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First experiences with machine learning techniques at the 1.5 GeV synchrotron light source DELTA

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

Introduction

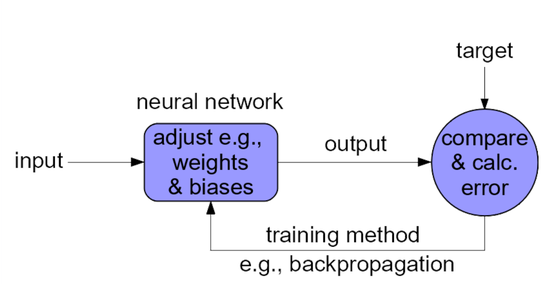
Recently, artificial intelligence (AI) has experienced a renaissance in many fields. AI-based concepts are nature inspired and can also be used in the field of accelerator controls [1,12, 23]. At DELTA various studies on this subject have been carried out in the past [2-6].
Due to increasing computing performance and great advances in theoretical AI research as well as the availability of powerful AI programming frameworks [7-11], this studies again met great interest and could be continued successfully. Among other possible applications, the use of neural networks for automatic correction of the electron beam position (orbit control) is of interest. Machine learning (ML) simulations with a DELTA storage ring model were already successful [3]. Recently, conventional Feed-Forward Neural Networks (FFNN) were trained on the basis of real machine data in order to carry out local and global beam position corrections in the 1.5 GeV storage ring Delta.

The facility is operated by the TU Dortmund University for approx. 3000 hours per year. More than 1000 hours are available exclusively for accelerator tests and optimizations. Thus, DELTA provides an ideal test environment for novel AI-based control system concepts.

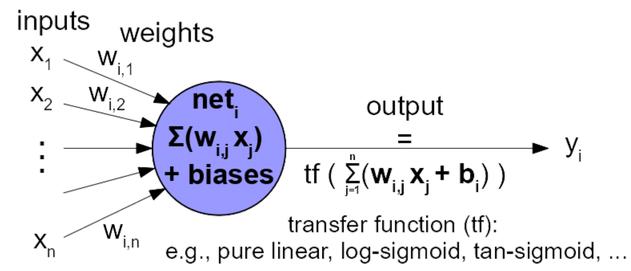
Neural Network (NN) Techniques for Orbit Control

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, 20, 21].

