

Orbit correction for a rapid cycling synchrotron using an adjacent-difference-constrained neural network

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In a rapid cycling synchrotron (RCS), closed-orbit correction is an important task for maintaining high beam quality and machine stability. Since the orbits in RCS change during energy ramping, response matrix-based orbit correction is performed in segments, which can result in the corrector current ramp rates exceeding safety limits and accuracy loss in orbits. To address these issues, this paper employs machine learning for orbit correction in RCS. An adjacent-difference-constrained neural network (ADCNN) was built and tested in both simulations and machine experiments at the China Spallation Neutron Source (CSNS). The correction results demonstrate the feasibility of using neural networks for RCS orbit correction. The ADCNN exhibits a correction effect equivalent to that of response matrix-based correction while effectively limiting the current ramp rates of the correctors.

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I. INTRODUCTION

The China Spallation Neutron Source (CSNS) is a high-intensity, proton accelerator-based, 100 kW pulsed neutron source and is the world's fourth pulsed spallation neutron source [1]. The accelerator complex consists of an 80 MeV linac, a 1.6 GeV proton rapid cycling synchrotron (RCS) [2–6] with a repetition rate of 25 Hz (20 ms acceleration period), and a 100 kW target station [7]. The RCS accumulates and accelerates an 80 MeV injection beam to 1.6 GeV and then extracts the high-energy beam to the target [8]. Its lattice exhibits a fourfold structure with four long straight sections for the injection, extraction, rf cavity and beam collimation, respectively. As illustrated in Fig. 1, the schematic layout of the accelerator is presented, while the main parameters are outlined in Table I.

Due to the manufacturing and installation errors in an RCS, the closed orbit will deviate from the ideal orbit, resulting in beam loss. Therefore, an orbit correction system is highly required [9].

The RCS in CSNS employs a response matrix (RM)-based orbit correction algorithm [10], which has been widely used in many modern storage rings and synchrotrons in routine operation and commissioning [11–15], and the RM-based orbit correction framework continues to be refined [16–18].

Since the orbits in RCS change during the 20 ms energy ramping, orbit correction is implemented in a time-sliced manner determined by the correctors. The programmable correctors accept discrete current set points at every integer millisecond (21 set points). The beam position monitors (BPMs) average turn-by-turn beam positions over 512 turns to obtain the closed orbit. At each set point, the orbit is obtained by interpolating these BPM-derived orbits, and then an RM-based correction is performed.

TABLE I. RCS design parameters.

Parameters	Value
Circumference	227.92 m
Superperiodicity	4
Injection energy	80 MeV
Single injection beam peak current	15 mA
Extraction energy	1.6 GeV
Repetition rate	25 Hz
Extraction beam power	100 kW
Design betatron tunes (h/v)	4.86/4.78

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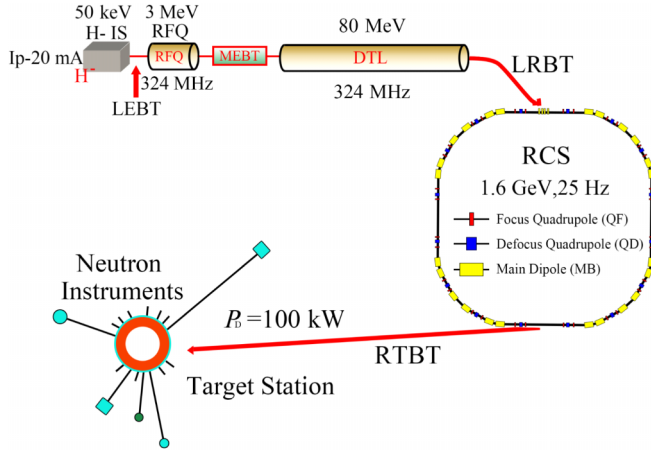


FIG. 1. Schematic layout of CSNS.

This correction method well meets the need for daily operation. However, the corrector currents obtained in each correction process may vary significantly, causing the current ramp rates of correctors to exceed safety limits. We must handle this situation very carefully, which greatly impacts our correction accuracy and efficiency. Moreover, during the process of obtaining 21 orbits from the BPM readings, part of the orbit accuracy is lost (a quantitative estimate is given below). Therefore, the resulting corrector set may be suboptimal.

To address these issues, we applied machine learning (ML) to the orbit correction in RCS. Recent work has explored ML-based methods as a possible complement to conventional RM-based orbit correction. In particular, supervised models such as neural networks have been studied for learning the mapping from measured orbits to corrector settings and enabling data-driven correction under given operating conditions [19–21]. In parallel, adaptive and online ML frameworks have been proposed to alleviate performance degradation caused by time-varying conditions, such as component drift, environmental changes, or nonlinear machine behavior, through updates based on recent measurement data [22,23]. However, these studies do not imply that ML methods are generally superior to RM-based approaches; rather, they indicate that ML may offer advantages in some situations, depending on the specific machine and operational context.

These advances indicate that ML approaches can provide fast, data-driven surrogate models that adapt to evolving accelerator states, reducing reliance on frequent response matrix measurements and enabling robust orbit control in the presence of slow drifts and nonlinear effects.

However, no studies have yet demonstrated a clear advantage of ML methods for the correction of time-dependent orbit in RCS during the energy ramp in one period.

In this paper, we focus on the RCS of the CSNS. Since it has a smaller orbit variation and a more easily completed

correction in the vertical direction, we concentrate only on the correction of horizontal orbits. An adjacent-difference-constrained neural network (ADCNN) is introduced to orbit correction for RCS. Simulation and experiment results show that ADCNN can effectively correct the time-dependent orbits in the RCS, achieving a level of correction result equivalent to that of the RM-based method. Meanwhile, the ramp rates of the corrector currents are explicitly constrained.

The rest of this paper is organized into three main sections. Section II introduces the RM-based RCS orbit correction method and presents correction results obtained from both simulation and actual machine. Section III details the structure of the ML model employed in this study, with its results in both simulation and machine experiment. Section IV summarizes main conclusions and outlines directions for future research.

II. RCS ORBIT CORRECTION BASED ON RESPONSE MATRIX

A. Orbit correction system of the RCS in CSNS

The orbit correction system in the RCS of CSNS contains 32 BPMs and 37 dipole correctors, of which 21 are for the horizontal plane and 16 are for the vertical plane. BPM data are expressed in turns, while the corrector currents are set by time. The booster ramp is divided into 38 time break points, and for each break point, the orbits are given by averaging every 512 turn-by-turn data measured by BPMs [24]. To establish the correspondence between orbits and time, the beam velocity during the ramp must be calculated from the magnetic rigidity curve.

