



Machine learning for beam correction study of the injection beamline at Wuhan Advanced Light Source

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Abstract

Wuhan Advanced Light Source (WALS), a fourth-generation synchrotron radiation light source operating at 1.5 GeV, is currently under design and will use a full-energy linear accelerator (LINAC) as the electron beam injector. The injection beamline adopts a three-stage scheme: First, the beam from the LINAC, which is 6 m below the storage ring, is horizontally deflected below the storage ring; second, it gradually climbs from underground to the same altitude as the storage ring; and third, the beam is delivered horizontally into the injection straight section inside the storage ring. Twiss parameter matching between the LINAC and storage ring was also completed. During the construction of the beamline, magnet manufacturing errors, installation errors, and beam injection errors from the LINAC will cause beam deviations from the predetermined ideal orbits and even particle losses. Therefore, electron beam correction is required during beam commissioning. In contrast with the single-plane beam correction used in general transfer lines, the horizontal and vertical directions of the beam are coupled in the WALS injection transfer line, which greatly increases the complexity and difficulty of beam correction. Machine learning technology has been extensively developed in recent years, and the powerful invertible neural network algorithm is expected to solve the beam commissioning challenge of the beam injection transfer line at the WALS. Therefore, an invertible neural network (INN) model has been designed and trained to simulate the beam transport and beam correction of the WALS injection beamline. By optimizing the number and positions of beam profile monitors, the accuracy of both bidirectional prediction and beam correction can be greatly improved. This method has important practical significance for the commissioning and operation of similar complex beam transport systems.

Keywords Beam correction · Injection transfer beamline · Machine learning · Beam dynamics · Invertible neural network

1 Introduction

Synchrotron radiation light sources are large-scale facilities for observing and studying the microscopic world using synchrotron radiation [1], and accelerators are important

components of synchrotron radiation light sources. After decades of development, they have evolved from the first generation as part-time light sources that simply use synchrotron light generated from particle accelerators to the fourth generation of diffraction-limited storage ring light sources that have ultra-low beam emittance and adopt a large number of undulator insertions. Several fourth-generation synchrotron radiation light source facilities are in operation or under construction worldwide. The MAX IV facility is currently in operation in Sweden and uses multi-bent achromat (MBA) lattices to reduce the beam emittance to below 0.1 nm·rad and increase the brightness by two orders of magnitude [2]. Sirius, located in Brazil, achieves a lower natural beam emittance compared to MAX IV through stronger horizontal focusing [3]. ESRF-EBS in Europe is the world's first 6 GeV storage ring light source upgraded from the ESRF, which significantly enhances its brightness

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and coherence [4]. HEPS [5], HALF [6], and several other fourth-generation synchrotron radiation light sources are under construction. Synchrotron radiation light sources have been widely applied in the fields of physics, materials science, chemistry, biology, life sciences, and electronic information engineering [7].

Wuhan Advanced Light Source (WALS), which is currently under design, is a fourth-generation diffraction-limited synchrotron radiation light source with a 1.5-GeV full-energy linear accelerator (LINAC) as its injector [8]. The electron beams are transported to the 1.5 GeV storage ring via a beam injection transfer line (BITL) [9–11]. To accommodate the future construction of a 4.0 GeV storage ring, the LINAC is 6 m underground and laterally offset relative to the 1.5 GeV storage ring. Because the LINAC is 6 m underground, the WALS BITL adopts a “three-stage” design scheme: First, the beam is horizontally deflected below the storage ring, then it gradually climbs from the underground tunnel to the same altitude level as the storage ring, completing a vertical climb with a height of 6 m, and finally, the beam is transferred horizontally into the injection straight section inside the storage ring [12]. This special design scheme results in horizontal and vertical beam coupling during beam transport. In particular, for the dispersion function, the two transverse directions must be considered and corrected simultaneously when the beam is commissioned. For such a complex beam dynamics problem, where beam diagnostic equipment is limited in practice, neither the traditional beam commissioning method, such as the singular value decomposition (SVD) linear fitting algorithm [13–16] nor the global beam commissioning method [12] proposed for the WALS BITL, is optimal. Therefore, it is necessary to take advantage of machine learning algorithms to simulate the beam transport and perform horizontal and vertical beam corrections simultaneously for the WALS BITL.

In recent years, machine learning algorithms have been widely applied in the field of accelerator physics. The multi-hidden layer structure of neural networks and the nonlinear transformations provided by the activation functions can accurately model beam dynamics of particle beams in accelerators. Applications of machine learning have been reported at many light sources. For example, SLAC National Accelerator Laboratory trained two independent neural network models at its Linac Coherent Light Source (LCLS) [17, 18] to achieve accurate prediction of 2D images of electron bunches [19]. The Shanghai Synchrotron Radiation Facility (SSRF) [20–23] used machine learning to extract beam information bunch by bunch and correct beam orbits of the storage ring [24]. Using a convolutional neural network (CNN) [25, 26], the National Synchrotron Radiation Laboratory (NSRL) at the University of Science and Technology of China (USTC) successfully determined beam cross-section dimensions by suppressing noise in the collected

beam images [27]. In addition, online correction using Lasso regression [28, 29] and beta function correction using neural networks have been carried out [30]. An increasing number of light sources are using machine learning algorithms to solve problems in the field of accelerator physics [31, 32].

In our study, an invertible neural network (INN) [33, 34] containing 8 affine coupling modules [35] has been successfully designed after many tests, where the ReLU (Rectified Linear Unit) activation function [36, 37] is applied, and the Adam (adaptive moment estimation) algorithm [38] and the back-propagation algorithm [39, 40] are introduced. By learning a dataset consisting of two groups of variables, where one group is the magnet K -values (in units of m^{-2}) of quadrupole magnets with adjustable currents in the WALS BITL (as input x), and the other group is the horizontal (σ_x) and vertical (σ_y) beam sizes collected at beam profile monitoring systems (as output y), not only the forward prediction from the magnet K -values to the beam sizes σ , but also the inverse prediction from the beam sizes σ to the magnet K -values can be realized. The AT toolbox in MATLAB was used to model the WALS BITL and collect beam-related data, and to verify the inverse prediction results of the INN model. Beam correction was successfully optimized in the simulation for the WALS BITL.