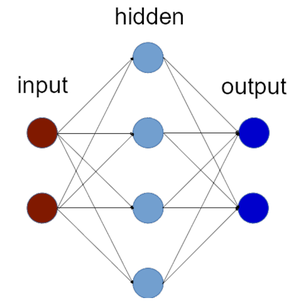
Supervised Learning



Neuron Model



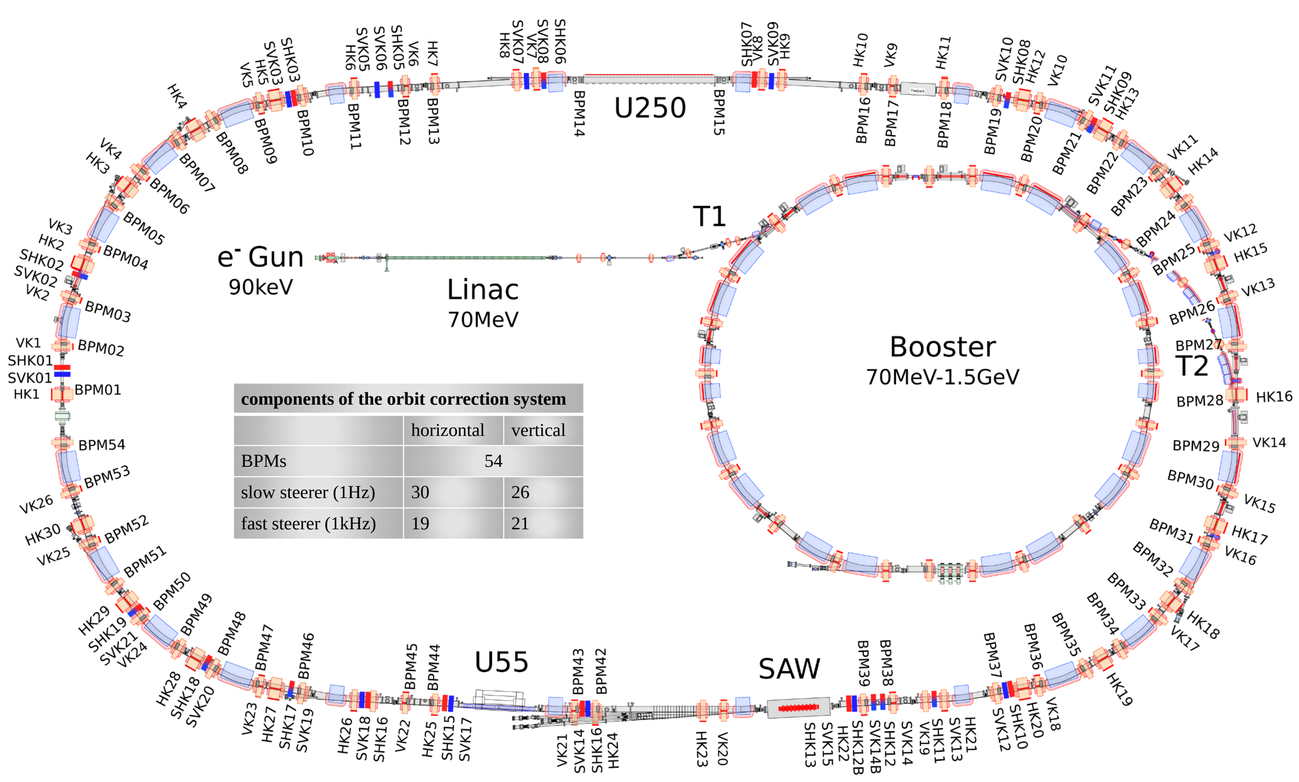
Network Topology



Global Orbit Correction Setup

The DELTA accelerator facility consists of a 90keV electron gun, followed by a linear accelerator (70MeV), a first transfer line (T1) between linac and booster, a booster synchrotron (70MeV to 1.5GeV), a second transfer line (T2) connecting the booster and the storage ring (1.5GeV). Three insertion devices (U250, U55, SAW) generate dedicated synchrotron light in various wavelength ranges.

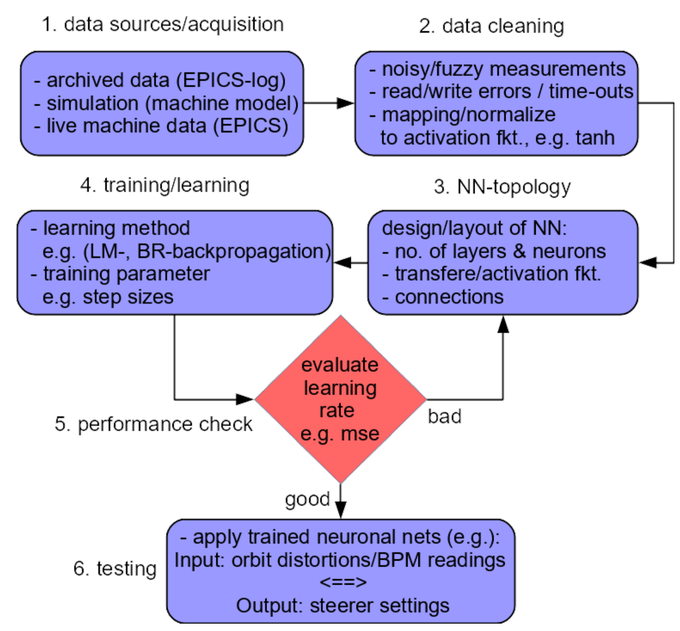
The global orbit correction system of the 115 m long storage ring is composed of 54 beam position monitors (BPMs), 30/26 horizontal / vertical corrector magnets (approx. 1Hz). In addition 19/21 fast horizontal / vertical steerer magnets can be used for fast orbit correction (some 100Hz) [22].