The magnetic rigidity of the beam in our machine can be expressed as a function of time as

$$B\rho(t) = 4.6434 + 3.3237 \sin\left(\frac{\pi t}{20 \text{ ms}} - \frac{\pi}{2}\right), \quad 0 \leq t \leq 20 \text{ ms}, \quad (1)$$

where $B\rho$ is in $[T \cdot m]$. The magnetic rigidity is related to the beam momentum through

$$B\rho(t) = \frac{p}{q}. \quad (2)$$

The total energy is then given by

$$E = \sqrt{(pc)^2 + (m_p c^2)^2}, \quad (3)$$

with the proton rest energy $m_p c^2 = 0.938 \text{ GeV}$. Therefore, the relativistic velocity factor can be written as

$$\beta(t) = \frac{v(t)}{c} = \frac{p(t)c}{E(t)}. \quad (4)$$

TABLE II. Timetable for orbits read by the BPMs.

Index	Time (ms)	Index	Time (ms)	Index	Time (ms)
1	0.4971	14	9.1780	27	15.0051
2	1.4712	15	9.6596	28	15.4317
3	2.3851	16	10.1324	29	15.8568
4	3.2525	17	10.5976	30	16.2806
5	3.9948	18	11.0564	31	16.7034
6	4.7036	19	11.5096	32	17.1253
7	5.3623	20	11.9580	33	17.5464
8	5.9805	21	12.4022	34	17.9668
9	6.5660	22	12.8427	35	18.3868
10	7.1249	23	13.2801	36	18.8063
11	7.6621	24	13.7147	37	19.2255
12	8.1814	25	14.1469	38	19.6445
13	8.6859	26	14.5770		

The accumulated number of turns from injection to time t is obtained by

$$N(t) = \frac{1}{C} \int_0^t c \beta(\tau) d\tau, \quad (5)$$

where C is the circumference. By letting $N(t_k) = 512k$ ($k = 0, 1, 2, \dots$), the boundary time of each 512-turn interval can be determined. The average time assigned to the k th block is then defined as the midpoint of the interval, $\bar{t}_k = (t_{k-1} + t_k)/2$. In this way, each orbit is associated with a time stamp on the booster ramp, which is listed in Table II.

As shown in Fig. 2, where different colors represent the orbits at different moments, the orbits in RCS change with increasing energy and the largest uncorrected closed-orbit

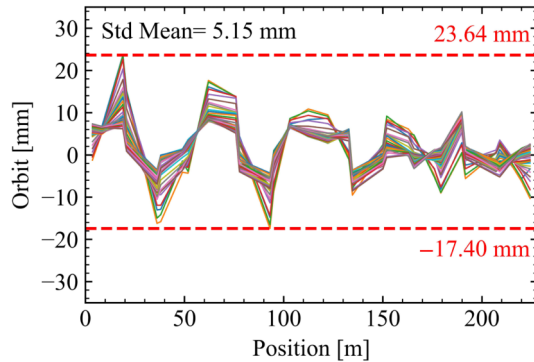


FIG. 2. Uncorrected horizontal closed orbits measured in CSNS-RCS over one acceleration cycle. Each colored curve corresponds to a closed orbit at 1 of the 38 time stamps along the ramp. Here $x = 0$ is defined with respect to the mechanical centers of the magnets. The red dashed lines indicate the maximum observed COD envelope, spanning $(-17.40 \text{ mm}, 23.64 \text{ mm})$, and the mean standard deviation of the 38 orbits is 5.15 mm. The working point is 4.80/4.86, the beam pulse width is 100 μs , and the beam power is 20 kW.

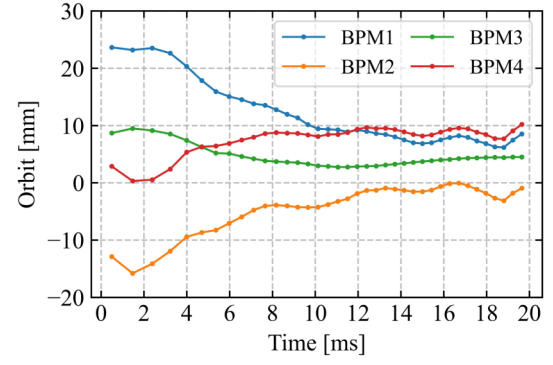


FIG. 3. Uncorrected closed-orbit trajectories measured at four BPM locations over one acceleration period: BPM1 ($s = 18.94 \text{ m}$), BPM2 ($s = 38.03 \text{ m}$), BPM3 ($s = 122.31 \text{ m}$), and BPM4 ($s = 189.88 \text{ m}$).

distortion (COD) reaches $\pm 20 \text{ mm}$. The variation is clearer in Fig. 3, where we have shown the orbits measured in a portion of the BPMs in one period.

Different from the orbits reading, the correctors are given 21 current sets for every integer millisecond from 0 to 20 ms. During correction, orbits given by BPMs are interpolated to 21 orbits at every integer millisecond. Then the corrector strengths are obtained by the SVD method [25] with the corresponding interpolated orbit and a premeasured RM.

As the orbit correction is performed in segments, a significant difference in orbit or RM between adjacent time leads to high current ramp rates in correctors, which can exceed the safety limits, risking supply trips and reducing long-term stability.

B. Response matrix-based orbit correction in off-line simulation

Using the Accelerator-Toolbox package [26], we built a PYTHON simulation program of the RCS in CSNS. Random alignment errors and magnet-strength errors were imposed on the lattice to generate time-dependent orbits. The error model used here is intended to provide a representative test environment for evaluating the proposed orbit correction method, rather than a high-fidelity reconstruction of all possible error sources in the real machine. Therefore, machine-specific effects that may also contribute to orbit distortion, such as magnetic leakage fields, are not included in the present study. The uncorrected orbits are shown in Fig. 4.

In the simulation, the exact orbits at any moment can be calculated. By comparing the exact calculated orbits at every interger millisecond with the ones interpolated from orbits read by BPMs according to the timetable in Table II, we quantify the orbit accuracy loss caused by the interpolation.

As shown in Fig. 5, the interpolation-induced accuracy loss is more pronounced at earlier times. During the first

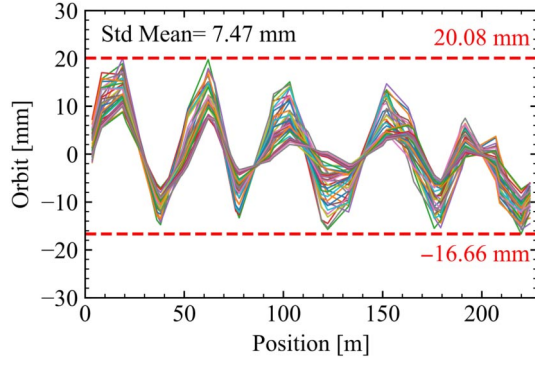


FIG. 4. Simulated uncorrected orbits in the x plane of the CSNS-RCS lattice with errors. The COD is distributed within $(-16.66 \text{ mm}, 20.08 \text{ mm})$, and the average standard deviation of the orbits is 7.47 mm.