The remainder of this paper is organized as follows. Section 2 introduces the layout of the WALS BITL and the global beam correction method proposed at the beginning of the beamline design. Section 3 introduces the INN model designed for the WALS BITL, which is described from six aspects: model structure assumptions, beam correction process, placement and quantity settings of beam profile monitoring systems, dataset preparation, model structure setup, and training results. Section 4 describes the verification of the beam correction method for the INN model. Section 5 describes the analysis of the beam correction method, in which the dynamic relationships of the method, the definition of the loss function, and the selection of evaluation metrics are introduced. The summary and conclusions of the work are described in Sect. 6.

2 The WALS BITL and global beam correction

2.1 Design of the WALS BITL

For synchrotron radiation light sources, an injection transfer line is required to deliver the electron beam into the storage ring with high quality and high transmission efficiency. The stable operation of a synchrotron radiation light source highly relies on the precise design and construction of the injection transfer line. When designing the transfer line, one must ensure that the Twiss parameters of the beam are

accurately matched, and the dispersion functions are controlled. At the same time, considering the installation errors, injection errors from the LINAC, magnet manufacturing errors, and many other factors during beamline construction, it is necessary to perform beam correction based on the theoretical design. In general, beam diagnostic devices such as beam position monitors (BPMs) [41] and beam profile monitoring systems are placed along the beamline to collect beam information, and horizontal/vertical correction (HVC) magnets are arranged for beam orbit corrections.

At the WALS, the BITL consists of three sections, as mentioned earlier. The first section of the transfer line is designed with two 15° dipole magnets and three quadrupole magnets to form a horizontal achromatic unit, supplemented by ten quadrupole magnets for beam envelope manipulation. In the second section, the beam is deflected by 30° vertically,

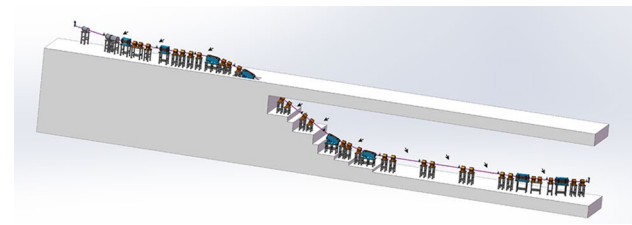
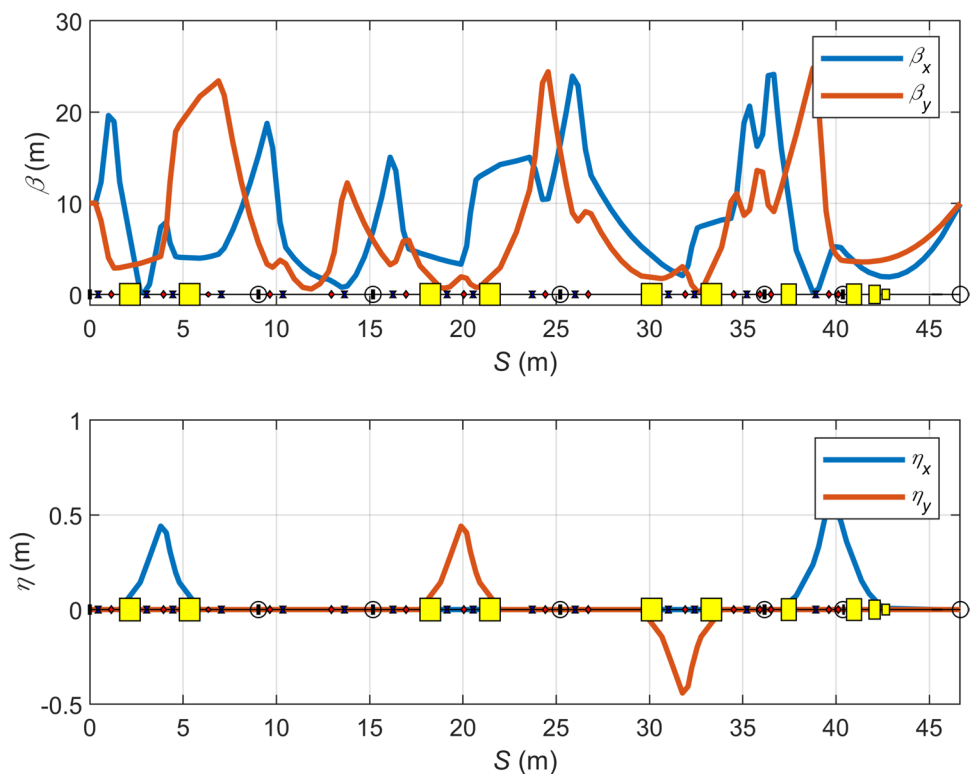


Fig. 1 (Color online) 3D model of the WALS BITL. Arrows indicate the potential locations for the placement of the beam profile monitoring systems

Fig. 2 (Color online) Twiss parameters (β and η) along the WALS BITL. In the beamline, the dark blue boxes represent the HVC correction magnets, the yellow boxes represent the dipole magnets, the circles represent the BPMs, and the rest represents the quadrupole magnets



climbing over a 6-m slope, and then deflected back by 30° to arrive at the same horizontal plane as the storage ring. Both ends of the second section are designed with two 15° dipole magnets and three quadrupole magnets to form a vertical achromatic unit. The two vertical achromatic units in the second section adopt the same magnet parameters as those in the horizontal achromatic unit in the first section to reduce the complexity of beam commissioning. In the third section, four quadrupole magnets are used to deliver the beam from the transfer line to the entrance of the storage ring. A horizontal achromatic unit consisting of two 10.5° dipole magnets, an injection septum, and three quadrupole magnets is used to match the Twiss parameters. Figure 1 shows a 3D model of the WALS BITL. Figure 2 shows the evolution of the Twiss parameters along the WALS BITL, with the beta function not exceeding 25 m and the dispersion function not exceeding 0.6 m. Figure 3 presents the beam sizes in the BITL. Beam size refers to the standard deviation of the electron beam bunch that follows a Gaussian distribution.