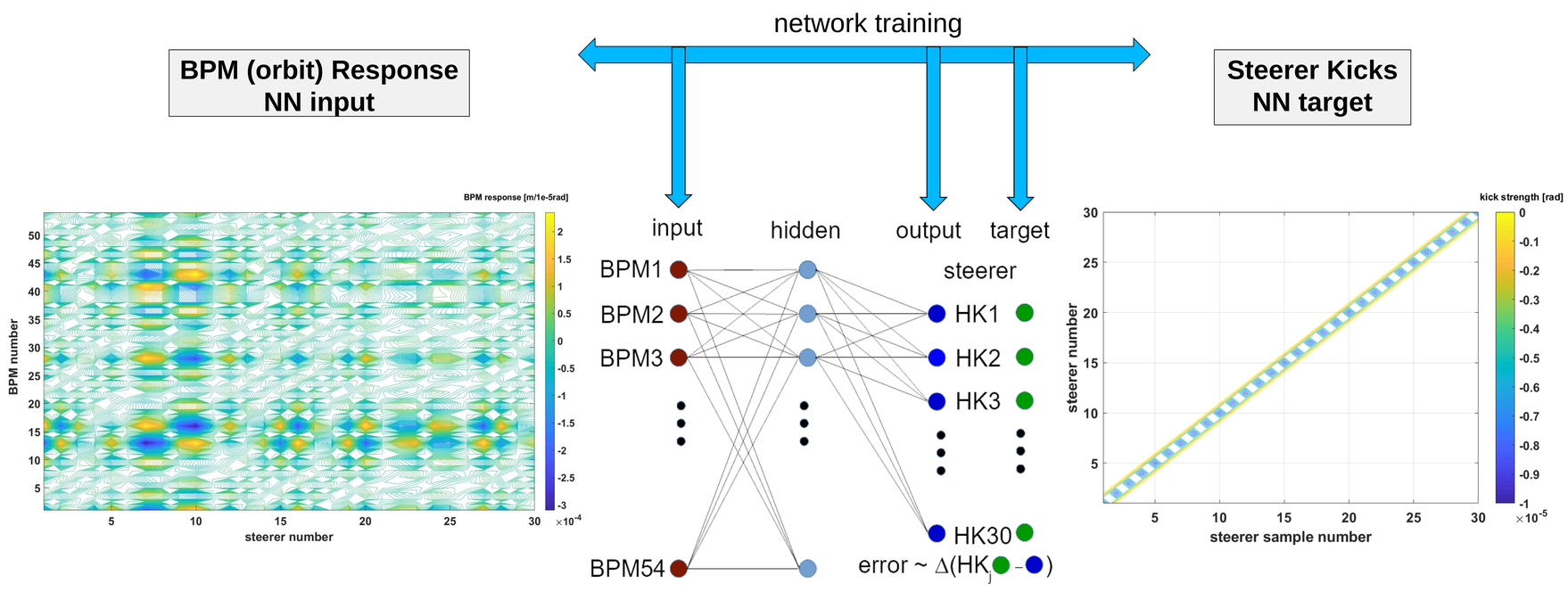
components of the orbit correction system	horizontal	vertical
BPMs	54	
slow steerer (1Hz)	30	26
fast steerer (1kHz)	19	21

NN Development Stages

The six essential steps from data acquisition to the application of neural networks. In particular, the quality of data mining and preparation (e.g. data cleaning) plays a significant role in machine learning.

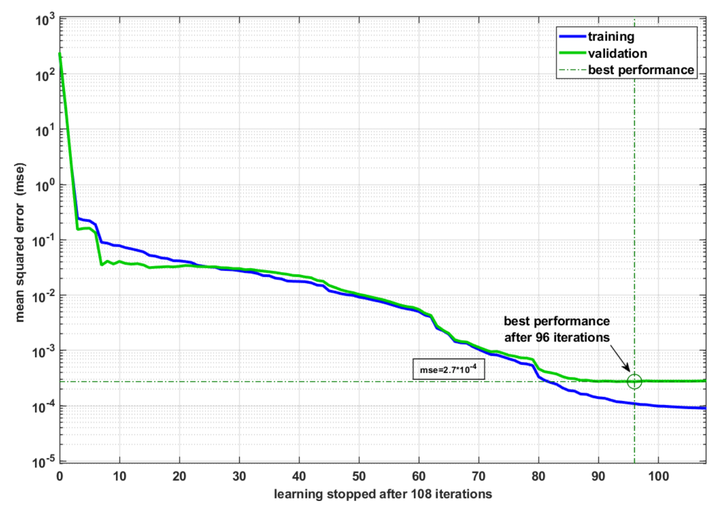


Global Orbit Correction with Feed-Forward-Neural-Networks (FFNN)

