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Applications of Machine Learning for Control and Optimization at the DELTA Accelerator Facility

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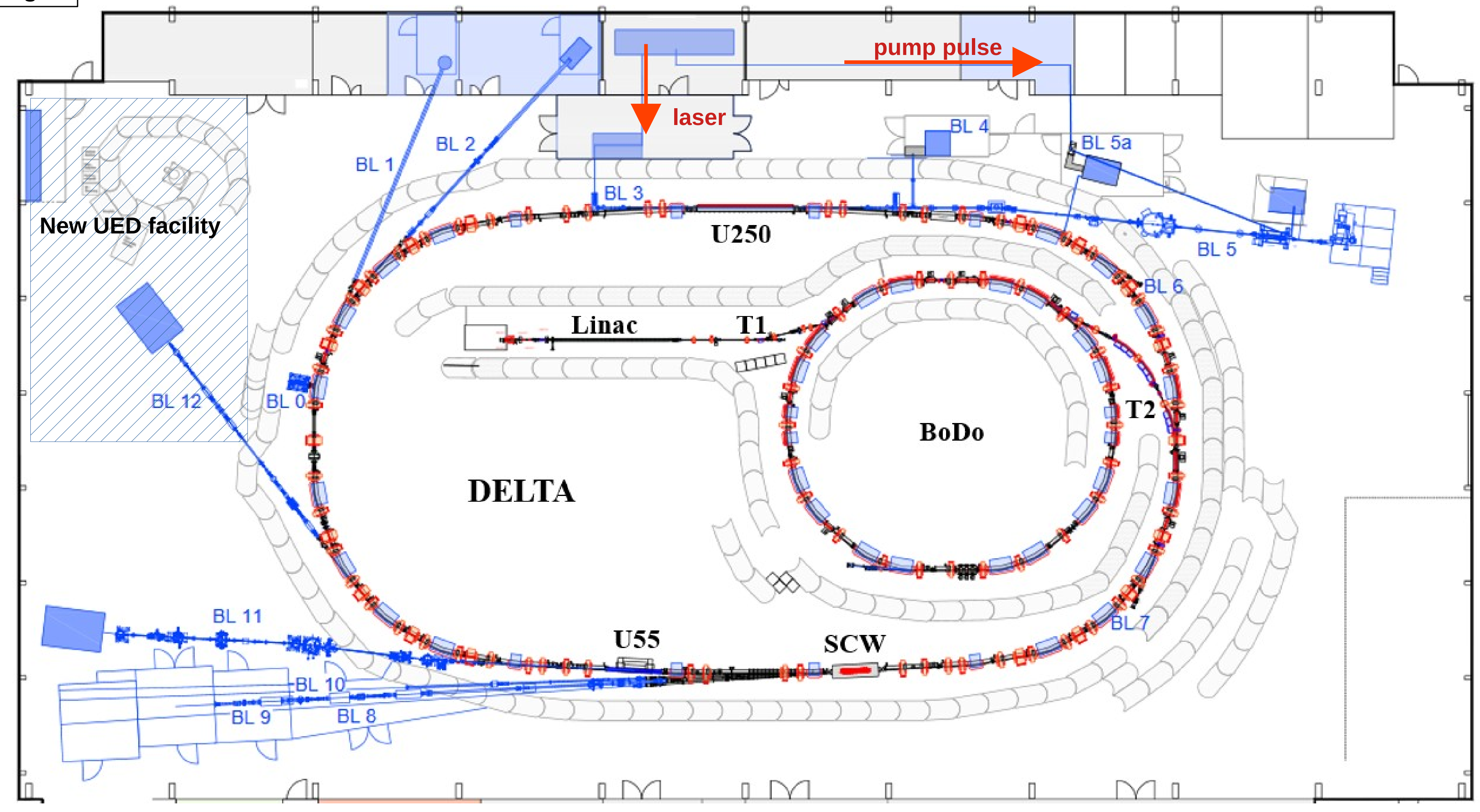
Abstract

The DELTA 1.5-GeV electron accelerator facility (Fig.1), operated by the University of Dortmund in Germany, provides an excellent testing environment for developing and validating concepts of novel, machine learning (ML)-based control and optimization methods. Successful implementations to date include a feed forward neural network (FFNN)-based orbit correction method (1), as an alternative to the singular value decomposition (SVD)-based approach, as well as NN-based feedback systems designed to control the betatron tunes (2) and chromaticity values (3) of the 1.5-GeV electron storage ring. Further more, machine learning algorithms have been employed to improve the electron transfer rate (4) from the booster synchrotron to the storage ring (injection efficiency, 4). Another use case is the application of convolutional, multilayer neural networks (CNNs) to analyze radiation spectra produced by an experimental setup utilizing the so-called coherent harmonic generation (CHG) principle (5).

DELTA 1.5-GeV Storage Ring Facility

Fig. 1



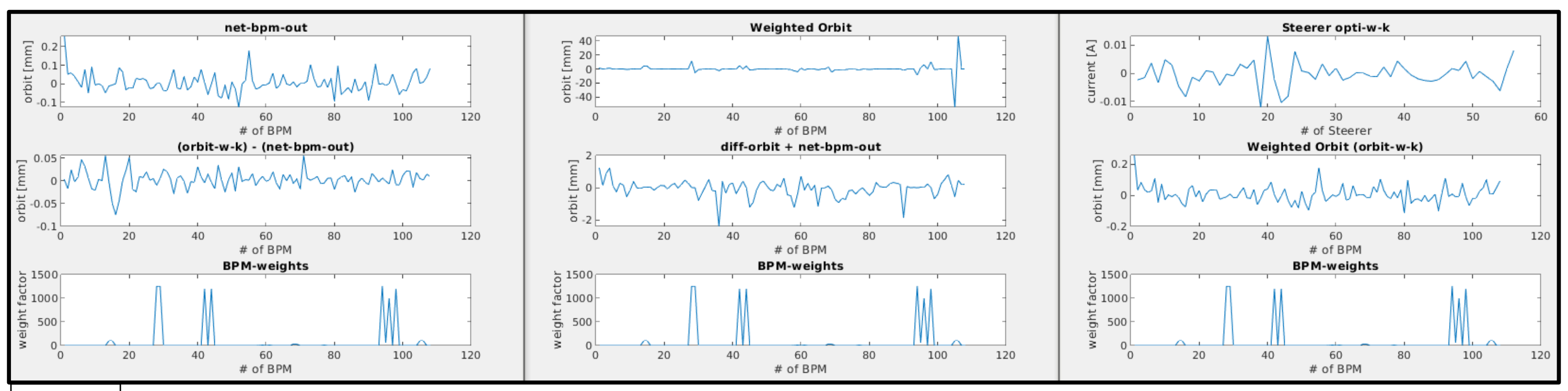


Fig. 2

DAQ for ML

NN Layout & Training

Deployment Results

1. Orbit correction

This ML-based study demonstrates the successful implementation of classical FF-NNs for local and global correction of electron beam orbits (**Fig.2**). Shallow fully connected FF-NNs (**Fig.4**) were trained using measured beam position data and corresponding steerer strengths (**Fig.3**), showcasing competitive results but with fewer correction steps compared to conventional orbit correction methods like SVD (**Fig.5**) [12-16].