2.2 Global correction method

During beamline construction, installation, manufacturing, and other errors may occur, which can prevent the particle beam from following the predetermined orbit, thus resulting in a Twiss parameter mismatch and beam losses. Therefore, it is necessary to optimize the beam correction of the beamline. The global correction method was applied

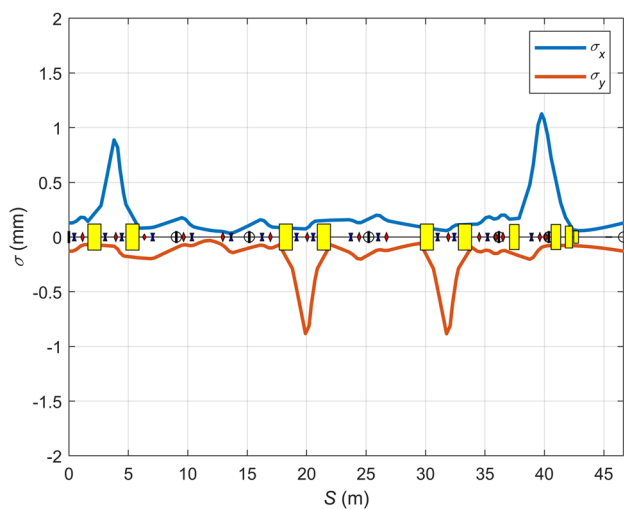


Fig. 3 (Color online) Beam sizes along the WALS BITL. In the beamline, the dark blue boxes represent the HVC correction magnets, the yellow boxes represent the dipole magnets, the circles represent the BPMs, and the rest represents the quadrupole magnets

in the design of the WALS BITL [12]. Considering the horizontal–vertical coupling problem of the WALS BITL, especially for the correction of the dispersion function, it is essential to correct both the horizontal and vertical directions simultaneously; therefore, we first proposed a global correction method for beam correction.

The global correction method involves two steps: orbit correction and optical correction. The orbit correction is achieved using six sets of HVC magnets and BPMs placed in pairs. In Figs. 2 and 3, the specific locations of the HVCs and BPMs can be observed. Optical correction is realized using the AT toolbox simulation in MATLAB, which involves randomly generating 20–50 sets of quadrupole magnet seeds to test the parameters, retaining the seeds with better results (such as lower maximum beta function and lower dispersion function at the end of the beamline), and iterating until the ideal quadrupole setting is found. By employing this overall computational approach, simultaneous bidirectional beam correction can be realized in the simulation. Because the quadrupole magnets of the WALS BITL are powered individually, the 18 quadrupole magnets in the non-dispersion region and the 12 quadrupole magnets in the dispersion region (30 in total) can be adjusted separately. Twenty error seeds were randomly generated, and the beam optics parameters and beam sizes under different error seeds were analyzed. In the global correction simulations, the orbit correction was performed with the help of six sets of HVC magnets and BPMs, whereas the optical correction was realized using MATLAB calculations, in which beam information along the beamline was collected and applied for the optical correction.

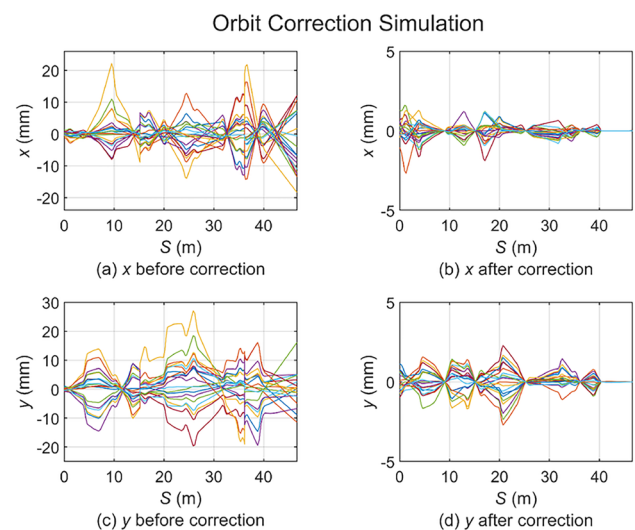


Fig. 4 (Color online) Global correction method: comparison before and after beam orbit correction. **a** and **b** represent the x -orbit before and after correction; **c** and **d** represent the y -orbit before and after correction

Figure 4 shows a comparison of the conditions before and after beam orbit correction, where x and y represent the horizontal and vertical orbits, respectively. The curves correspond to the 20 error seeds mentioned earlier. By comparing (a) and (b), it was observed that the maximum error in the horizontal direction of the orbit before correction was 22 mm, with the end values ranging between -18 mm and 12 mm. After correction, the maximum error in the orbit was reduced to 2.7 mm, and the end values were nearly 0 mm (ideal orbit). Similarly, by comparing (c) and (d), it was found that the maximum error in the vertical direction of the orbit before correction was 27 mm, with the end values ranging between -11 mm and 16 mm. After correction, the maximum error in the orbit was reduced to 2.7 mm, and the end values were also close to 0 mm. The positions and directions of the orbit at the injection point were ideally corrected.

For the beam optics parameters, Fig. 5 shows the results before correction, and Fig. 6 shows the results after correction. The curves correspond to the 20 error seeds mentioned earlier. By comparing Fig. 5 and Fig. 6, it is found that after correction, the maximum value of β_x at the end decreases from 17.8 m to 12.6 m. For β_y , the maximum value at the end decreases from 12.3 m to 10.4 m. The maximum value of η_x at the end decreases from 0.5 m to 0.01 m, and the maximum value of η_y at the end decreases from 0.4 m to 0 m. Overall, the beta function at the end is close to 12 m, and the dispersion function is close to 0 m, meeting the correction requirements of 15 m and 0.2 m, respectively.

To compare with the INN method, 20 new seeds were selected for correction using the global method. These 20

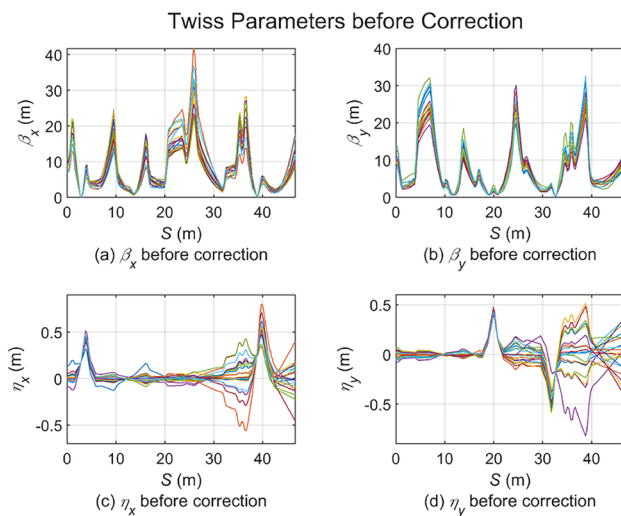


Fig. 5 (Color online) Global correction method: beam optics functions before correction. **a** represents β_x before optical correction; **b** represents β_y before optical correction; **c** represents η_x before optical correction; and **d** represents η_y before optical correction