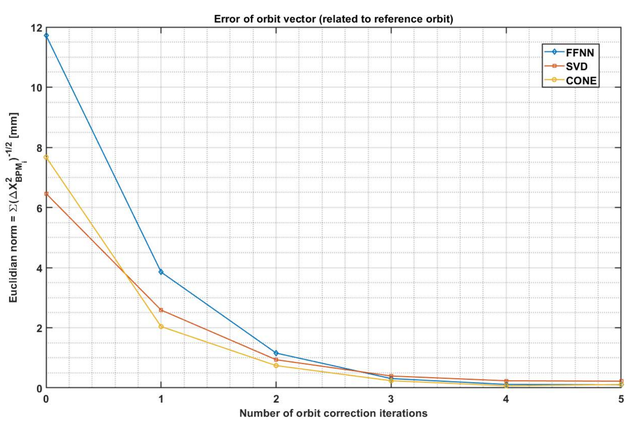


The neural network topology for the global orbit correction was defined as a classical fully connected three-layer Feed-Forward Neural Network (FFNN) with 54 input neurons (input layer corresponds to 54 beam position monitors (BPMs)), 54 hidden neurons (hidden layer) and 30 output neurons (output layer corresponds to 30 horizontal steerer magnets). This net was trained with two response matrices (BPM readings for positive and negative single steerer kicks) and 1500 arbitrary orbits, generated by randomly distributed steerer kicks [+/- 200mA].

FFNN Training Results

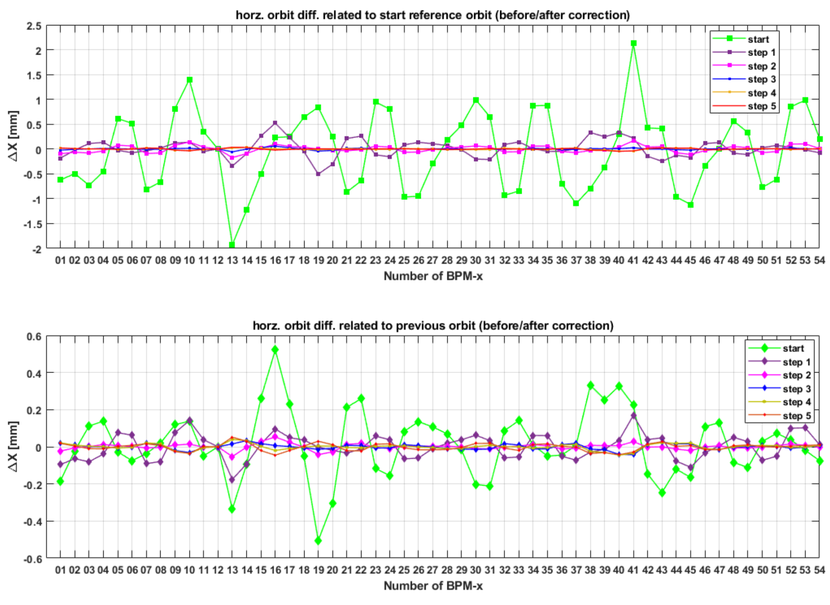


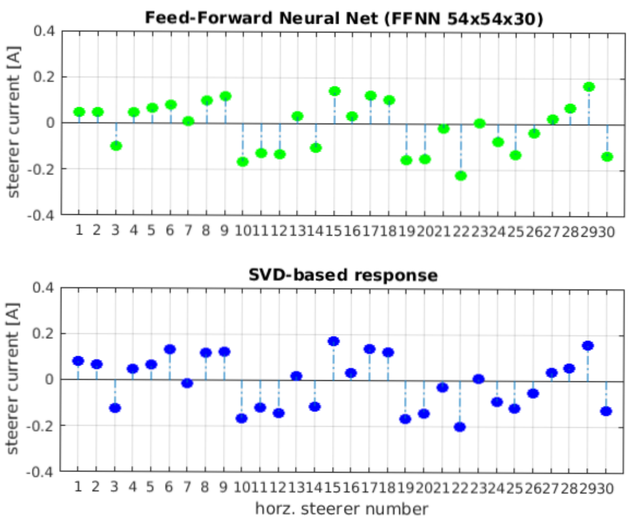
FFNN supervised learning performance (mse, BR) with approx. 1500 measured machine data records (orbit/steerer-data sets). Best validation performance (mse) of $2.7*10^{-4}$ was reached after 96 BR-training iterations of all records.



FFNN Orbit Correction Results

Iterative application of the trained (Bayesian Regulation) FF-Neural-Network referred to the previously corrected orbit, starting from a randomly disturbed orbit (start=iter.0). After 5 successive correction steps the rms-error (euclidian norm) is less than 0.1mm (see figures left and right).