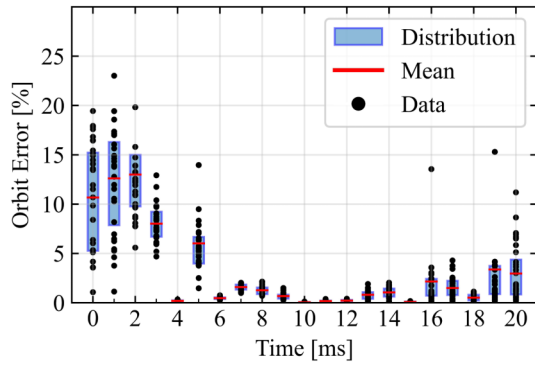


FIG. 5. Relative error between the exact orbits and the interpolated orbits at each integer millisecond.

5 ms, the mean relative error is around 10%, and the maximum value can exceed 20%. For the interpolation points between 0 and 3 ms, the original BPM data used for interpolation are typically separated from the target time stamps by about 0.3–0.5 ms, which results in relatively large interpolation errors. This is mainly due to the lower beam energy in the early stage of acceleration and the sparse temporal distribution of BPM orbit measurements. In contrast, when the target time stamp is close to an original BPM measurement, the interpolation becomes much more accurate. For example, at 4 ms, the time difference is only about 0.01 ms, and the resulting interpolation error is therefore almost negligible.

By sequentially activating each corrector and recording the orbit changes, we can obtain all response matrices. Then we employ the SVD method to perform RM-based orbit correction on the simulation of RCS.

As shown in Figs. 6 and 7, in the RM-based method, COD of the simulated orbits has been reduced to $\pm 3 \text{ mm}$. However, the current ramp rates of partial correctors exceed the safety limit. Such corrector currents cannot be directly applied to actual machines for extended periods. Consequently, the current orbit correction process

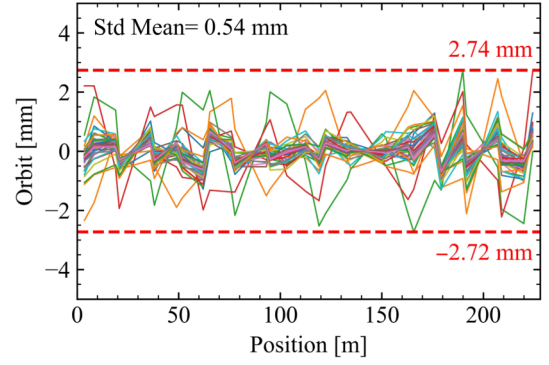


FIG. 6. Simulated orbits in the x plane after RM-based correction. The COD is distributed within $(-2.72 \text{ mm}, 2.74 \text{ mm})$, and the average standard deviation of the orbits is 0.54 mm.

relies to some extent on the correction experience of the scientists.

C. Response matrix-based orbit correction in the actual CSNS-RCS machine

Similar to the correction process in the simulation, we conducted RM-based orbit correction experiments on the actual machine. The orbits after RM-based correction are shown in Fig. 8, and Fig. 9 shows the corrector currents used. As can be seen, many of the correction currents obtained in the RM-based correction have ramp rates that are very close to, or even exceed, the safety limit. As shown in the experimental results, the orbit correction performance in the real machine is noticeably worse than that obtained in simulation. The relatively large residual COD at CSNS may be attributed to machine-specific error sources that are not fully included in the simulation, including BPM offsets, dynamic field errors, alignment errors, and other sources. For comparison, the residual COD after correction at the J-PARC RCS was reported to be within approximately $\pm 2 \text{ mm}$ [27]. However, a direct comparison should be made with caution because the CSNS RCS employs a triplet-based lattice [28], whereas the J-PARC RCS uses an FODO structure [29]. In addition, BPM offset calibration at CSNS has not yet been completed for all BPMs because the group-powered quadrupoles cannot be independently varied for conventional offset measurements. Previous studies have also shown that field deviations among the CSNS dipoles and quadrupoles can introduce additional closed-orbit distortion and beta beating [30,31]. These combined effects increase the initial orbit distortion and make the subsequent correction more challenging, thereby contributing to the larger residual COD observed in the real machine.

In the practical orbit correction, before setting the corrector currents into the machine, we need to address corrector currents exceeding the ramp rate limits. Generally, two approaches can be adopted: using fewer singular values when performing RM-based orbit correction using SVD or

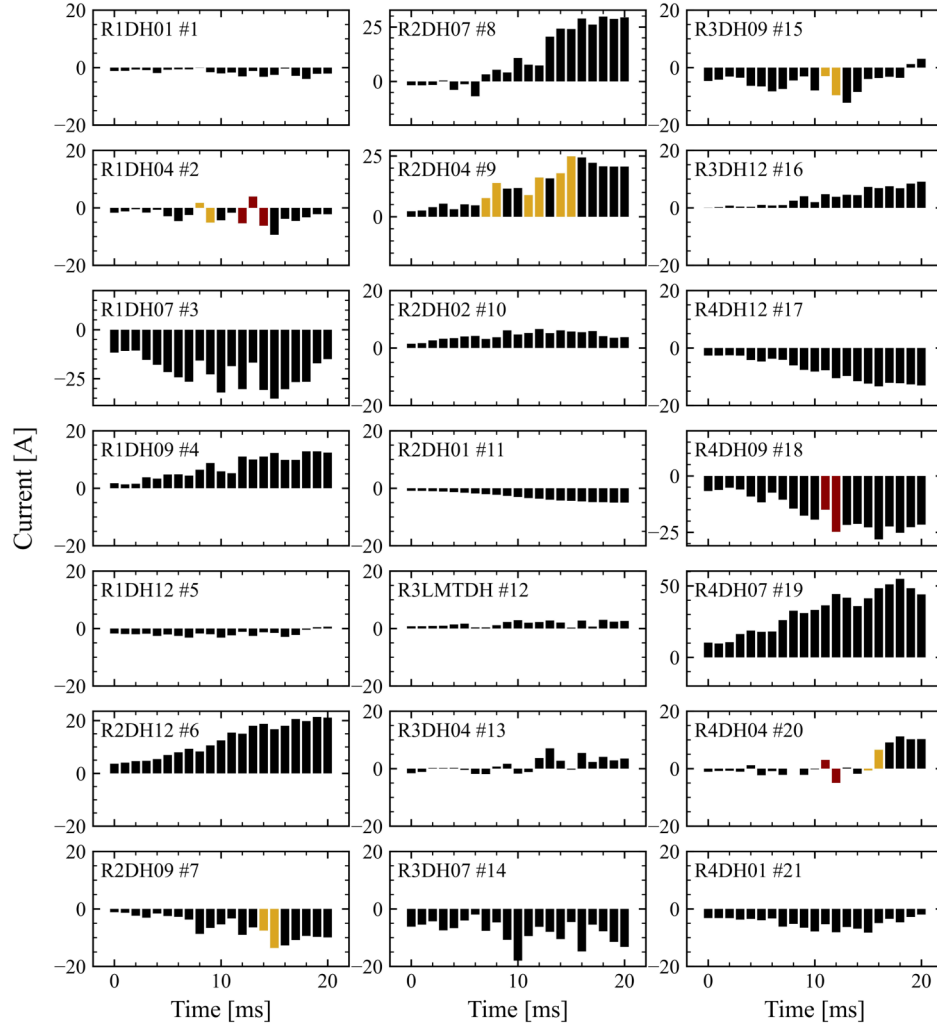


FIG. 7. Corrector currents of all horizontal correctors in the RM-based correction of the RCS simulation. The red bars indicate current ramp rates that exceed the safety limit, while the yellow bars indicate the one that reached 80% of the safety limit.

