed DSP-Based Beam Diagnostics and Global Feedback System for Ramped Electron Storage Rings: Development, Construction and Applications", dissertation, Phys. Dept., TU Dortmund, Germany, 2003.

[15] M. Grewe, "SVD-basierte Orbitkorrektur am Speicherring Delta", dissertation, Phys. Dept., TU Dortmund, Germany, 2005.

[16] S. Koetter, *et al.*, "Evaluation of a Cone-Program Based Approach to Orbit Correction at the Electron Storage Ring DELTA", presented at IPAC'18, Vancouver, British Columbia, Canada, April 2018, paper THPAK114, this conference.

[17] E. Bozoki, A Friedman, "Neural Networks and Orbit Control in Accelerators", in *Proc. PAC'94*, London, England, pp. 1589–1591.

[18] E. Meier, Y. R. E. Tan, G. S. LeBlanc "Orbit Correction Studies Using Neural Networks", in *Proc. IPAC'12*, New Orleans, Louisiana, USA, pp. 2837–2839.

[19] D. Schirmer *et al.*, "Control System Projects at the Electron Storage Ring DELTA", in *Proc. ICALEPCS'17*, Barcelona, Spain, pp. 1361–1365.

[20] A. Terebilo, "Accelerator Toolbox for MATLAB", SLAC-PUB-8732, 2001.

[21] A. Terebilo, "Accelerator Modeling with Matlab Accelerator-Toolbox", in *Proc. PAC'01*, Chicago, USA, pp. 3203–3205.

[22] P. Hartmann and D. Rohde, private communication, April, 2018.

[23] K. A. Brown *et al.*, "Experience with machine learning in accelerator controls", in *Proc. ICALEPCS'17*, Barcelona, Spain, pp. 258–264.