Comparison of FFNN (green dots) and SVD-based (blue dots) calculations after network training with real machine data. Both orbit correction methods show similar results.

Comparison of different computing methods: Single Value Decomposition (SVD) [13, 15], qpcone-based (convex optimization) [16] and machine learning based (FFNN), lead to comparable results after multiple successive correction steps..

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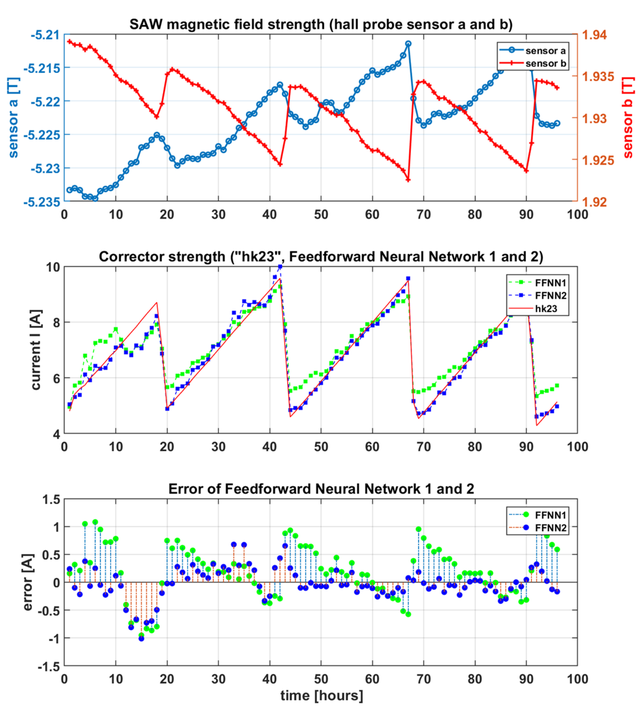
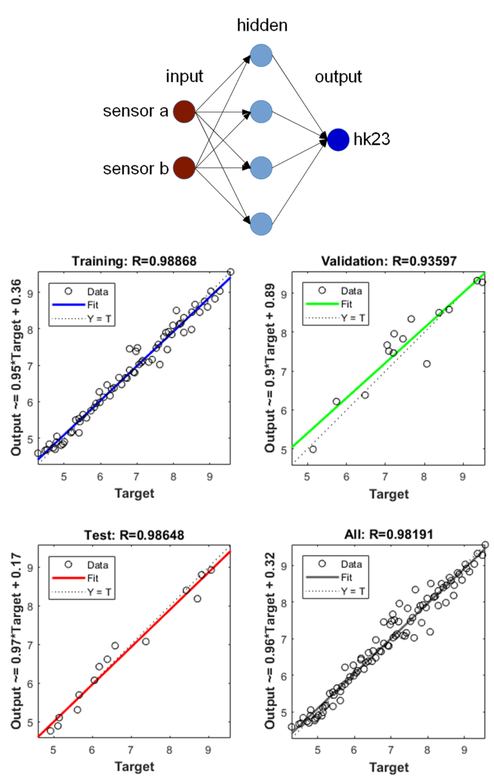
Local Orbit Drift Compensation with NN

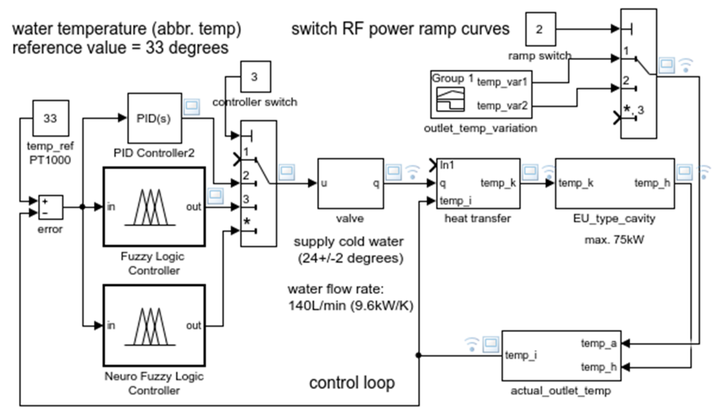
The magnetic field of the wiggler magnet (SAW) decrease over time (~0.5mT/h) which results in a significant horizontal orbit drift. This drift is compensated by a standard SVD-based orbit correction program, mainly by adapting the strength of the most effective horizontal steerer magnet ("hk23"). The time-dependent evolution of the magnetic field strengths (hall probe sensor a, b), in correlation with the steerer strength over one synchrotron user week is shown in the Figure. All data were extracted from the epicslog database archiver 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 feed-forward neural network (FFNN with 2 input, 4 hidden and 1 output neuron). After supervised training of 96 input-output-target data combinations, the neural nets (FFNN1 and 2) are able to estimate an adequate corrector strength for given magnetic field strengths.