Fig. 3

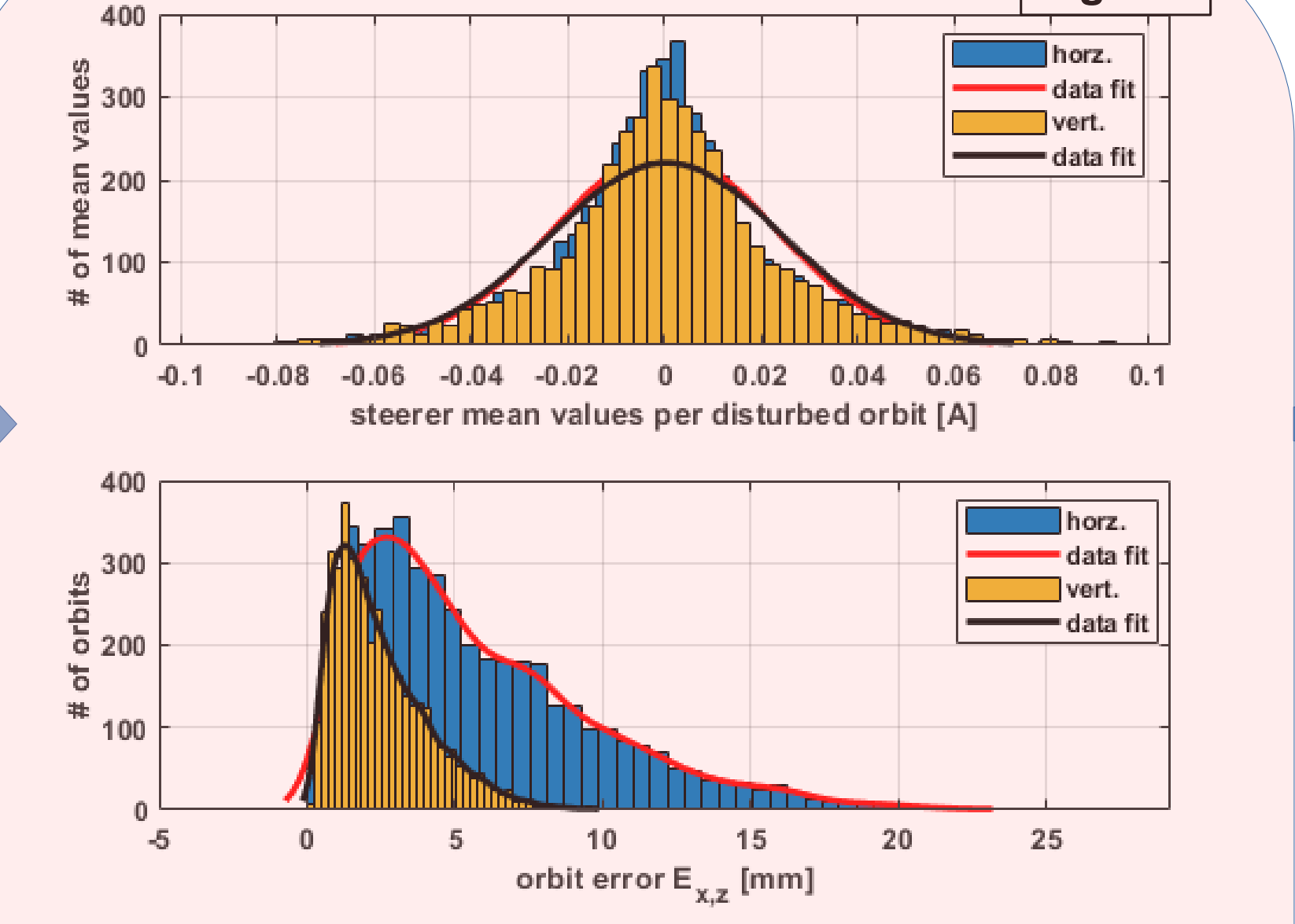


Fig. 4

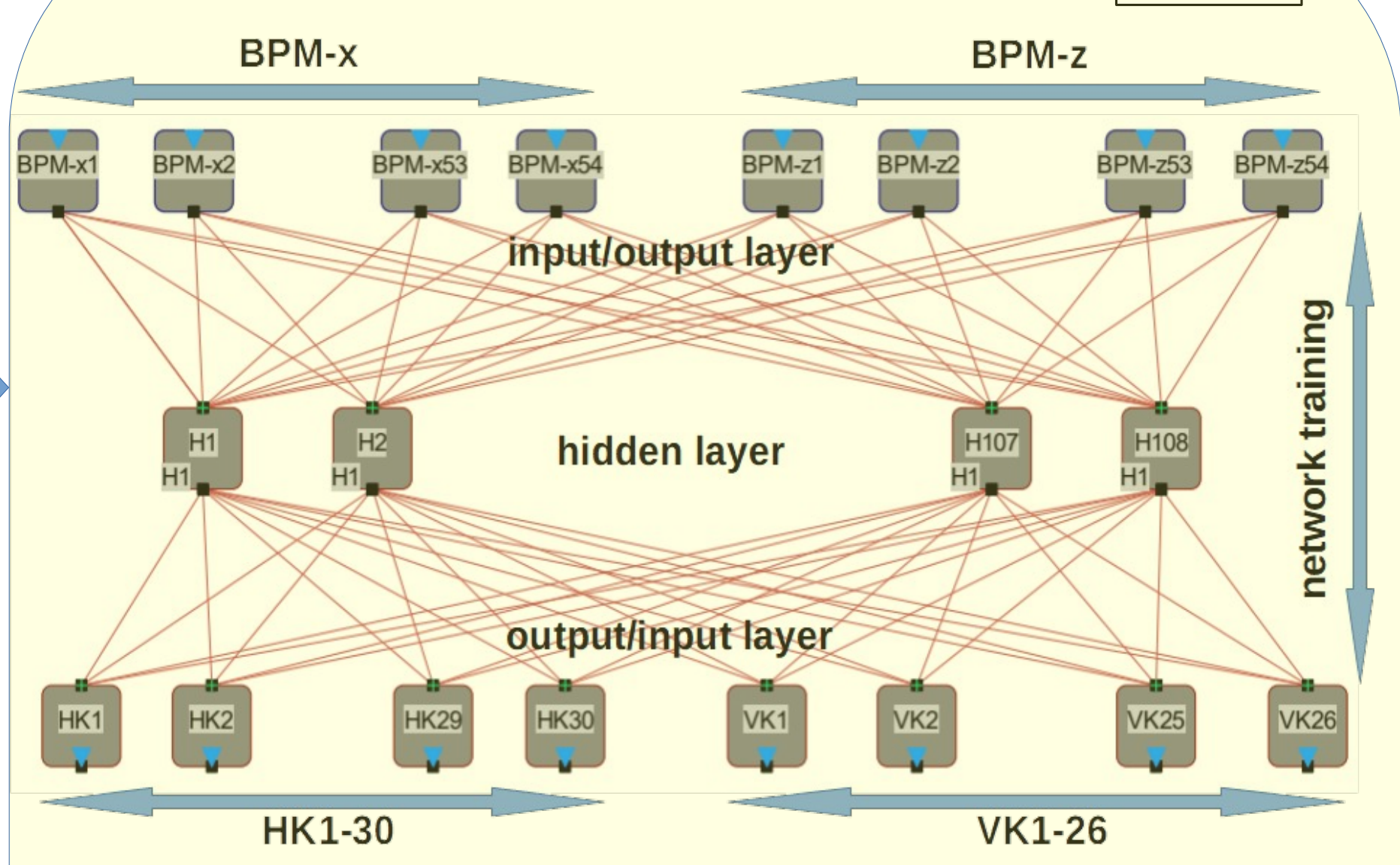
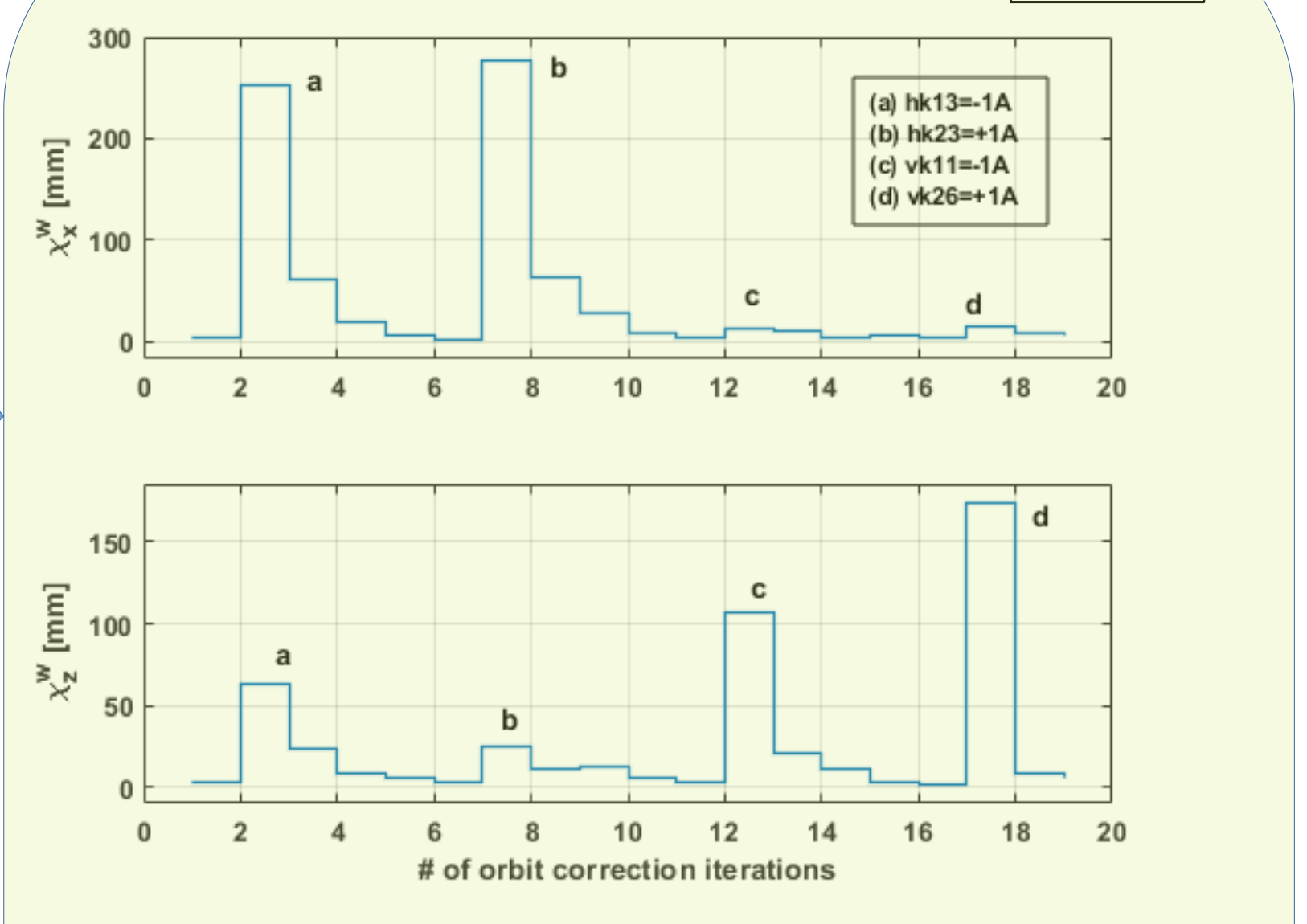


Fig. 5



2. Tunes control

Similar to the chromaticity adjustment, ML-driven techniques were employed to tunes control. Therefore, quadrupole strengths were systematically and randomly varied, and the impact on tune shifts were measured (**Fig.6**). These data sets serve for supervised training of FF-NNs (**Fig.7**) which subsequently were used for an automatic tune feedback system (**Fig.8**). This approach was successfully deployed for the simulated storage ring, in real machine operation, and crosswise [11,16].