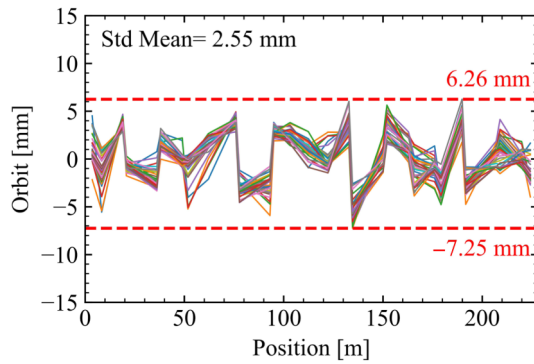


FIG. 8. RM-based corrected orbits in the x plane of the actual RCS machine. The COD is distributed within $(-7.25$ mm, 6.26 mm), and the average standard deviation of the orbits is 2.55 mm.

manually adjusting the corrector currents. Both methods reduce the correction effectiveness and efficiency.

III. RCS ORBIT CORRECTION BASED ON NEURAL NETWORK

Driven by rapid growth in computing power, machine-learning (ML) methods have shown great advantages across many disciplines [32–34]. An increasing number of studies now apply ML to accelerator physics [35,36]. Many laboratories have begun applying various machine-learning algorithms to practical applications, such as CERN, BNL, and IHEP [37–42].

NNs, a core branch of ML, compute the output through a layered mesh. By training the weight of every node, the network reproduces the input-output relation [43].

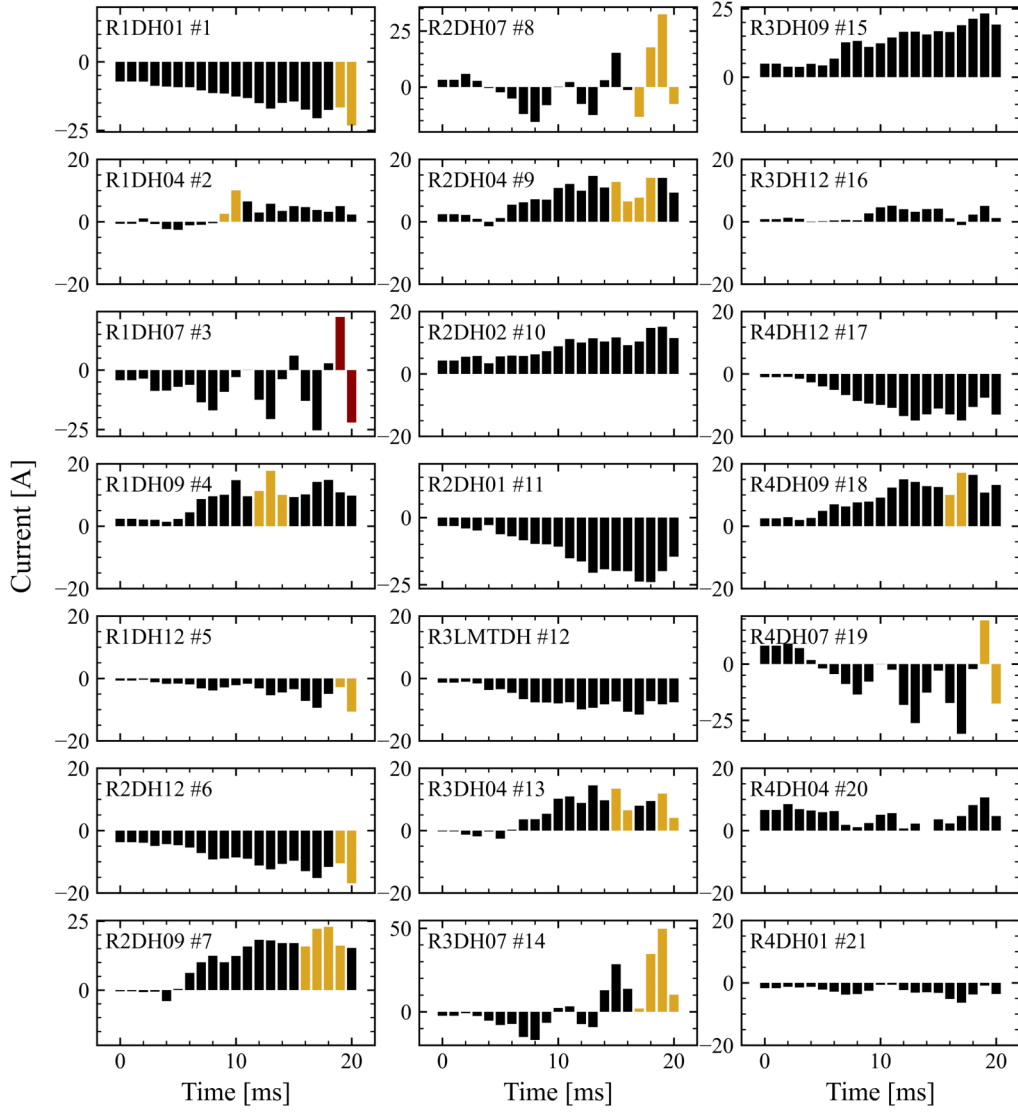


FIG. 9. Corrector currents of horizontal correctors in the RM-based correction of the actual RCS machine.

Theoretically speaking, with enough hidden layers and neurons, the network can fit any continuous nonlinear function [44].

A. Adjacent-difference-constrained neural network for orbit correction in RCS

From the earlier description of the orbit-correction system, a horizontal correction uses 32 BPMs that give 38 orbits, while 21 correctors need 21 current sets.

Based on the orbit-correction system described above, the horizontal correction uses 32 BPMs. For each acceleration cycle, each BPM provides orbit measurements at 38 time points along the ramp. The programmable correctors accept 21 discrete current setpoints (one per integer millisecond from 0 to 20 ms), corresponding to 21 horizontal correctors. Therefore, the measured orbits are mapped (via interpolation to the 21 slices) to

a set of 21 corrector current vectors for horizontal orbit correction.

It can be clearly demonstrated that each orbit at 38 time points is affected by only two sets of corrector currents, as

$$\Delta x_i = f_i(I_{[t_i]}, I_{[t_i]+1}), \quad (6)$$

where Δx_i denotes the orbit deflection of the i th closed-orbit slice induced by the correctors, f_i represents the mapping between the correctors and the orbit for the i th slice, and t_i denotes the time stamp associated with x_i , and $I_{[t_i]}$ and $I_{[t_i]+1}$ are the corrector current set points at $[t_i]$ and $[t_i] + 1$ millisecond, respectively.