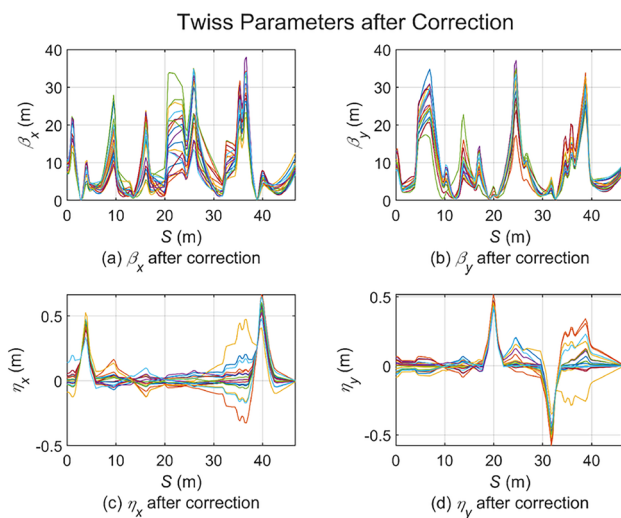


Fig. 6 (Color online) Global correction method: beam optics functions after correction. **a** represents β_x after optical correction; **b** represents β_y after optical correction; **c** represents η_x after optical correction; and **d** represents η_y after optical correction

seeds were different from the previous 100 seeds [12] and had a slightly smaller error range. The global correction achieved results similar to those in the previous study. The correction of the dispersion function, especially its deviation in the middle part of the beamline, was the key focus in the previous work, resulting in better overall correction. However, the correction results at the injection point of the injection straight section inside the storage ring were very close to each other.

The global correction method achieves beam correction for the WALS BITL because it captures information from all points along the transport line in the simulations. However, in reality, there are limited locations where beam diagnostic elements can be placed, and the available information during actual beam correction is far less than that in the simulations. Therefore, the global correction method is not applicable in actual beam correction. Consequently, it is necessary to develop a new beam commissioning method, which can not only solve the problem of horizontal and vertical beam corrections at the same time, but also complete the beam correction under limited information. Therefore, we studied the beam correction of the WALS BITL using machine learning algorithms and proposed the use of an invertible neural network (INN) model for beam correction of the WALS BITL.

3 Invertible neural network model

With the continuous progress of artificial intelligence, machine learning systems have developed rapidly [42]. An increasing number of researchers are attempting to use machine learning technology for cutting-edge research [43–46], especially in physics [47–50]. Applications of machine learning technology in beam commissioning are also under rapid development in the field of particle accelerators.

3.1 Network structure for the WALS BITL

At present, machine learning algorithms are often used to design storage rings or study beam instabilities, where the number of hidden layers of neural networks designed generally ranges from one to three, while the number of nodes ranges from tens to thousands. Multi-objective genetic algorithms [51, 52] are typically applied to find the best working point of each component of particle accelerators. In our case, beam transport at the WALS BITL is unidirectional, there are few adjustable components, and the three-stage beamline design is highly specific. Therefore, it is necessary to design a unique neural network model for beam correction at the WALS BITL. There are 30 quadrupole magnets that can be adjusted and limited locations to place beam profile monitoring systems for diagnostics along the BITL. It is expected that the neural network can determine the K -values of quadrupoles to provide the required horizontal beam sizes (σ_x) and vertical beam sizes (σ_y) at the beam profile monitoring systems.

In the beam transfer line, it is known that the forward process from the magnet K -values to the beam sizes σ is accurately defined; however, the inverse process from the beam sizes σ to the magnet K -values is underdetermined,

and there is even the possibility of a “many-to-one” solution. Therefore, an INN model was designed to correct the beam at the WALS BITL. Through the forward learning of the network model, the K -values of quadrupole magnets can predict the beam sizes, whereas through the invertible mapping of the network model, the K -values of 30 quadrupole magnets corresponding to the expected beam sizes can also be predicted. The network can not only realize the forward prediction from the magnet K -values to the beam sizes but also realize the inverse prediction from the beam sizes to the K -values of the quadrupole magnets, with the inverse prediction being based on the forward prediction. The forward learning process is in accordance with the physical nature of the beam dynamics along the WALS BITL, and the inverse prediction results are also highly accurate. Therefore, this method is efficient for the actual beam commissioning of the WALS BITL.

The beam size was considered as a learning feature for the following reasons: (1) It can be easily collected from beam profiles; (2) to ensure that the electrons are efficiently transported and not lost, beam size is the primary objective of beam commissioning; (3) as the storage ring has strict requirements on beam dispersion when injecting the electron beam, the dispersion function is also an important correction target. The beta function and other optical parameters should also be considered, as shown in Eq. 1, where the beam size is determined by the beta function and the dispersion function. Considering the actual situation of the WALS BITL, in order to save beam diagnostic elements to the greatest extent, the beam size is selected, which can be expressed as

$$\sigma_i^2 = \beta_i \epsilon_i + (\eta_i \sigma_e)^2, \quad (1)$$

where σ_i is the beam size, β_i is the beta function, ϵ_i is the beam emittance, η_i is the dispersion function, and σ_e is the energy spread (i refers to the horizontal or vertical direction). As shown in the equation, the beam size changes along with the beta function and dispersion function when the beam emittance and energy spread are constant.

The Adam optimization algorithm was introduced as an optimizer. The Adam optimization algorithm differs from the common stochastic gradient descent algorithm. It combines an adaptive learning rate and a momentum approach to efficiently and automatically adjust the learning rate and the speed of parameter updates during the training process. The back-propagation algorithm was chosen to compute the gradient of the function. Compared with forward propagation, which transmits the input data forward to the output layer, back-propagation is based on the chain rule, which finds the partial derivatives of all parameters and passes them backward, and constantly adjusts the weights and biases of the network so that the neural network model can

better fit the data and improve the generalization ability of the model [39].

Machine learning techniques are typically applied to accelerator physics using an artificial neural network (ANN). However, considering the unique characteristics of the WALS BITL, an INN model is selected. Because the electron beam motion in the transfer line is unidirectional, it is possible that multiple quadrupole magnet combinations correspond to the same beam size. Therefore, the main goal of this study is to quickly obtain a feasible combination of K -values of quadrupole magnets based on the given target beam sizes. The INN model is very suitable for this purpose because its forward learning process can simulate beam transport more accurately, and its inverse prediction process can quickly obtain a feasible K -value combination.