Fig. 6

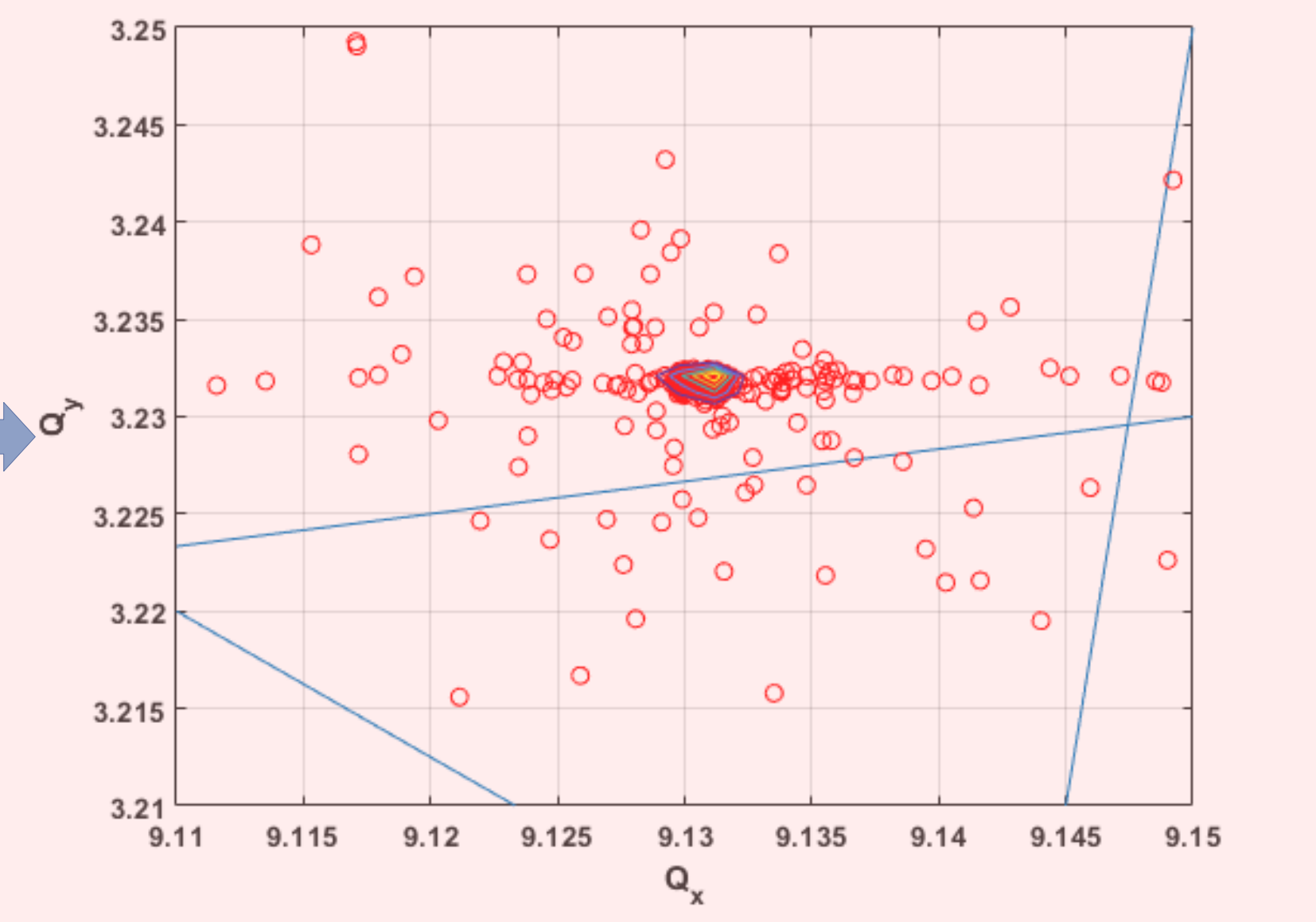


Fig. 7

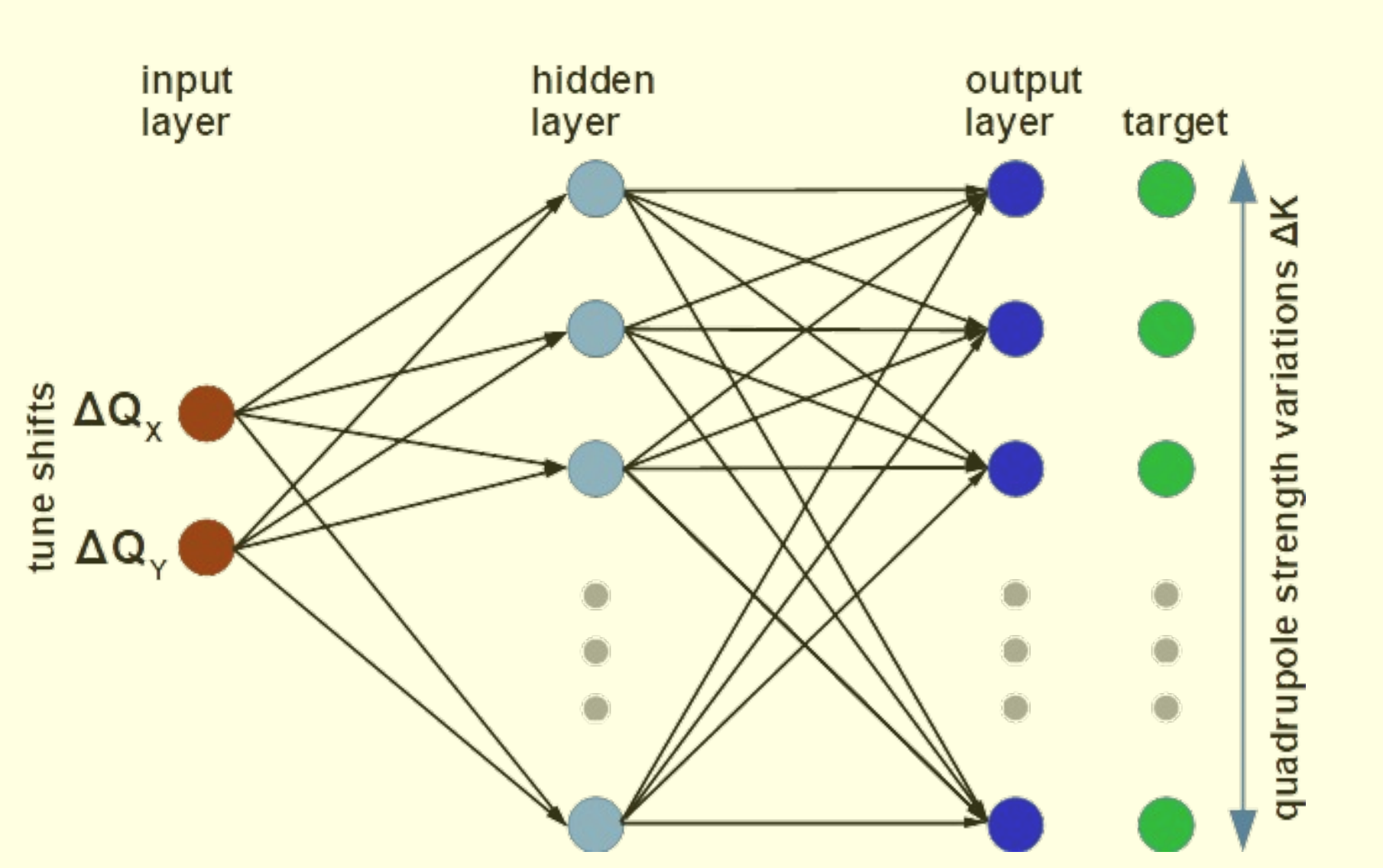
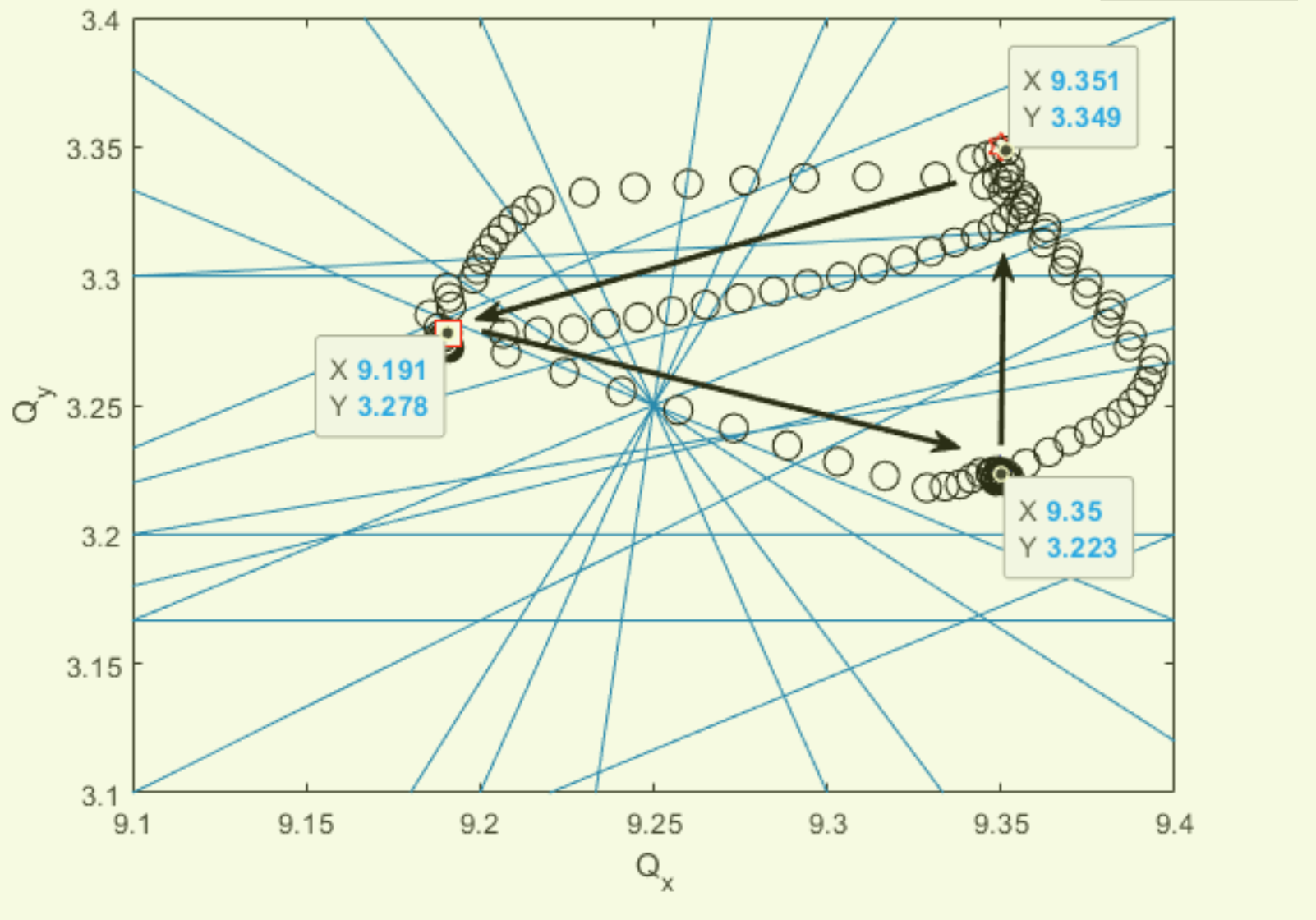