Conversely, each set of corrector currents influences the orbit within a 1 ms time window before and after it. Therefore, theoretically, we can use several adjacent orbits to calculate the optimal set of corrector current points, as

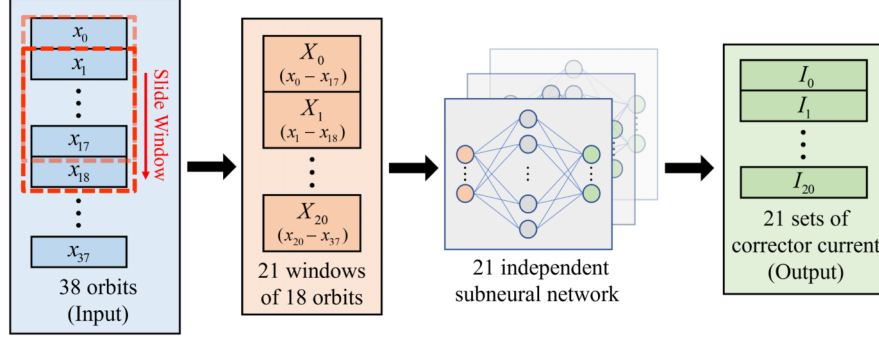


FIG. 10. Architecture diagram of multi-subnetwork model.

$$I_i = g_i(\{\Delta x_j | -1 < t_j - i < 1\}), \quad (7)$$

where I_i is the corrector current set point at i th milisecond, g_i denotes the mapping used to determine I_i from the orbit deflections, and $\{\Delta x_j | -1 < t_j - i < 1\}$ is the set of all orbit deflections Δx_j at time slices whose time stamps t_j lie within 1 ms of i (i.e., the orbit slices that can be affected by the current set point I_i).

So we can design a model with multiple sub-NNs: for every corrector current set we dedicate an NN whose input is only the orbit that would be influenced by this current set. The concept is sketched in Fig. 10.

In this ML model, we use a sliding window of 18 consecutive orbits. This choice is dictated by the data structure and the correction timing: each acceleration cycle provides 38 orbit measurements along the ramp, while the corrector system requires 21 time slices (0–20 ms). Using an 18-orbit window yields exactly $38 - 18 + 1 = 21$ overlapping windows, which can be naturally aligned one-to-one with the 21 correction slices and thus simplifies model construction and training. Each sub-NN therefore receives 576 inputs and outputs one set of corrector currents, so the input layer has 576 nodes and the output layer 21. By grouping the data and creating multiple sub-NNs, we embed the known relation between orbits and correctors into the model, which speeds the convergence and raises the prediction accuracy.

However, the model above still cannot address the issue of excessive current ramp rates. In the model in our research, we added a cumulative summation process at the end, which can be described as

$$I_k = \sum_{i=k}^{19} (O_i \times \text{Range}_{\Delta I}) + O_{20} \times \text{Range}_I, \quad (8)$$

where I_k is the set of current points of k ms, O_i represents the outputs of i th sub-NN, $\text{Range}_{\Delta I}$ and Range_I are the safety limit of the current changing rate and maximum current. Here, we set the activation function for the final layer of each neural network to hyperbolic tangent ($\tanh$), thereby constraining each output within the range $(-1, 1)$.

As outlined above, the structure of the ADCNN has been established, as shown in Fig. 11. The orbit data ($x_0 - x_{37}$) read by BPMs is divided into groups ($X_0 - X_{20}$) using a sliding window. Then, each group is trained using an NN, with the output ($O_0 - O_{20}$) constrained to $(-1, 1)$. Finally, a simple cumulative sum process is applied to obtain the final corrector currents ($I_0 - I_{20}$).

Noting that the correction system of the RCS in CSNS has 32 BPMs and 21 horizontal correctors, the detailed information of the model layers is listed in Table III.

The *input* layer receives the orbit matrix of shape $(32, 38)$ (32 BPM readings for 38 orbits in one cycle). Then the *Slide Window* layer applies a slide window to

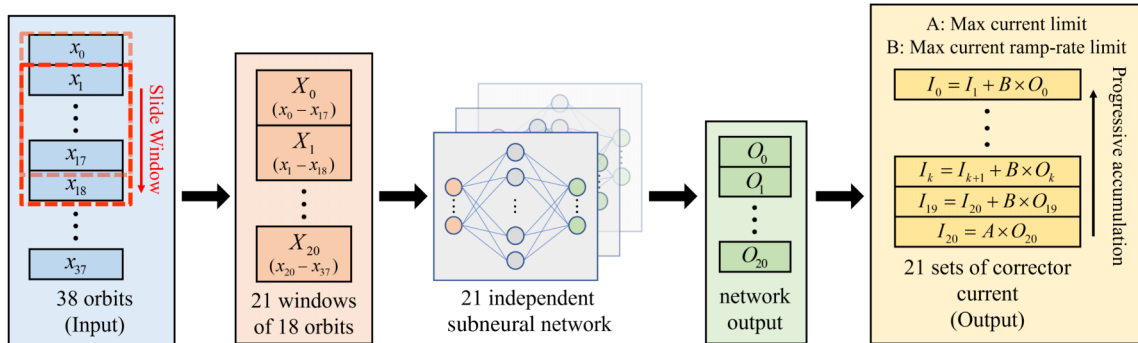


FIG. 11. Architecture diagram of the adjacent-difference-constrained neural network.

TABLE III. Model summary of the adjacent-difference-constrained neural network.

Layers	Shape	Param
Input	(32, 38)	0
Slide window	(21, 32, 18)	0
Flatten	(21, 576)	0
Fully connected (ReLU)	(21, 256)	3 M
Norm	(21, 256)	1 k
Fully connected (tanh)	(21, 21)	113 k
Output	(21, 21)	0

form 21 overlapping samples, which are then reshaped by the *Flatten* layer. Next, the first *Fully Connected* (*ReLU*) layer maps (21, 576) to a 256-dimensional latent representation (21, 256) with a ReLU nonlinearity. The *Norm* layer then normalizes the 256-dimensional features to improve training stability and prediction accuracy. The second *Fully Connected* (*tanh*) layer maps (21, 256) to (21, 21) and applies *tanh* activation function to bound the outputs in $[-1, 1]$. Finally, the *output* layer uses a cumulative summation to provide a (21, 21) array, corresponding to 21 sets of current (0–20 ms) of 21 correctors.

In this model, a sliding window is employed to group the orbit, which serves as a local feature extraction process. This local feature extraction method is advantageous in many ML tasks, such as time-series analysis and language processing, where local features can capture the essential characteristics of the data. In our study, this grouping process introduced the physical prior knowledge of orbits and correctors into the model, accelerating its convergence speed while enhancing its precision and overall performance. More importantly, it provided the basis for the constraints on the current ramp rates of correctors.