3.2 Beam correction process

The overall learning process of the INN model is shown in Fig. 7. There are mainly 5 steps from Fig. 7a to c. In Fig. 7a, Step 1, the AT toolbox of MATLAB is used to model the transfer line, where the injection parameter errors from the LINAC and magnet installation errors are randomly generated within the error ranges to establish error seeds; Step 2, the beam orbit is corrected with HVC magnets in the simulation (in reality, orbit correction can be completed in the transfer line without machine learning); Step 3, multiple sets of quadrupole magnet K -values are randomly generated for each error seed, and the horizontal (σ_x) and vertical (σ_y) beam sizes simulated by AT (or measured during actual beam commissioning) at each profile are collected. K -values and beam sizes are treated as input x and output y , respectively, to form a dataset for learning (the ratio of training set, validation set, and test set is 4:1:1.25). In Fig. 7b, Step 4, the model is preliminarily trained with error seed No. 1, and the network structure and related hyperparameters are continuously adjusted to design the most reasonable model. At Step 5 as shown in Fig. 7c, the model usability is verified: The dataset made using the error seed is learned and predicted; if the prediction result is reasonable, this error seed is replaced by the next one. If it is unreasonable, the hyperparameters of the model are reset until the 10 error seeds can be reasonably predicted. Subsequently, the INN model is considered to have a reasonable structure and sufficient usability, and the beam transfer line can be corrected in the simulation. The R^2 (coefficient of determination) is selected as the criterion for judging the rationality of the prediction results. When the average value of the forward prediction R^2 is greater than 0.90 and the average value of the inverse prediction R^2 is greater than 0.85, the INN model structure and hyperparameters are considered to be well designed. When these criteria are met, the INN model is used to correct the WALS BITL under the ten error seeds.

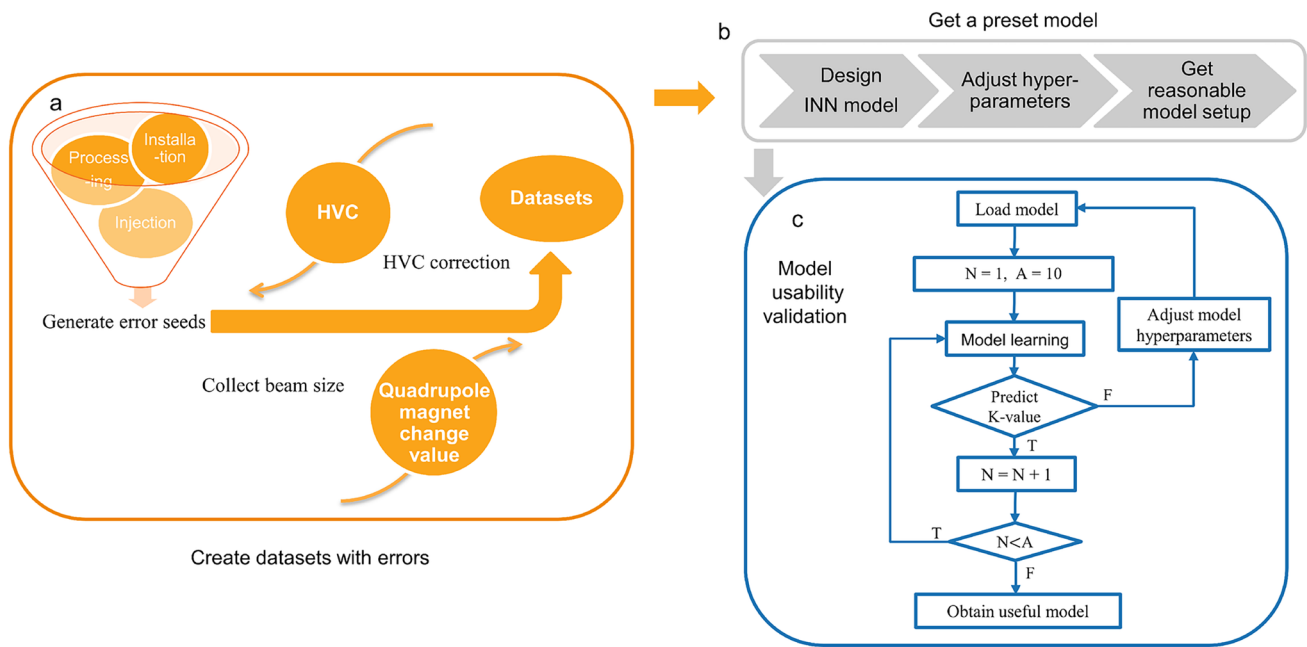


Fig. 7 (Color online) Learning flowchart of the neural network system

Table 1 Comparison of the R^2 values with different numbers of beam profile monitoring systems

Profile number (position)	Forward prediction R^2	Inverse prediction R^2
10 (all)	0.9662	0.8442
8 (1-2-4-6-7-8-9-10)	0.9391	0.8296
7 (1-2-4-6-8-9-10)	0.9423	0.6797
6 (2-5-7-8-9-10)	0.9441	0.6933
5 (1-5-7-9-10)	0.9111	0.1817

3.3 Optimization of beam profile monitoring system settings

There are approximately ten locations where beam profile monitoring systems can be installed in the WALS BITL, defined as No. 1 to No. 10 from the beginning to the end of the beamline. The specific distribution of locations is indicated in Fig. 1 with arrows. To save space and cost, the number of beam profiles should be reduced as much as possible, while ensuring sufficient beam correction accuracy. An optimization was performed using the ideal error-free WALS BITL, starting from Step 3, as shown in Fig. 7a. Table 1 lists the R^2 values for different profile numbers. Beginning with a total of ten beam profile monitoring systems, the number was continuously reduced to allow for comparisons.

Because the model uses the Adam optimizer, there are some fluctuations in R^2 values under this scheme. As shown in Table 1, when the number of profiles is reduced to five,

the inverse prediction R^2 value drops sharply. The fewer profiles used, the fewer points can be observed, and less data can be learned by the model. Considering the practical requirements of the model and the cost of the devices, the number of profiles was finally determined to be six. Considering that the application of the final model is to predict the quadrupole magnet K -values according to the desired beam sizes, a beam profile monitoring system must be placed in position No. 10 behind the last quadrupole magnet. Because positions No. 1, No. 2, No. 3, and No. 4 are quite close to each other, and there are only a few quadrupole magnets nearby, one or two representatives should be sufficient for these four positions. Based on this, comparisons were carried out between various combinations of six profile locations, as listed in Table 2. Finally, positions No. 1, No. 4, No. 5, No. 6, No. 8, and No. 10 were selected to ensure that the R^2 value was sufficiently good.