Fig. 8



3. Chromaticity adjustment

This project explores ML-based methods for adjusting the storage ring chromaticity values. By systematically varying sextupole magnet strengths and analyzing their effects on chromaticity shifts $\Delta\xi_{x,y}$ (**Fig.9**), Gaussian Process Regressors (GPRs) and NNs were trained (**Fig.10**) to predict optimal magnet settings. Results showed significant improvements in chromaticity control within few iterations (**Fig.11**) [6,10,16].

Fig. 9

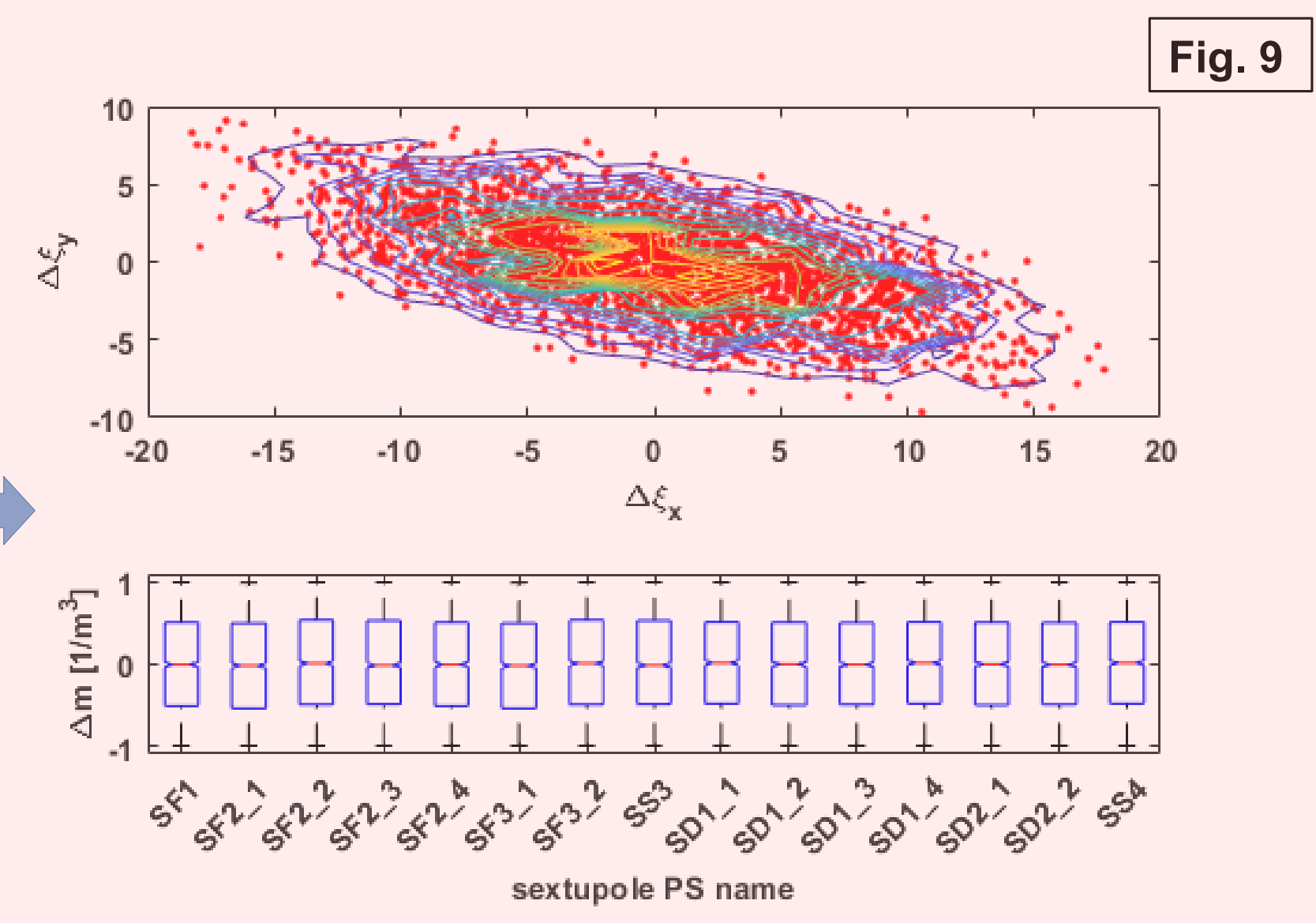


Fig. 10

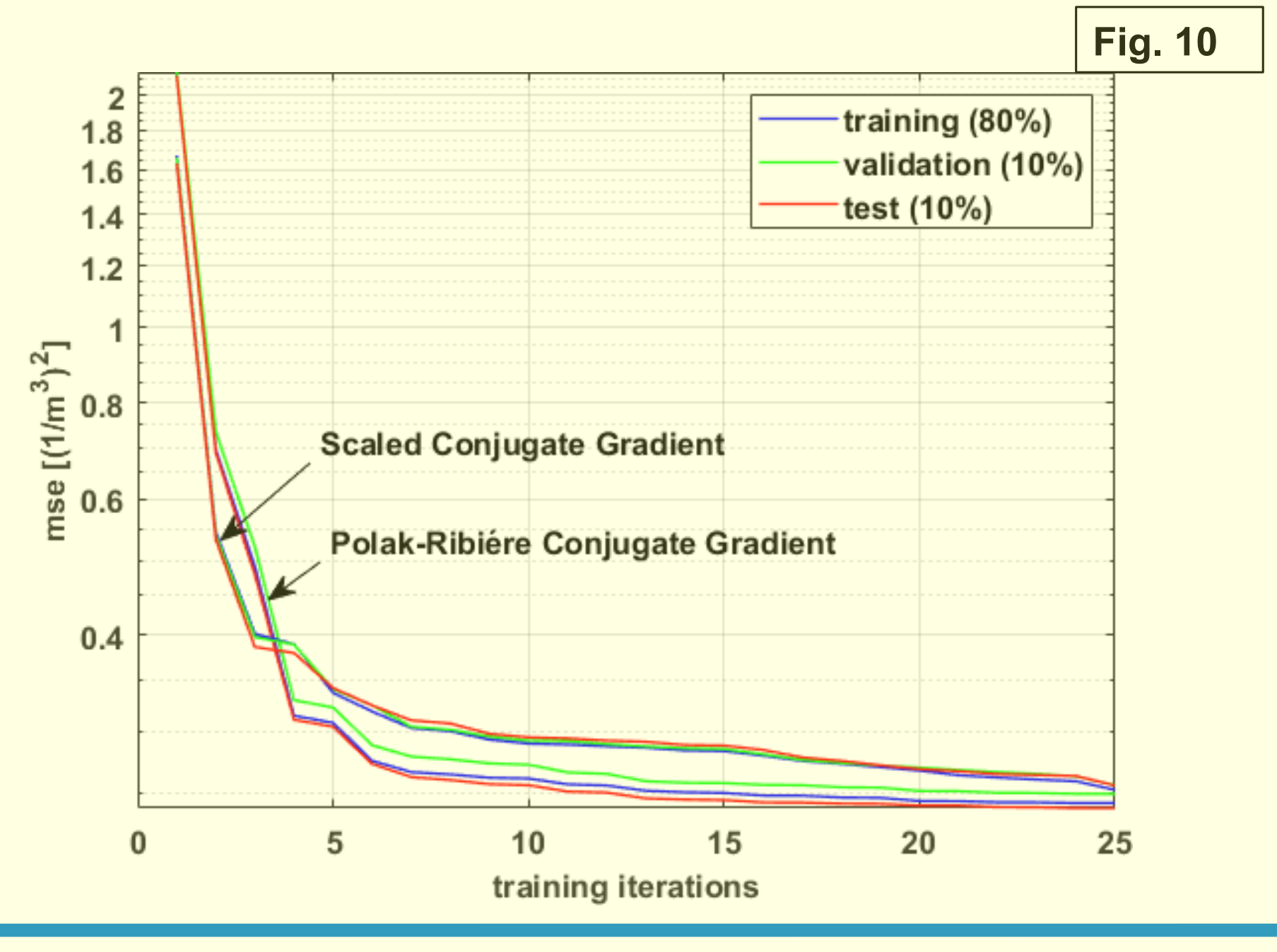
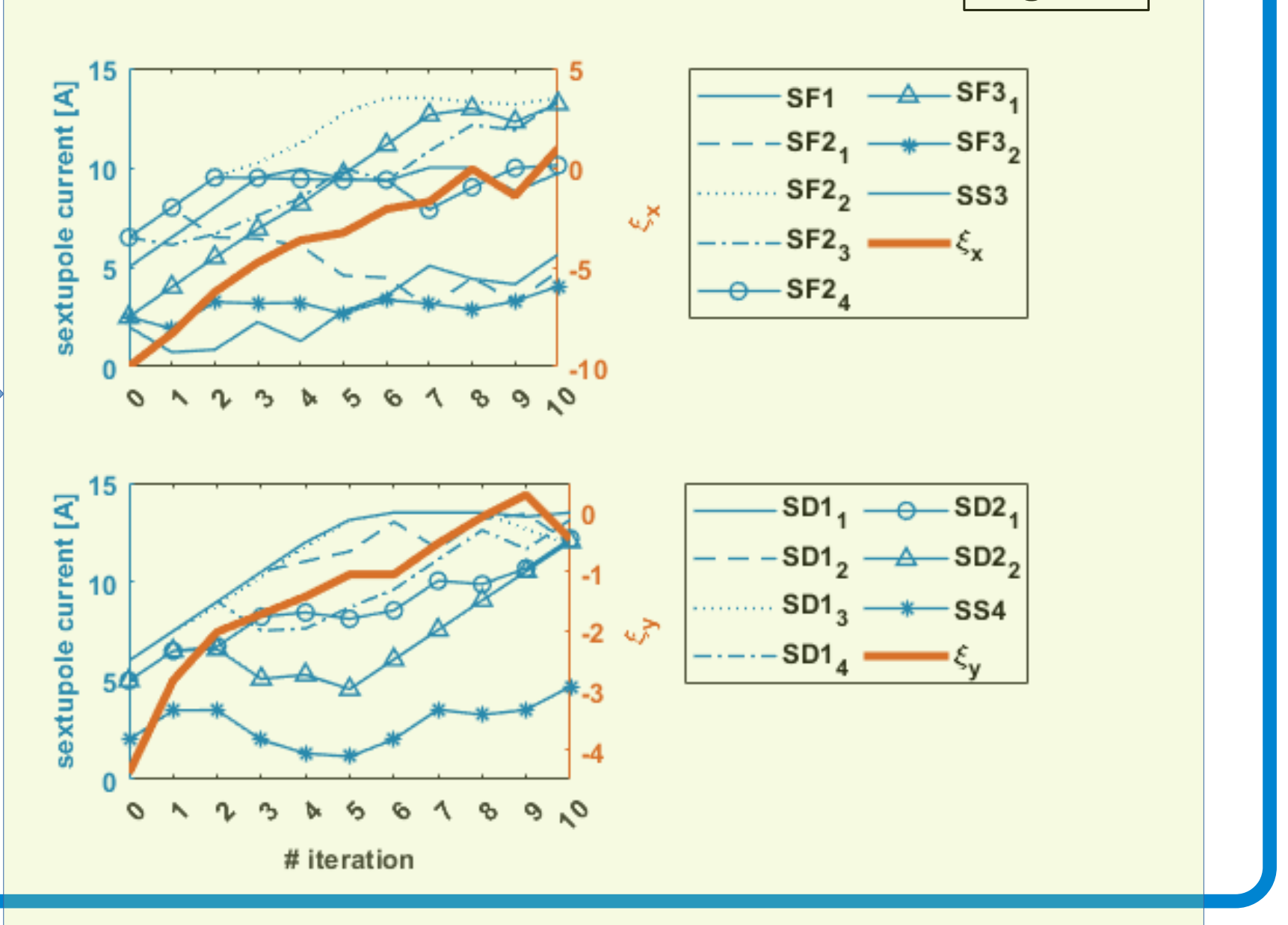


Fig. 11



4. Injection optimization

A novel ML-based approach was implemented to optimize injection efficiency from the booster synchrotron BoDo to the storage ring (**T2**, **Fig.1**). By ML-trained (**Fig.12**) predictive models (NNs, GPRs (e.g. **Fig.13**), DTs) and the aid of heuristic as well as stochastic optimization algorithms, injection settings were dynamically adjusted during real machine operation, resulting in enhanced electron transfer rates (**Fig.14**) [5-9,16].