B. ML-based orbit correction in off-line simulation

In the simulation, we corrected the orbit with a standard fully connected neural network (FCNN) and the ADCNN described above. The input of the model is the desired orbit change, and the output is the currents of the correctors. A dataset containing 1,000,000 was built by randomly sampling corrector currents and computing the corresponding orbit change, 80% of which were used for training and 20% for testing.

In the RCS, as the beam energy increases, the required corrector strength also increases to achieve the same correction angle. To enhance the model's accuracy, we applied weighted mean absolute error as a loss function during the model training process. And we used the adaptive moment estimation (Adam) as the optimizer.

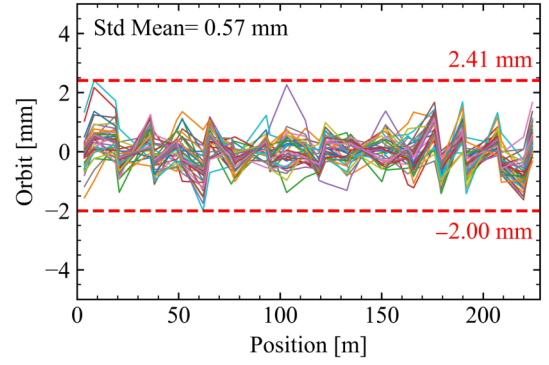


FIG. 12. FCNN corrected orbits in the x plane of the RCS simulation. The COD is distributed within $(-2.00 \text{ mm}, 2.41 \text{ mm})$, and the average standard deviation of the orbits is 0.57 mm.

1. Orbit correction with fully connected neural network

To first test the effectiveness of ML algorithms in the RCS orbital correction, we trained an FCNN with a single hidden layer of 512 units.

As shown in Figs. 12 and 13, the FCNN effectively corrects the time-dependent orbit in RCS, demonstrating that ML is viable for this task. Yet, like the response-matrix approach, it offers no limits on the ramp rates of the corrector currents.

Next, to address the orbital accuracy loss caused by the interpolation process in the RM-based correction method, we trained two identical FCNNs using the original orbit data and interpolated orbit data, respectively, to correct the first 5 ms orbits.

Figure 14 represents the correction results of the first 5 ms orbits obtained by these two networks. As shown, due to the loss of orbit accuracy during the interpolation process, the correction result of the network trained using the interpolated orbits is inferior to that of the network trained using the original orbits. This result demonstrates that by employing machine-learning algorithms, we can better handle the relationship between RCS orbits and correctors, achieving equivalent or even better correction effect.

2. Orbit correction with adjacent-difference-constrained neural network

Following the same procedure, we trained an ADCNN with one hidden layer of 128 units in each subnetwork and employed the network in the orbit correction of the simulated RCS.

As shown in Figs. 15 and 16, the ADCNN also effectively corrects the orbit while simultaneously imposing effective constraints on the ramp rates of corrector currents.

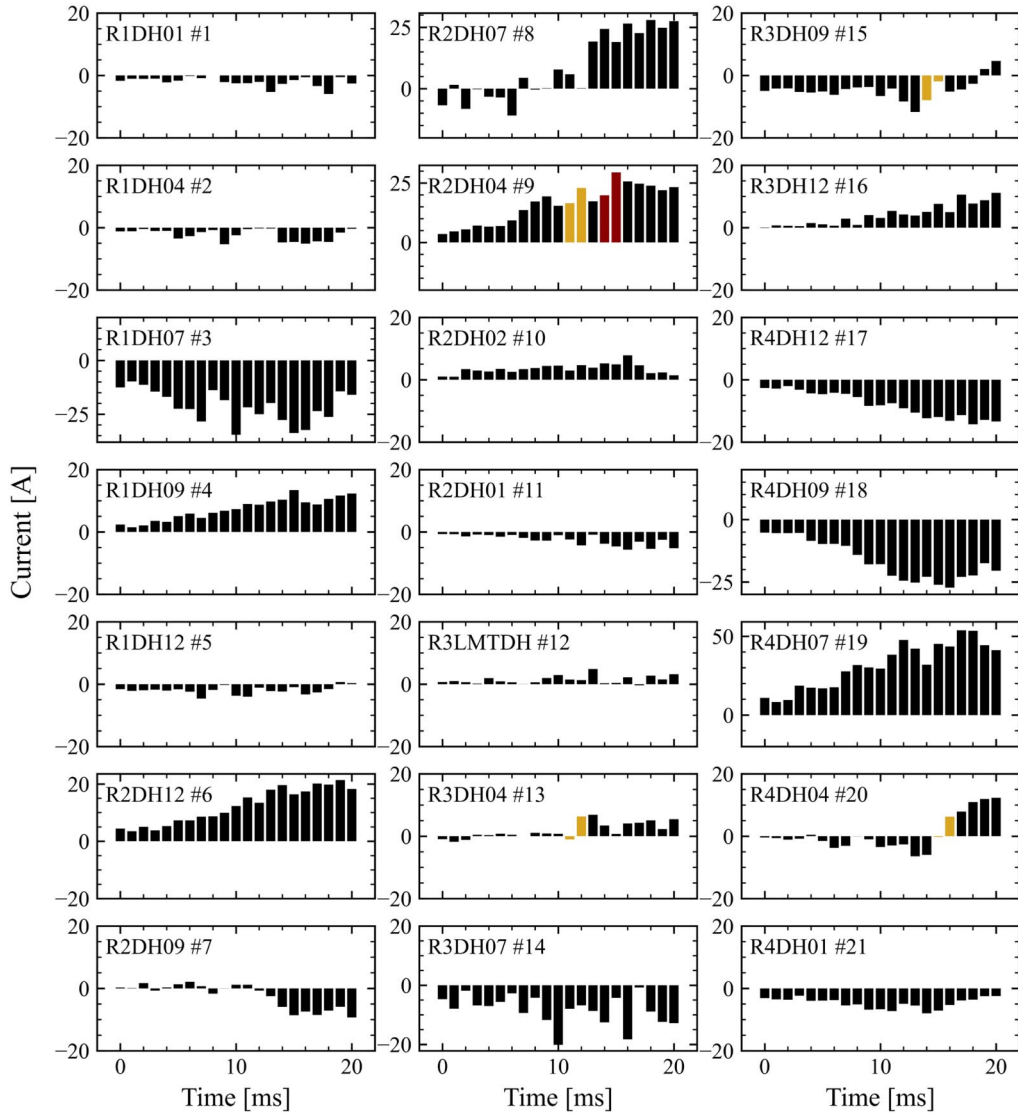


FIG. 13. Corrector currents of horizontal correctors in the correction of the RCS simulation using FCNN.