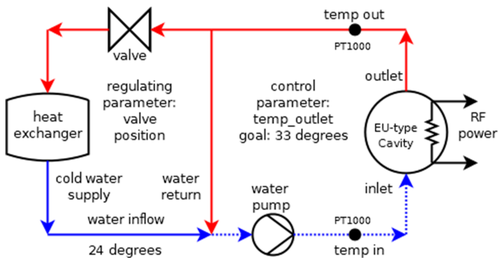




Outlook: From PID to Neuro-Fuzzy Control

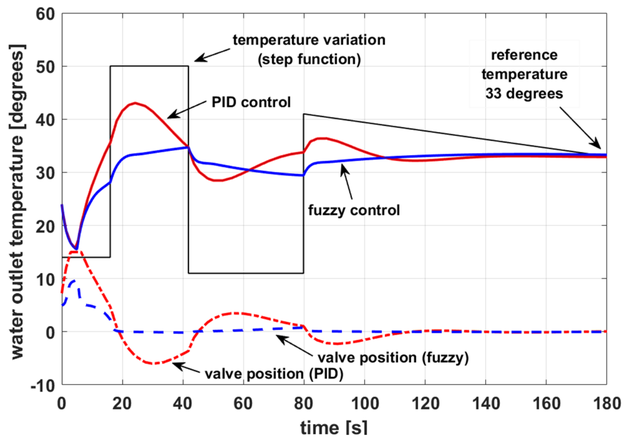
The water cooling system for the new EU-type cavity was schematically modeled in the Matlab/Simulink software framework [11]. The goal is to keep the water outlet temperature constant at a level of 33+/-0.5 degrees. In most cases, conventional PID algorithms fulfill the requirements but they have several important limitations as the number of monitoring parameters increases. Here, adaptive controls like (neuro)-fuzzy logic systems could offer alternative approaches.