3.4 Preparation of datasets

The errors mainly considered in the WALS BITL include injection errors at the start point of the BITL, for example, Twiss parameter and position errors, magnet installation errors, and magnetic field errors of dipoles and quadrupoles. Using the MATLAB AT toolbox, the corresponding ten error seeds were randomly generated. For each error seed, a dataset was produced for the neural network model to learn, wherein the input x is the K -values of the quadrupole magnets, and the output y is the horizontal and vertical beam sizes at the six beam profile monitoring

Table 2 Comparison between various combinations of 6 beam profile monitoring system positions

Profile position	Forward prediction R^2	Inverse prediction R^2
2-5-7-8-9-10	0.8328	0.7317
1-3-5-7-9-10	0.9146	0.5795
1-4-6-8-9-10	0.9395	0.6994
1-5-6-8-9-10	0.9394	0.8372
1-4-5-6-8-10	0.9290	0.9255

Table 3 Assumed positioning errors of the injected beam from the LINAC

Direction	Distance (mm)	Angle (mrad)
Horizontal	± 0.5	± 0.3
Vertical	± 0.5	± 0.3

Table 4 Assumed Twiss parameter errors of the injected beam from the LINAC

Direction	β (%)	α	η (m)
Horizontal	± 30	± 0.3	± 0.03
Vertical	± 30	± 0.3	± 0.03

systems. Each dataset contains 10,000 groups of x and y . The ranges of the aforementioned errors are listed in Tables 3–6. Specifically, Tables 3 and 4 show the positioning and Twiss parameter error ranges of the injected beam from the LINAC. Table 5 lists the installation error ranges of the dipole and quadrupole magnets. Table 6 lists the magnetic field error ranges of the dipoles and quadrupoles. The ten random error seeds were generated within the error ranges listed in Tables 3–6. For each error seed, a dataset containing the K -values of the quadrupoles was produced for the neural network model based on the values listed in Table 6.

Ten random error seeds were selected to verify whether the model structure and hyperparameter settings of the INN model were appropriate. If the model can successfully correct the beam under ten different error seeds, it also proves that the model has good versatility.

Table 6 Assumed magnetic field errors of dipoles and quadrupoles in the WALS BITL

Magnet type	Magnetic field error (%)
Dipole	± 0.1
Quadrupole	± 0.2

3.5 Design of the network structure

After comprehensive consideration, an INN model with eight affine coupling modules has been designed, in which the ReLU activation function is applied, and the Adam and back-propagation algorithms are introduced. Figure 8 shows a schematic of the neural network structure.

3.6 Training results

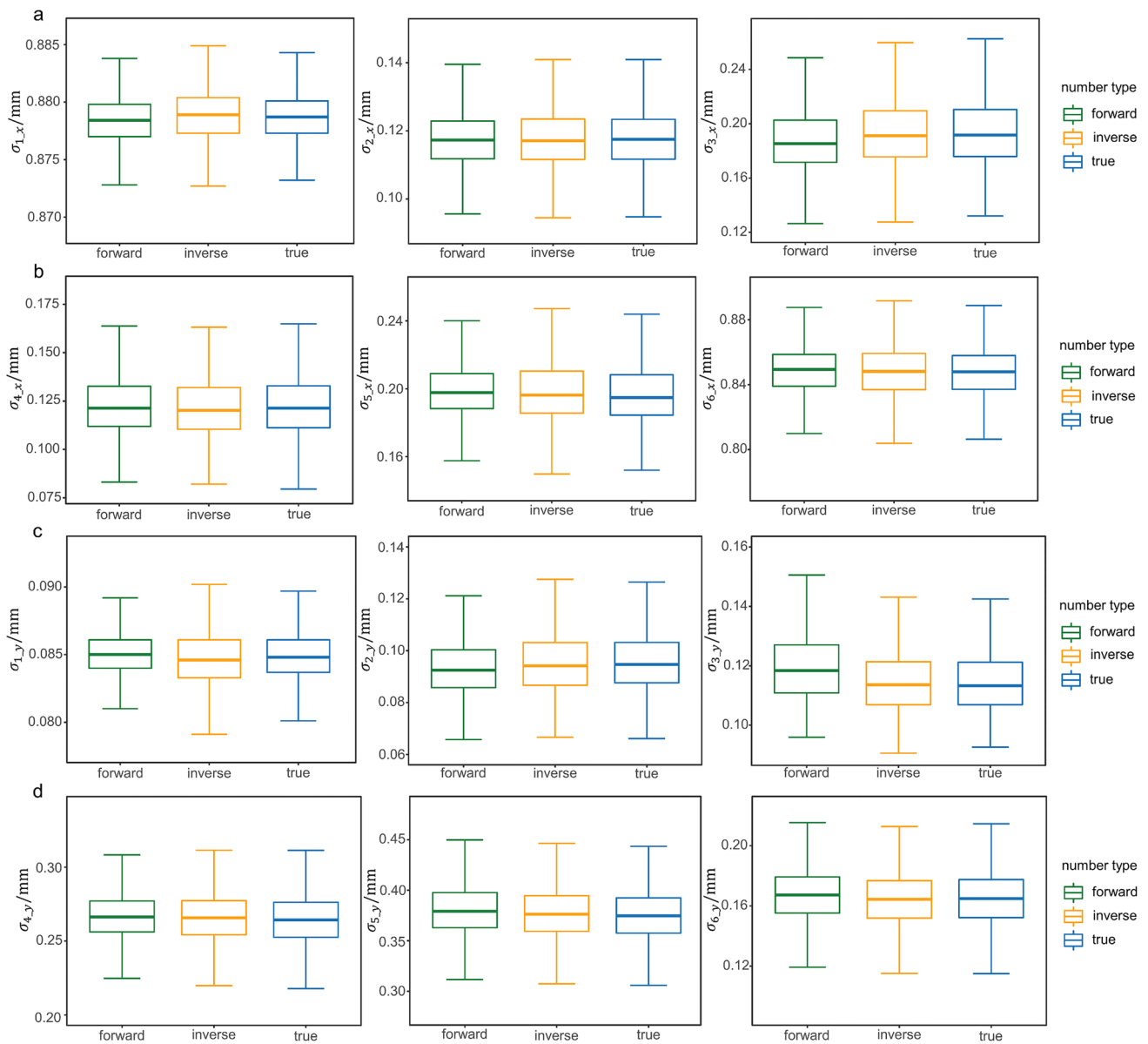
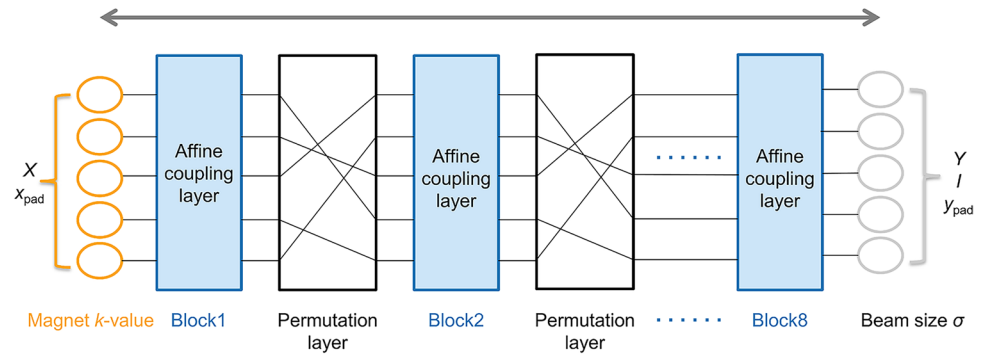
The prediction results of the test set were visually analyzed, where the true value of the beam size and the predicted values of both the forward and inverse processes were compared. The Box-plot [53] was applied for visual analysis. The Box-plot can clearly and concisely display the quartiles of the data and, hence, reflect the distribution of data more realistically. As can be seen from Fig. 9, for the beam size, the median error was not more than 0.015 mm between the forward, inverse, and true values, whereas 75% and 25% of the data, as well as the maximum and minimum values, were almost symmetrically distributed on both sides of the median.

