# MACHINE LEARNING-BASED ORBIT CORRECTION IN THE RCS OF CSNS

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*Abstract*

The rapid cycling synchrotron (RCS) of The China Spallation Neutron Source (CSNS) accumulates and accelerates the injection beam from 80 MeV/300MeV to the energy of 1.6 GeV and then extracts the high energy beam to the target. During each cycle of the RCS ring, beam positions at the same BPM vary over time due to energy and mode transitions. Traditional orbit correction averages turn-by-turn (TBT) data over 512 turns, producing 20 points over 20 ms, and applies the response matrix method to correct each orbit independently. However, this approach overlooks temporal orbit variations and inter-orbit correlations, limiting correction accuracy. To address these limitations, we implemented a machine learning-based orbit correction system. Using raw BPM orbit data as inputs and corrector changes as outputs, the model learns the relationship between orbit deviations and correction actions. Results demonstrate that this method effectively corrects time-varying orbits, achieving significantly improved performance. This paper presents a detailed overview of the machine learning-based approach.

## INTRODUCTION

The China Spallation Neutron Source (CSNS) is a 100-kW pulsed spallation neutron source facility. As shown in Fig. 1, its accelerator complex mainly consists of an 80 MeV linear accelerator, a 1.6 GeV rapid cycling synchrotron (RCS) operating at a repetition rate of 25 Hz, and a target station. During operation, the RCS accumulates the injected proton beam from the linac, accelerates it to the design energy of 1.6 GeV, and then extracts the beam to the target station for neutron production. However, due to alignment, installation, and mechanical errors of accelerator components such as magnets and beam-position monitors, the actual closed orbit may deviate from the ideal design orbit. Such closed-orbit distortion can increase beam loss, reduce transmission efficiency, and potentially affect the reliability of routine operation. Therefore, closed-orbit correction plays an important role in beam commissioning, machine tuning, and stable user operation at CSNS. The CSNS upgrade project is currently underway, aiming to increase the linac energy from 80 MeV to 300 MeV and raise the beam power from 100 kW to 500 kW, together with target replacement and the construction of new instruments. As the facility moves toward higher beam power, accurate and efficient orbit correction becomes increasingly critical for controlling beam loss, improving operational stability, and supporting reliable high-power operation [1].

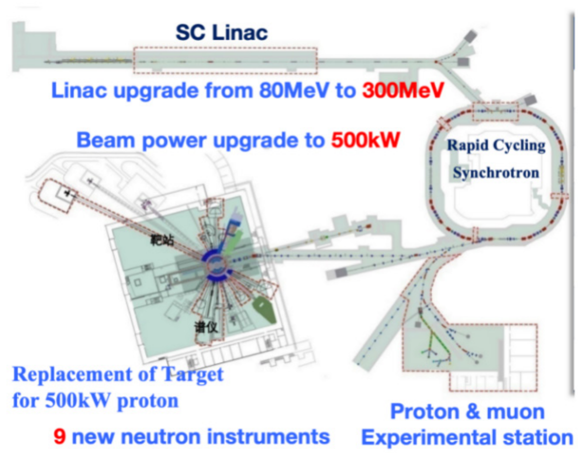


Figure 1: Schematic layout of the CSNS facility and its upgrade plan, including the linac upgrade, beam-power upgrade, target replacement, new neutron instruments, and proton/muon experimental station.

## ORBIT CORRECTION SYSTEM

### *Orbit Correction System of RCS*

The orbit correction system of the CSNS-RCS consists of 32 beam position monitors (BPMs) and 37 dipole correctors, including 21 horizontal and 16 vertical correctors [2]. The BPM system provides turn-by-turn beam position data, which are used to obtain time-dependent closed-orbit information during the acceleration process. In contrast, the programmable correctors are controlled by current waveforms defined as a function of time. During one acceleration cycle, the BPM turn-by-turn data are averaged over every 512 turns, resulting in 38 closed-orbit measurements along the acceleration ramp. Meanwhile, the corrector power supplies accept 21 discrete current setpoints from 0 to 20 ms, corresponding to integer-millisecond correction points. Therefore, a timing mismatch exists between the orbit measurements obtained from BPM data and the time-based corrector settings. To construct a consistent orbit correction scheme, the BPM-derived orbit data must first be assigned to their corresponding time stamps and then interpolated to the 21 correction time points. This procedure enables the measured closed-orbit distortion along the ramp to be properly matched with the programmable

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corrector currents, providing the basis for accurate time-dependent orbit correction in the CSNS-RCS.