Fig. 12

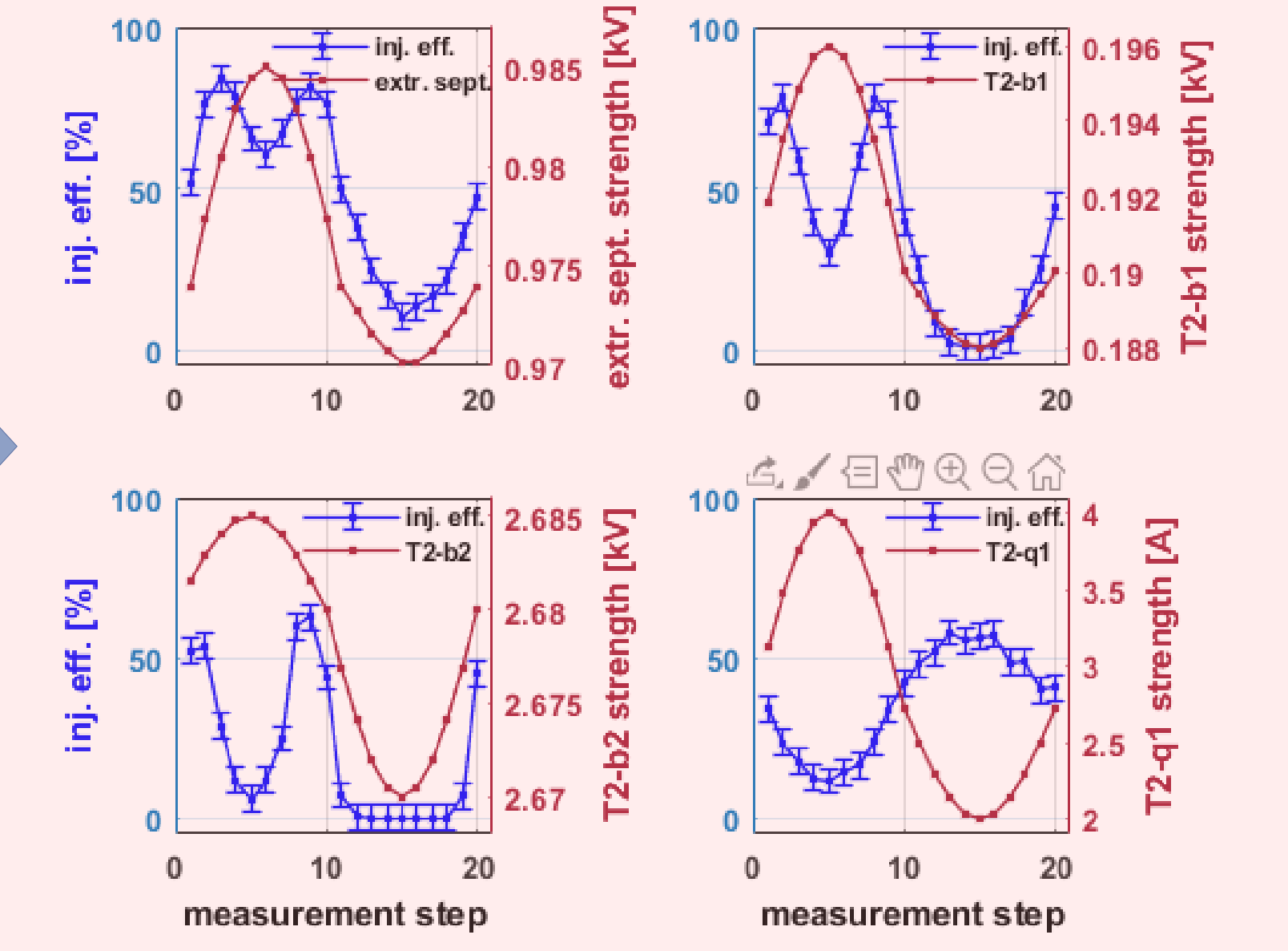


Fig. 13

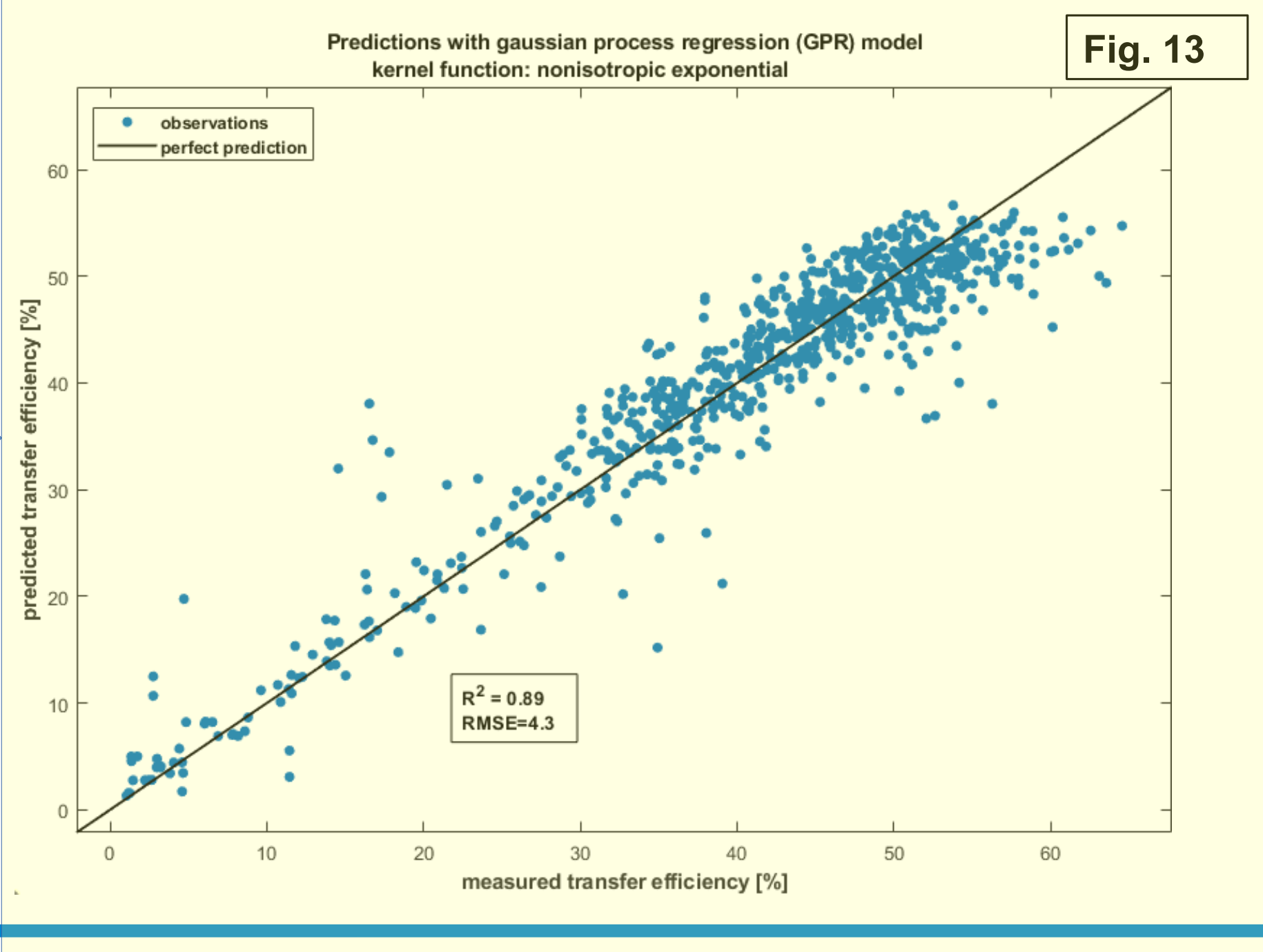
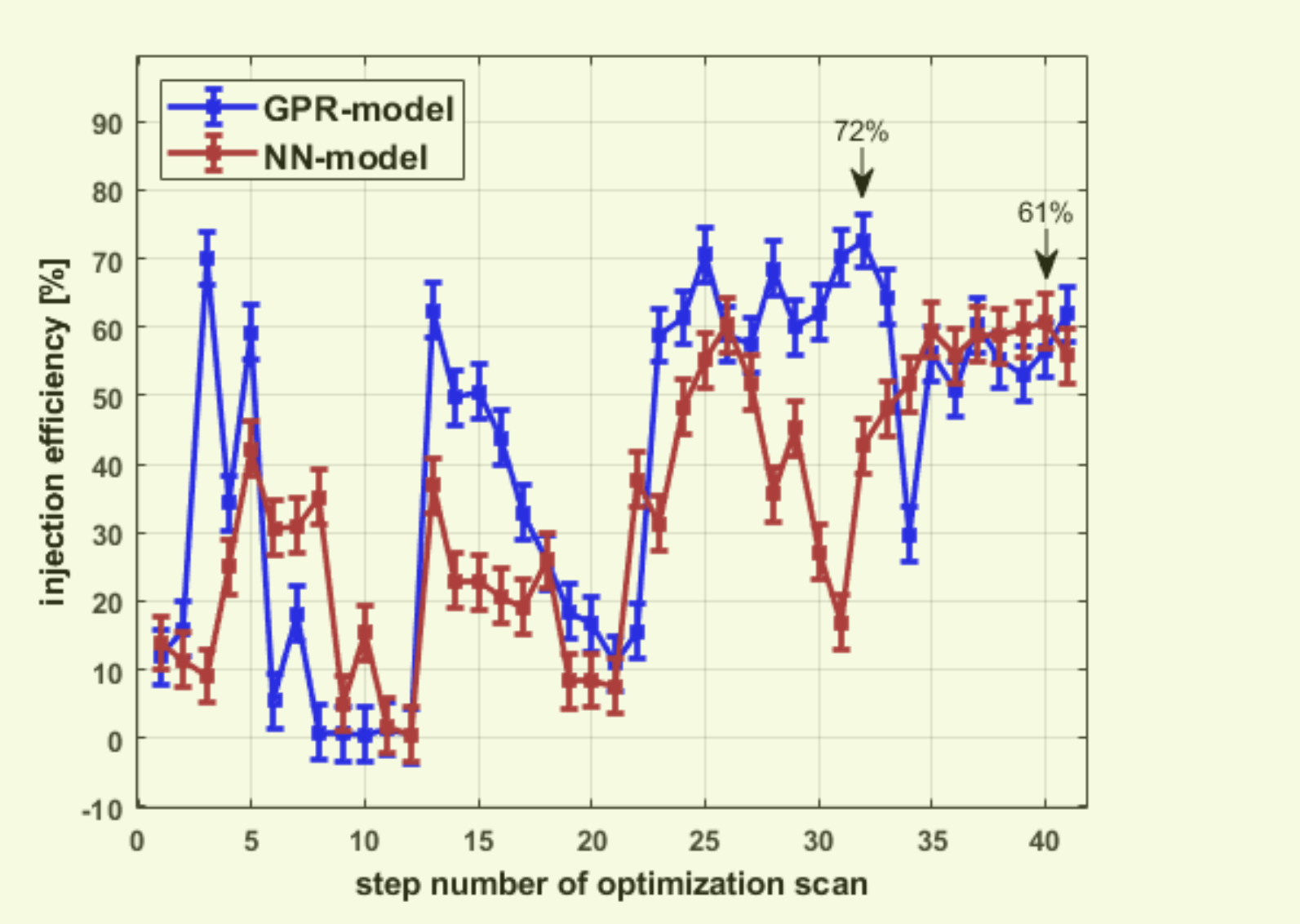