For the forward prediction, the result of σ_{3-y} is approximately 0.015 mm larger than the inverse and true values. However, the model is eventually used for inverse prediction, so the difference between the inverse process and the true value is more relevant. As can be seen, the difference between the data distributions of the inverse-predicted value and the true value is negligible for each beam profile monitoring system.

Figure 10 compares the prediction and true values of the beam sizes at the first and last beam profile monitoring locations. Each point in the figure corresponds to an individual in the test set. From Fig. 10, the minor deviations between the true and predicted values are more transparent and informative.

Table 5 Assumed installation errors of dipoles and quadrupoles in the WALS BITL

Magnet type	Horizontal installation (mm)	Vertical installation (mm)	Longitudinal installation (mm)	Rotation in the x -direction (mrad)	Rotation in the y -direction (mrad)	Rotation in the z -direction (mrad)
Dipole	± 0.5	± 0.2	± 0.5	± 0.5	± 0.5	± 0.2
Quadrupole	± 0.2	± 0.2	± 1.0	± 0.5	± 0.5	± 0.5

Fig. 8 (Color online) Diagram of the neural network structure**Fig. 9** (Color online) Comparisons of beam sizes between the true values and predicted values at the 6 beam profile monitoring systems

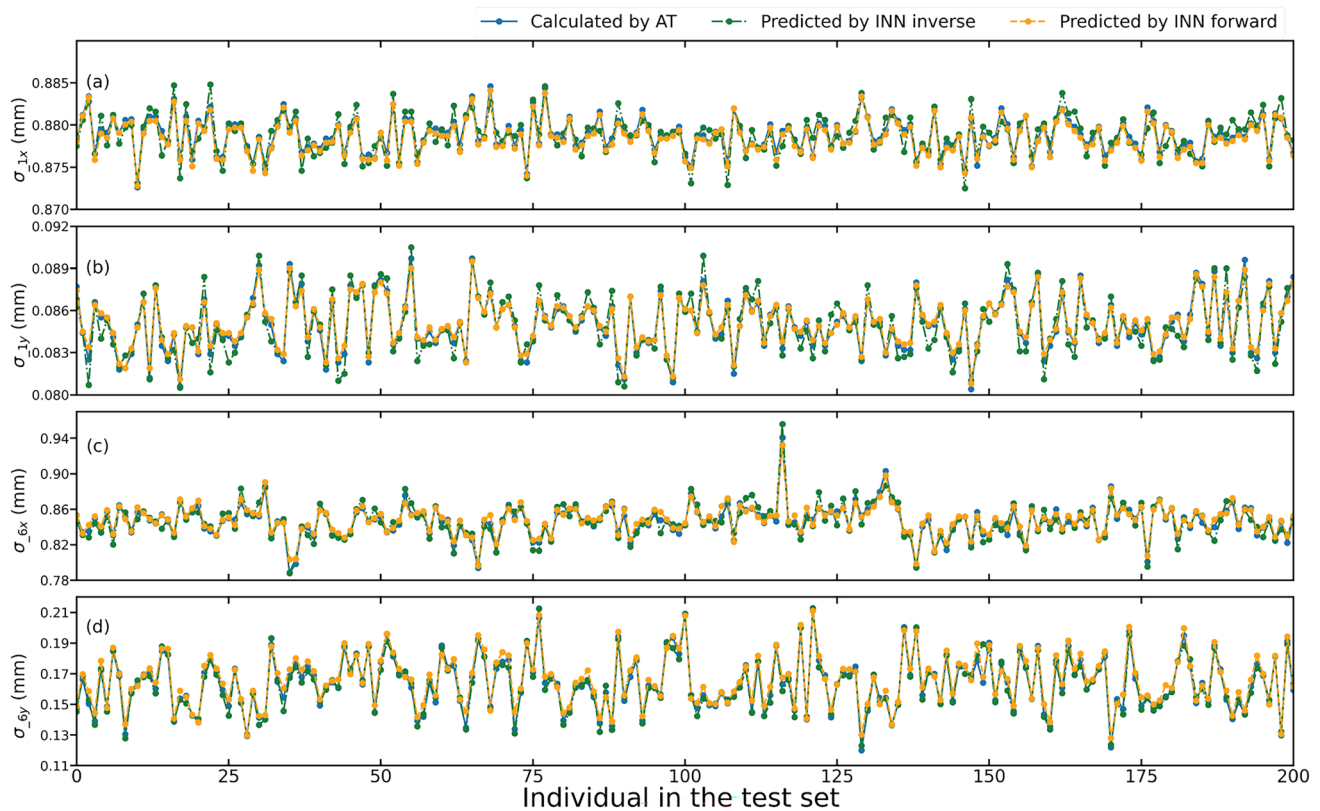


Fig. 10 (Color online) Comparison of predicted and true beam sizes at the first and the last beam profile monitoring systems. “Calculated by AT” represents the true value, “Predicted by INN forward” represents the predicted value (forward), and “Predicted by INN inverse” represents the predicted value (inverse)

sents the predicted value (forward), and “Predicted by INN inverse” represents the predicted value (inverse)

4 Verification

Because the WALS BITL has not been constructed yet, MATLAB was used to model it for virtual verification.