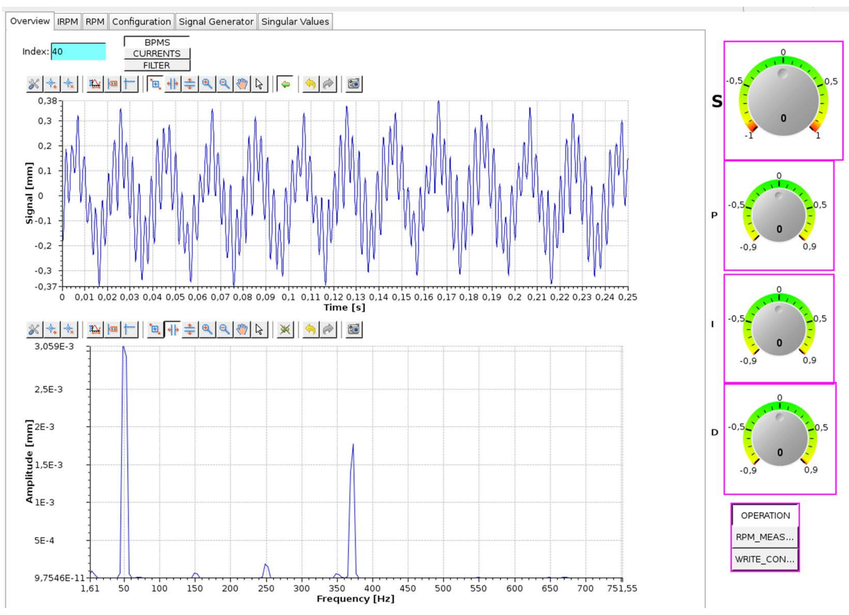


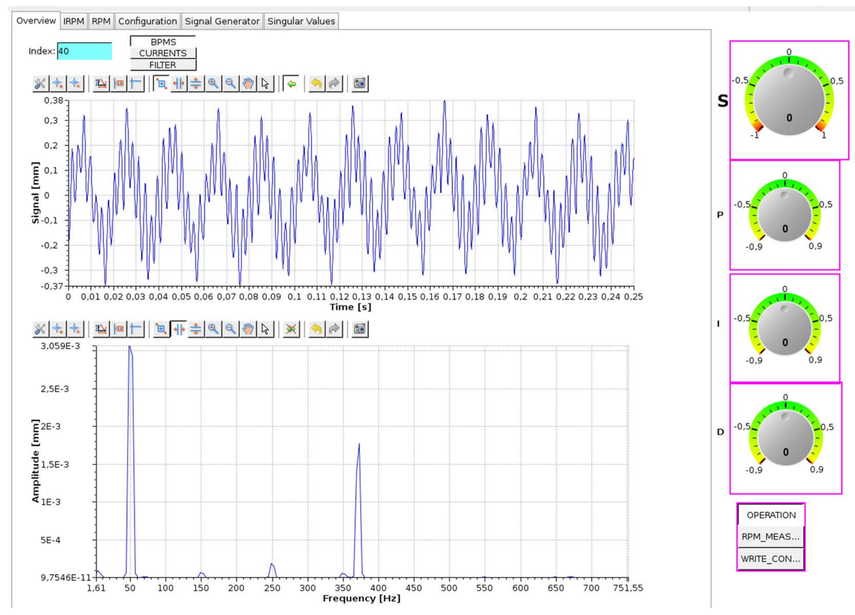


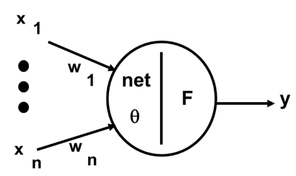
Conventional PID controllers follow an arbitrary step function heating curve with typical control over- and undershoots. The response behavior can significantly be improved by a fuzzy logic controller. Here, a set of five fuzzy rules (for the water temperature and valve position, respectively) with Gaussian membership functions were implemented as a first test.

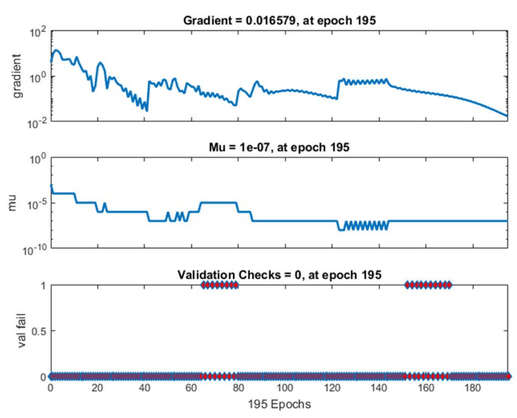
As soon as measured data are available, the controller will be extended by an adaptive neuro-fuzzy learning system. This system provides a method for the fuzzy modeling procedure to learn information about data sets in order to compute the membership function parameters that best allow the associated fuzzy interference system to track the measured input/output data. This learning method works very similar to that of neural networks.