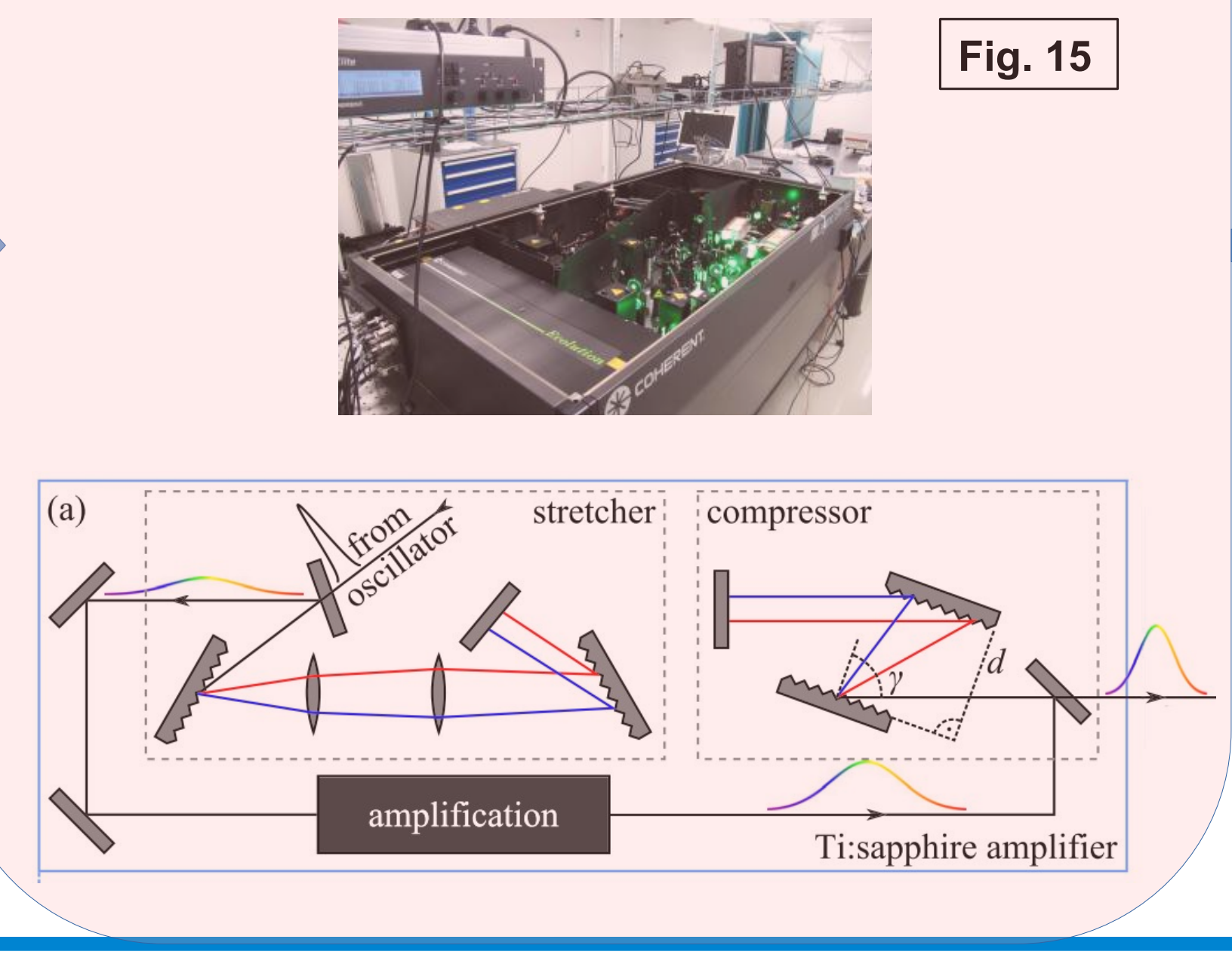
Fig. 14



5. CHG spectra analysis

To predict the GDD and TOD parameters of the pulsed seeding laser (**Fig.15**) from the measured CHG spectra, a convolutional neural network (CNN, **Fig.16**) was trained with >40000 numerically simulated spectra data sets for different GDD/TOD combinations. Subsequently, the trained surrogate models were capable of predicting the GDD/TOD values for different laser pulse properties, from the measured spectra (**Fig.17**) [2-4].

Fig. 15



- **Input:** CHG spectral map
- **Output:** GDD and TOD of the seed pulse
- **Training samples:** Simulated CHG spectral map using MATLAB (~ 43000 samples)
- Image augmentation to mimic the noise in the observations.
- Monte Carlo dropout for regularization and error estimation.