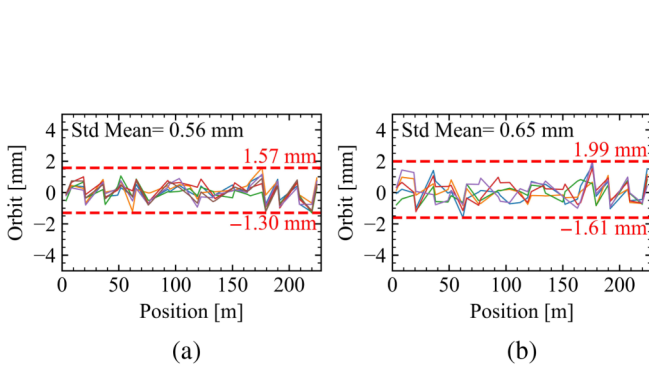


FIG. 14. The first 5 ms orbit correction results of FCNNs trained using original and interpolated data, respectively. (a) Original data trained FCNN. (b) Interpolated data trained FCNN.

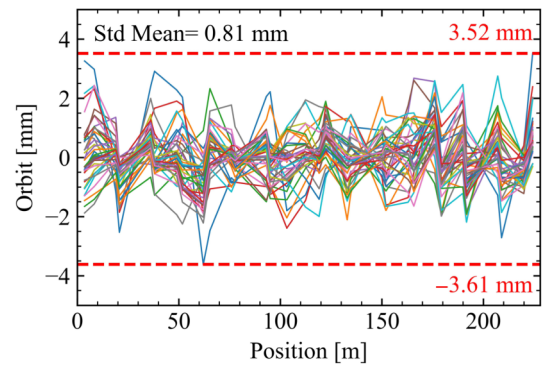


FIG. 15. ADCNN corrected orbits in the x plane of the RCS simulation. The COD is distributed within $(-3.61 \text{ mm}, 3.52 \text{ mm})$, and the average standard deviation of the orbits is 0.81 mm .

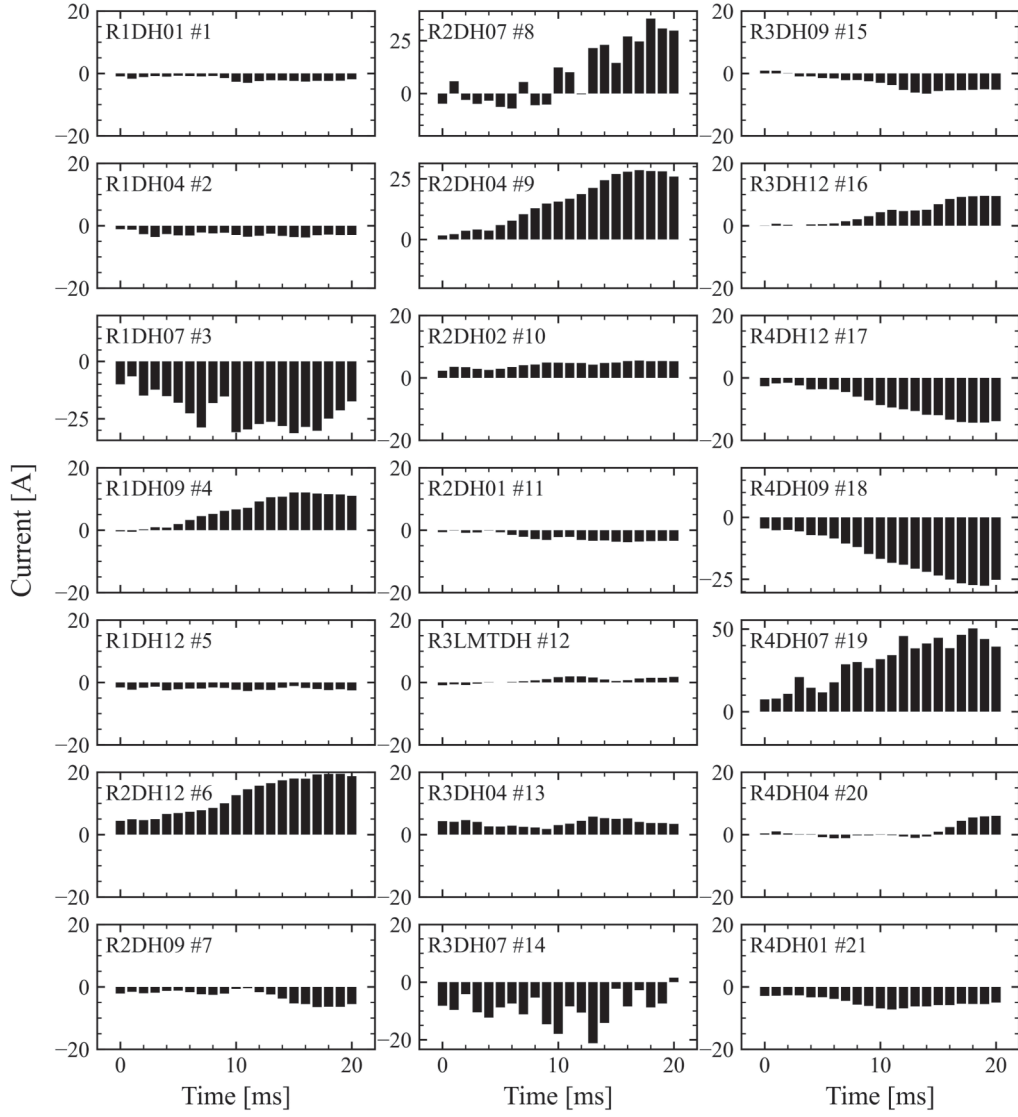


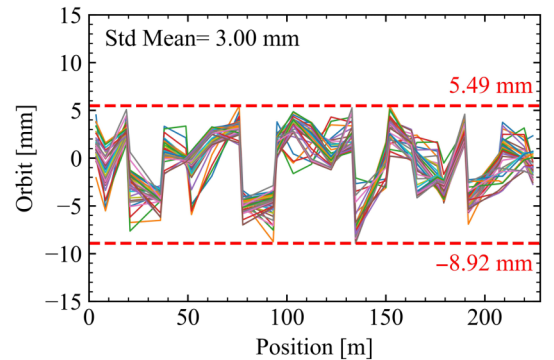
FIG. 16. Corrector currents of horizontal correctors in the correction of the RCS simulation using ADCNN.

C. Online machine correction

After the off-line simulations validated the effectiveness of the ML algorithm for RCS orbit correction, we conducted orbit correction experiments on the actual machine.

The results in Figs. 17 and 18 show that the ADCNN still delivers an effective correction. The COD after correction is slightly larger than that obtained with the RM-based method in Fig. 8, but the current ramp rates are now well controlled compared to that in Fig. 9.

Figure 19 shows the comparison of the corrector ramp rates obtained by these two schemes. The corrector current analysis shows that embedding the ramp rates constraint in the ML architecture cuts the maximum current ramp rates by 54% compared with the RM-based solution. The lower ramp rate improves operational stability and offers a possible route for future high-power running.