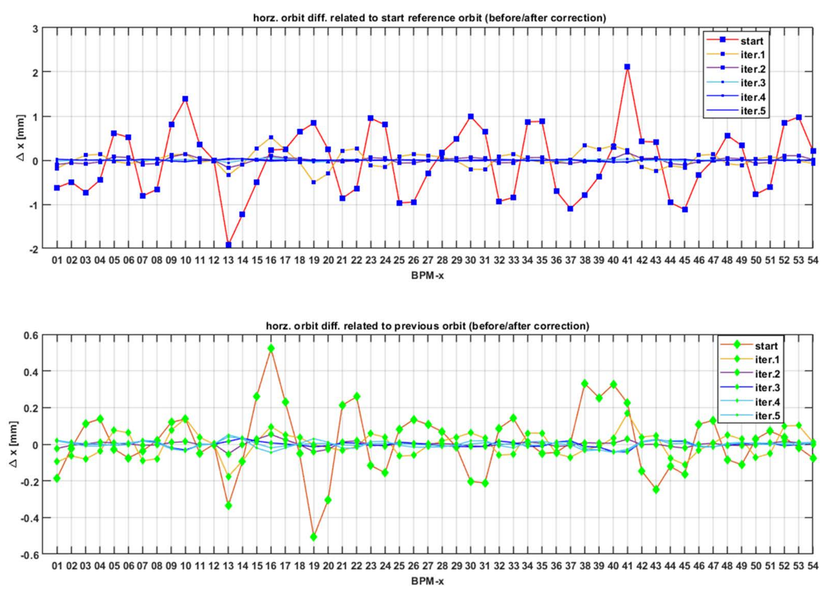


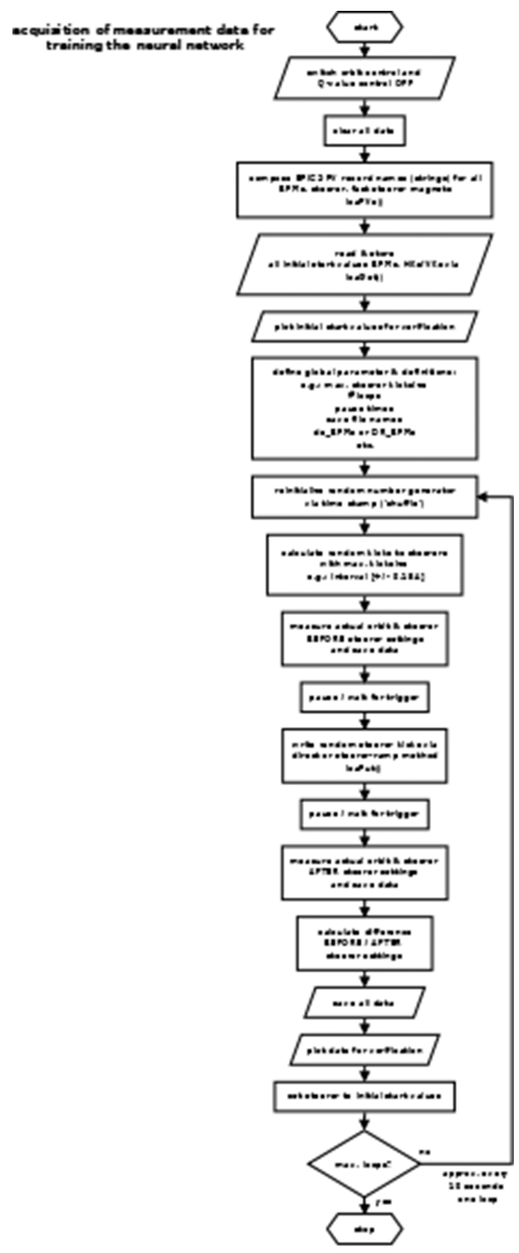


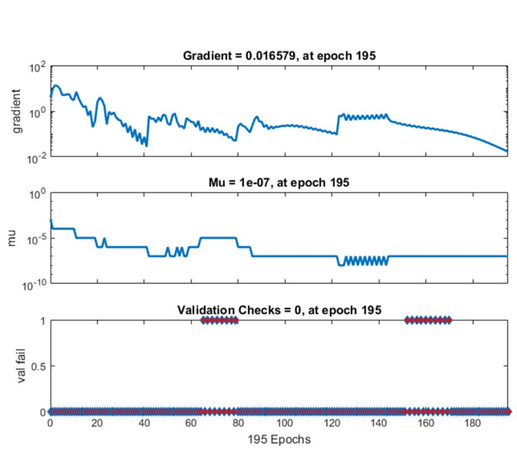


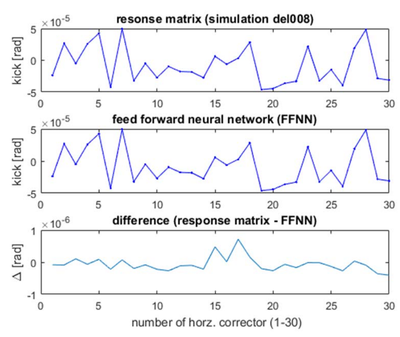


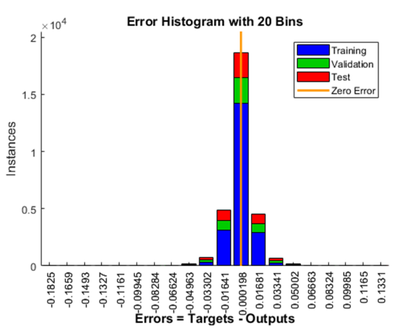












NN fit results for FFNN2: Regression R Values measure the correlation between “hk23” steerer strengths (outputs) and targets. An R value of 1 means a close relationship, 0 a random relationship.