Fig. 16

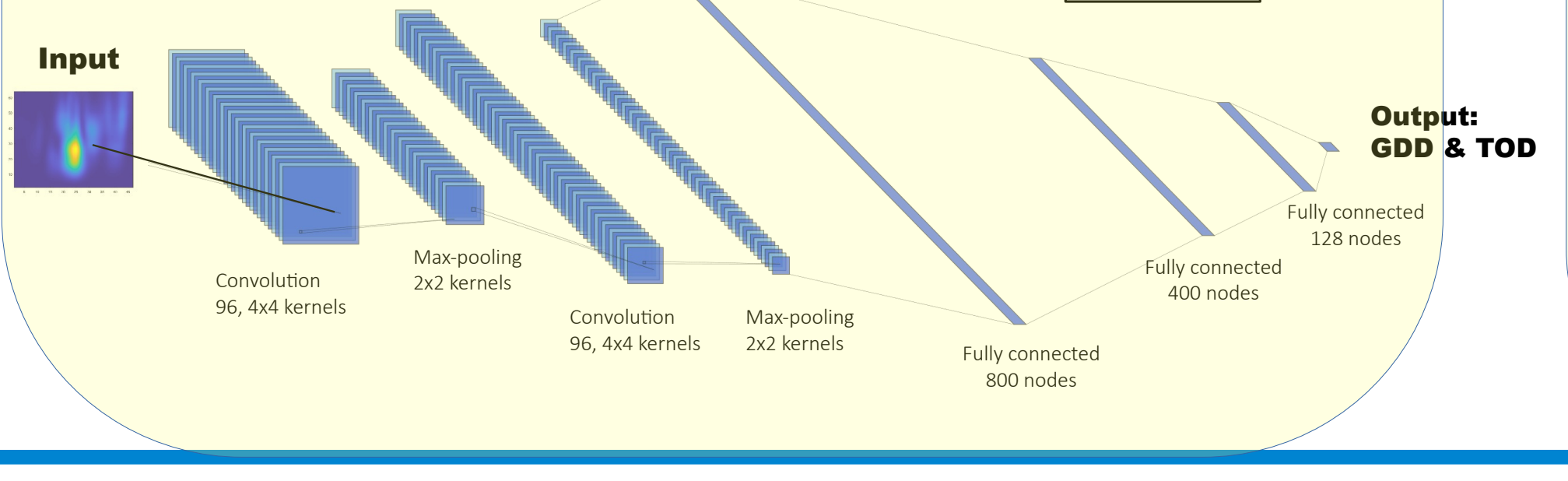
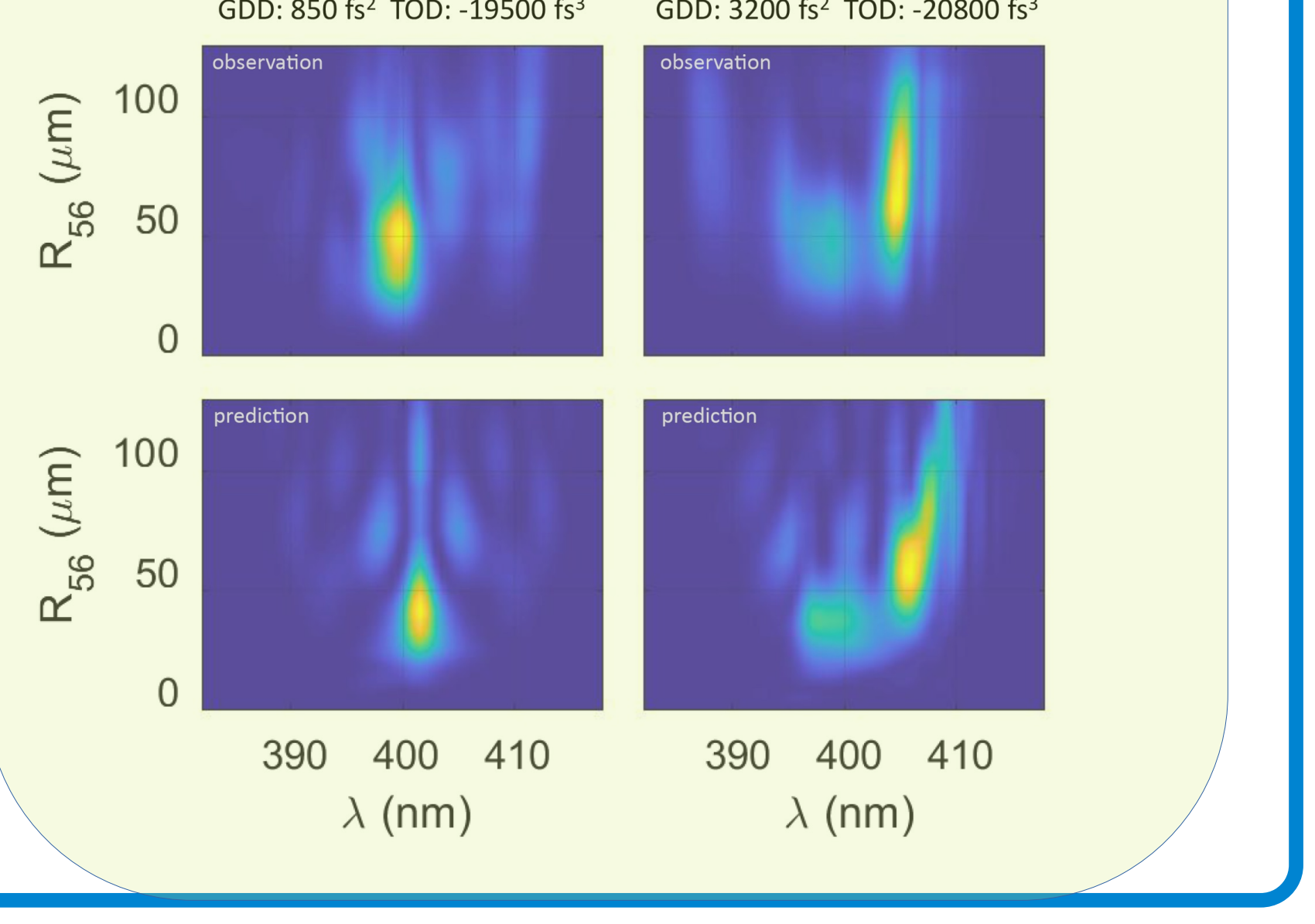
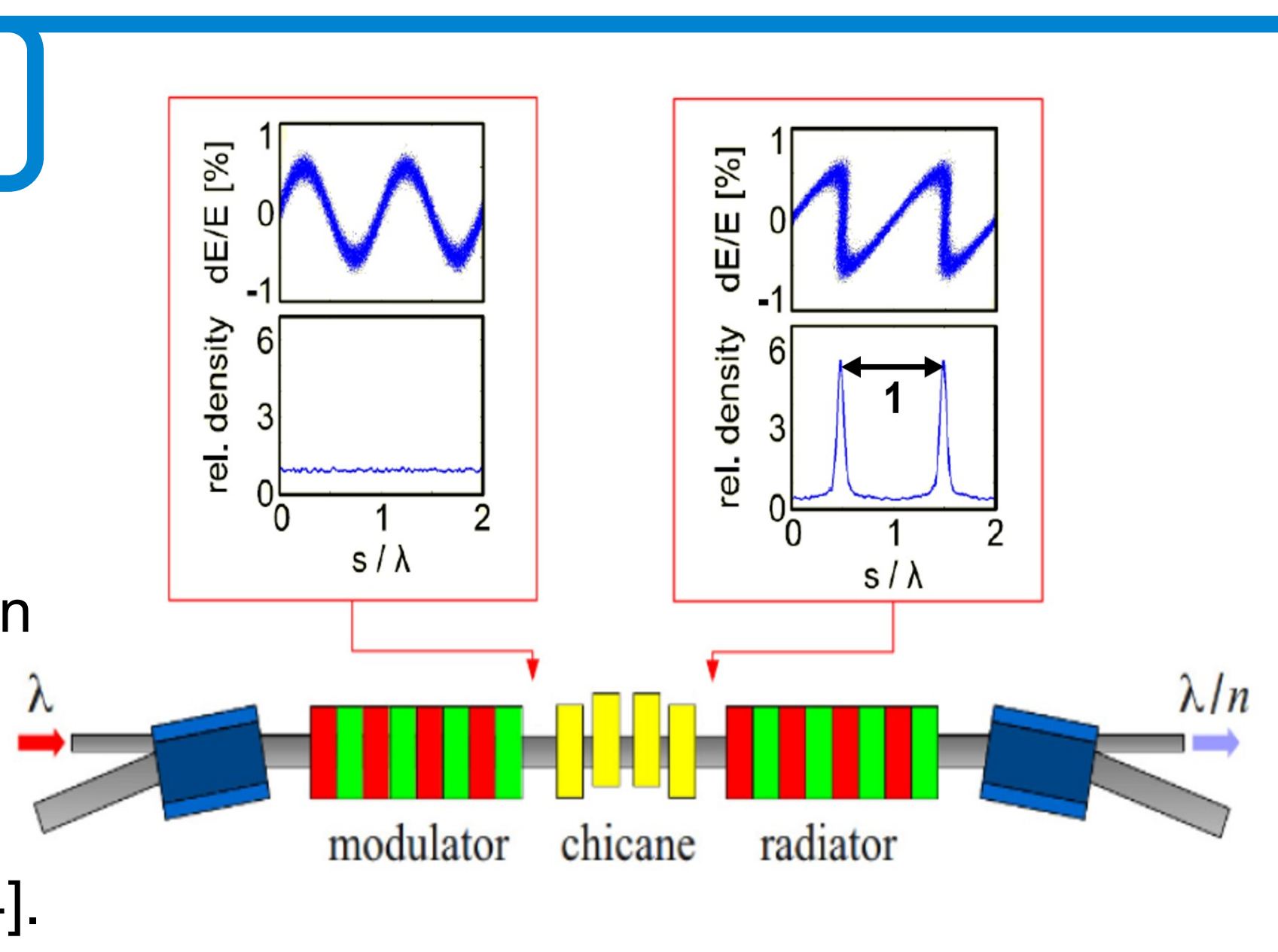


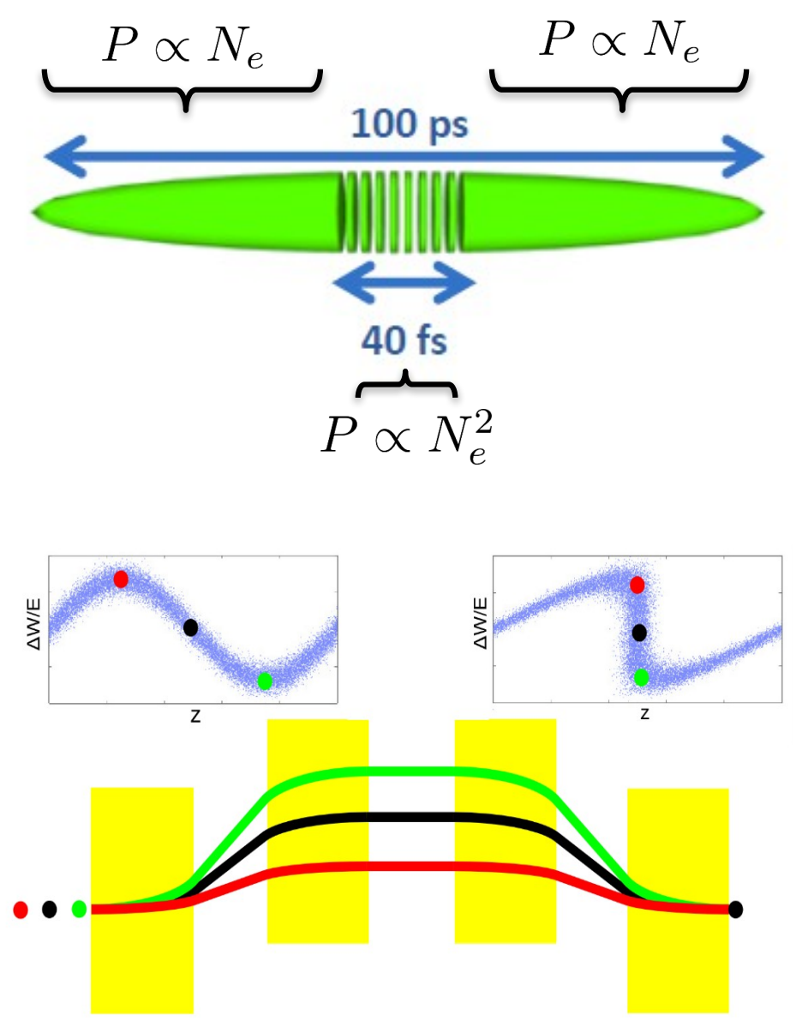
Fig. 17



CHG-scheme

To generate Coherent Harmonic Generation (CHG) radiation, a pulsed laser beam is overlapped with the stored electron beam in a specially configured undulator magnet (U250=modulator+ chicane +radiator) [2-4].





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