### *Limitations of RM-Based Correction*

In the conventional response-matrix (RM) method, the closed orbit at each time slice is corrected independently using singular value decomposition (SVD) and a pre-measured response matrix. This method is sufficiently effective for routine operation; however, it does not fully exploit the temporal correlations between neighboring orbit slices along the acceleration ramp. Since both the closed orbit and the response matrix may vary from one time slice to another, the calculated corrector currents can exhibit sharp changes between adjacent correction points. In practical operation, these rapid current variations may approach or even exceed the safety limits of the corrector power supplies. As a result, manual adjustment of the correction waveform or the use of fewer singular values in the SVD calculation is often required, which can reduce both correction efficiency and correction accuracy.

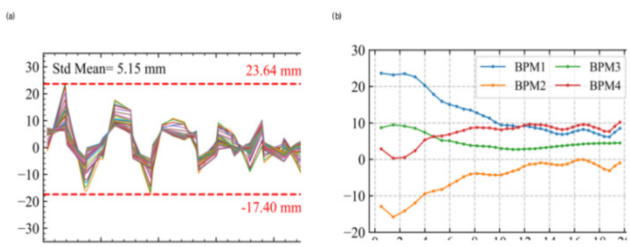


Figure 2: Time-dependent uncorrected horizontal closed orbits in CSNS-RCS. The upper plot shows 38 orbit slices during one acceleration cycle; the lower plot shows orbit evolution at four representative BPMs, illustrating clear orbit variation over the 20 ms ramp.

The need for improved time-dependent correction is further highlighted by the strong variation of the uncorrected horizontal orbit during acceleration. As shown in Fig.2, measurements show that the closed-orbit distortion (COD) envelope ranges from −17.40 mm to 23.64 mm over one RCS cycle, with a mean standard deviation of 5.15 mm across the 38 orbit slices. In addition, because the BPM-derived orbit data must be interpolated to match the integer-millisecond corrector setpoints, interpolation errors are inevitably introduced. This effect is particularly significant during the first 5 ms of acceleration, where the mean relative interpolation error is about 10%, and the maximum error can exceed 20%. These limitations indicate that a correction method capable of considering temporal orbit evolution and current-ramp-rate constraints is desirable for improving orbit correction performance in the CSNS-RCS.

## ML-BASED ORBIT CORRECTION METHOD

The machine-learning-based orbit correction method learns the relationship between closed-orbit deviation and corrector action directly from measured data [3, 4]. For horizontal orbit correction in the CSNS-RCS, the input is the orbit matrix measured by 32 BPMs at 38 time points within one acceleration cycle, while the output consists of the time-dependent current settings for the 21 horizontal dipole correctors. Since the BPM measurements and corrector settings are distributed along the acceleration ramp, a sliding-window strategy is adopted to group adjacent orbit slices. In this way, the model can capture the local temporal dependence between the measured orbits and the corresponding corrector-current settings, rather than treating each time point independently.

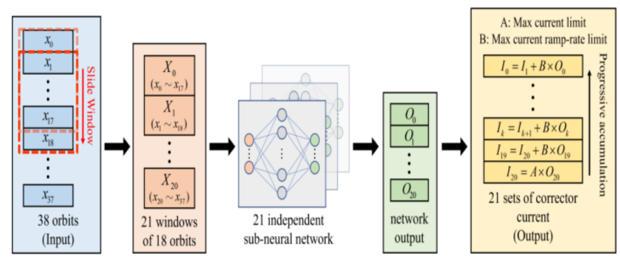


Figure 3. ML architecture for RCS orbit correction. Orbit data are divided by a sliding window, processed by sub-neural networks, and converted into 21 sets of corrector currents with a constraint on current ramp rate.