FIG. 17. ADCNN corrected orbits in the x plane of the actual RCS machine. The COD is distributed within $(-8.92 \text{ mm}, 5.49 \text{ mm})$, and the average standard deviation of the orbits is 3.00 mm.

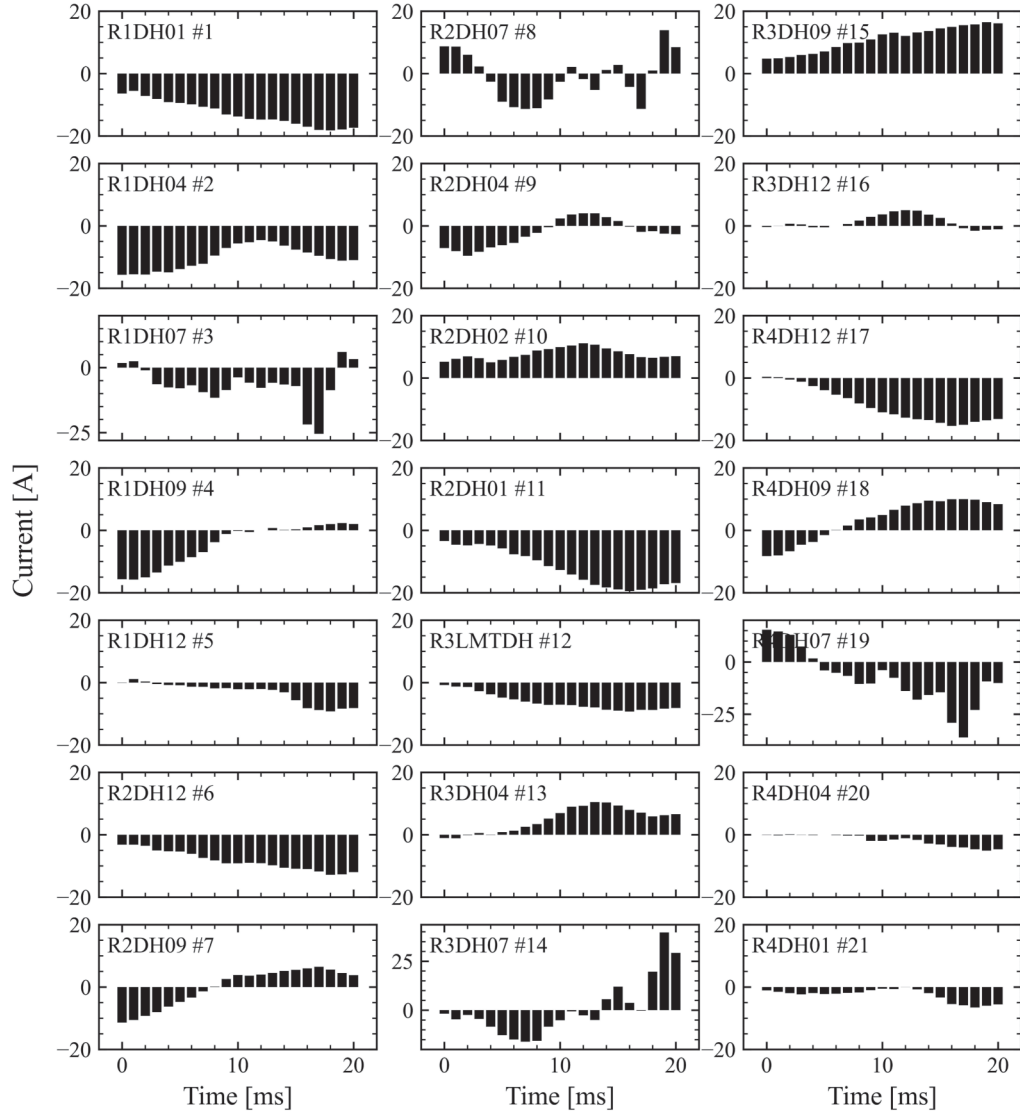


FIG. 18. Corrector currents of horizontal correctors in the correction of the actual RCS machine using ADCNN.

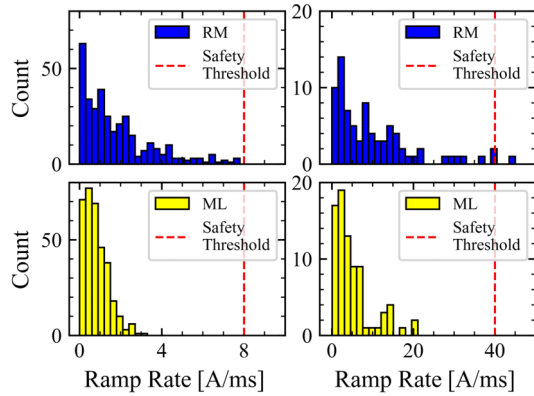


FIG. 19. Distribution of current ramp rates of two kinds of correctors with different safety limits of the two correction schemes.

IV. CONCLUSION

For RCS orbit correction, one of the challenges is how to correct the orbits that vary significantly while controlling the current ramp rates of correctors, which is precisely the shortcoming of the traditional RM-based method. In this paper, we propose an RCS orbit correction method using an ADCNN. Simulations and actual machine experiments both confirm that ML algorithms are feasible for orbit correction in RCS. By analyzing the issues of the present scheme, we devised a dedicated network that constrains the corrector current ramp rates. The correction effect of the ADCNN is equivalent to that of RM-based correction, and the current ramp rates of correctors are effectively constrained, thereby improving the stability of operation.

Although the present implementation is motivated by the specific interpolation structure of the CSNS RCS, the

underlying idea of constraining the differences between adjacent model outputs is not necessarily limited to this application. Similar constraints are common in accelerator operation, where power supplies, rf systems, and mechanical actuators cannot generally vary arbitrarily fast because of hardware bandwidth, operational stability, and equipment-safety requirements. Therefore, the proposed adjacent-difference-constrained output strategy may also be useful for other control problems involving actuator rate limits.

Additionally, applying ML into RCS orbit correction offers other general advantages. By continuously or periodically incorporating new real-time machine data during daily operation, the model can dynamically track time-varying systems without needing retraining [45–49]. This ensures the model remains aligned with the present machine operating conditions, enabling online updates to the orbit-correction system. Moreover, compared to the RM measurement process, the machine-learning model training process dilutes outliers into negligible noise through massive features and distributed parameters, demonstrating greater tolerance for data errors.

There are still some minor issues in our research. The present work focuses on demonstrating the feasibility of the ADCNN-based orbit correction scheme and its effectiveness under corrector constraints at the RCS. However, in practical RCS operation, the machine state may evolve over week-to-month time scales due to slow drifts from power supplies, rf systems, injection devices, ambient temperature changes, and possibly ground motion. Such effects may influence the long-term robustness and generalization of the model. In the future, we will explore its orbit correction performance over extended running periods and apply ML to local correction tasks.

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DATA AVAILABILITY

The datasets supporting the results presented in this article are publicly available in Ref. [50].

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