In Fig.3, The neural network maps each group of neighboring orbit slices to the corresponding corrector-current setpoint. This architecture incorporates prior physical knowledge of the correction process, namely that a given corrector-current setting mainly influences the closed orbit within a nearby time window. In addition, the final output layer introduces a cumulative-summation process together with a bounded activation function to constrain the variation of corrector currents along the ramp. This design allows the model to reduce closed-orbit distortion while also limiting the current ramp rate, thereby improving the operational safety and feasibility of the correction waveform. Overall, the proposed ML approach provides a data-driven framework for generating time-dependent corrector-current settings from BPM orbit measurements, while taking into account neighboring time-slice correlations and practical ramp-rate constraints.

## SIMULATION AND MACHINE RESULTS

Offline simulations were performed using an RCS model with alignment and magnet-strength errors to generate time-dependent orbits. A dataset of 1,000,000 samples was built by randomly sampling corrector currents and calculating the corresponding orbit changes. The neural network was trained with weighted MAE loss and the Adam optimizer. The FCNN results first confirmed that ML can effectively correct time-dependent orbits. Further tests showed that networks trained with original BPM orbit data perform better than those trained with interpolated orbit data, indicating that ML can reduce the orbit-accuracy loss caused by interpolation in RM correction. In simulation, the ML correction reduced the COD to the millimeter level, comparable to RM correction.

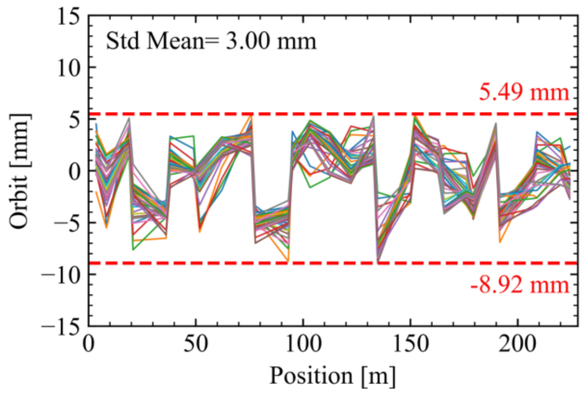


Figure 4. Horizontal orbits corrected by the ML method in the actual CSNS-RCS machine. The result demonstrates effective orbit correction during one acceleration cycle.

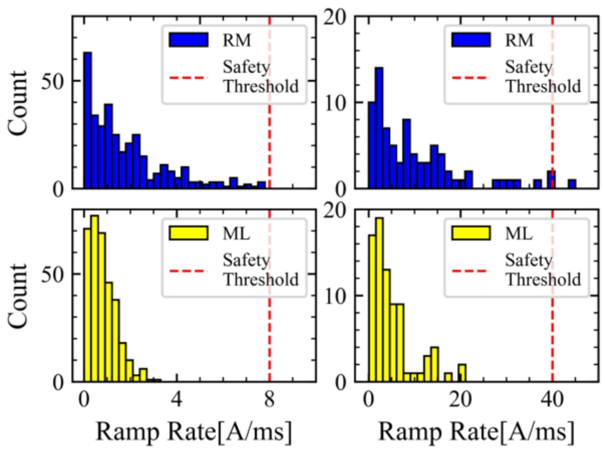


Figure 5. Comparison of corrector current ramp-rate distributions for RM-based and ML-based correction. The ML method strongly reduces excessive ramp rates and improves operational stability.

In actual machine experiments, as shown in Fig.4, the ML method also delivered effective correction. The corrected COD was within approximately -8.92 mm to 5.49 mm, with an average standard deviation of 3.00 mm. Although the COD was slightly larger than that of the RM method, the corrector-current ramp rates were well controlled (Fig. 5).

## CONCLUSION

The main challenge of RCS orbit correction is to correct orbits that vary significantly during the energy ramp while keeping corrector current ramp rates within safety limits. The proposed ML-based correction method uses time-dependent BPM data to predict corrector settings and incorporates the relation between adjacent orbit slices and current setpoints. Both simulations and machine experiments confirm that ML is feasible for RCS orbit correction. Compared with the RM method, the ML method achieves comparable orbit correction while explicitly constraining the current ramp rates; in the machine study, the maximum ramp rate was reduced by about 54%. This improves operational stability and provides a promising route for future high-power operation and online adaptive correction.

## REFERENCES

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