Figure 11 shows a comparison of the beam parameters before and after correction using the INN model with an error seed and $\pm 1\%$ field error of quadrupoles. The solid colored lines represent the dispersion function and beam size under the aforementioned errors, whereas the dark blue dotted lines marked with circles show the corrected beam parameters using the INN model. As can be seen in Fig. 11, both the dispersion function and beam size were well corrected. At the exit of the transfer line, the horizontal and vertical dispersions were 0.03 m, the horizontal beam size was 0.14 mm, and the vertical beam size was 0.12 mm.

Table 7 lists a comparison of the beam sizes between the expected and corrected values using the INN. The input values refer to the beam sizes expected and imported into the INN model. Based on the input values, the INN model predicts the K -values directly, and the corrected beam sizes are calculated by MATLAB using the WALS BITL with the predicted K -values from the INN. The corrected beam

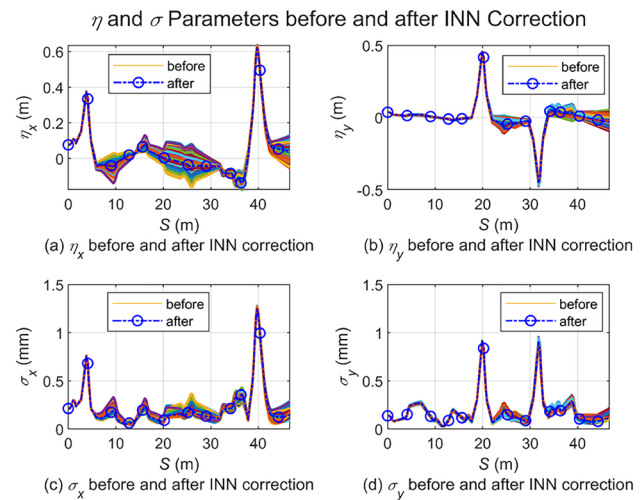
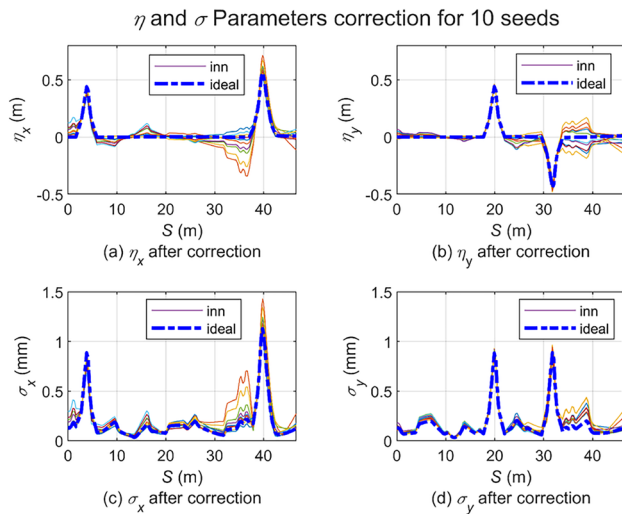


Fig. 11 (Color online) Beam dispersion function and beam size before and after correction using the INN model under errors. The solid colorful lines represent results before correction, while the dash-dotted lines are results after correction

Table 7 Comparison of beam sizes between the expected values and the corrected values

Value type	Direction	σ_1 (mm)	σ_2 (mm)	σ_3 (mm)	σ_4 (mm)	σ_5 (mm)	σ_6 (mm)
Input	x	0.7546	0.1630	0.0667	0.1406	0.2107	0.9885
	y	0.1145	0.1359	0.9122	0.0928	0.1785	0.1049
Corrected	x	0.7528	0.1623	0.0729	0.1500	0.2127	0.9956
	y	0.1153	0.1364	0.9108	0.0932	0.1812	0.1040

**Fig. 12** (Color online) Beam dispersion function and beam size after correction using the INN model for ten error seeds. The solid colorful lines represent results after the INN correction, while the dash-dotted lines represent ideal values required

sizes were very close to the expected values. Figure 11 and Table 7 further verify the accuracy of the INN model.

Figure 12 shows the beam dispersion function and beam size after correction using the INN model for ten error seeds. The dashed blue curves represent the theoretical or ideal beam parameters along the transfer line without error. The solid colored curves show the corrected results using the INN model under the ten error seeds. As can be seen from Fig. 12, the corrected dispersion function and beam size are close to the ideal conditions. The dispersion function at the exit of the transfer line is within 0.15 m, and the beam size can be corrected to be within 0.3 mm.

By comparing Fig. 12 and Fig. 6, it is found that in the x -direction, the global correction method corrects the dispersion function at the endpoint to within 0.01 m, whereas the INN model corrects it to within 0.1 m. In the y -direction, the global correction method corrects the dispersion function at the endpoint to close to 0 m, while the INN model corrects it to within 0.15 m. Both methods meet the correction requirement of 0.2 m. Although the global correction method can achieve more precise correction effects in simulation environments, this method is limited to simulations because it requires more beam information than what can be provided

Table 8 Configurable parameters of the INN model

INN model parameter configuration of the WALS BITL	
Data preprocessing	$x \in [0,1]$ $y \in [0,1]$
Potential spatial distribution dimension	$I = 1$
Loss function weights	$\omega_{\text{MSE}} = 50$ $\omega_r = 10$ $\omega_\alpha = 1$ $\omega_k = 50$ $\omega_l = 50$
Optimization algorithm	Adam
Activation function	ReLU function
Number of trainable parameters	137792
Number of affine coupling blocks	8
Learning rate	0.002
Sample batch size	32
Epochs	50

by actual beam diagnostic systems. In contrast, the INN model is specifically designed for practical beam correction applications and can effectively utilize limited beam diagnostic information for correction. This capability for practical application makes the INN model more advantageous in actual operations, especially when beam information is limited. Therefore, despite the global correction method's excellent performance in simulations, the feasibility and flexibility of the INN model in practical applications make it a more practical choice.

5 Method analysis

The code programming of the INN model designed in this study is based on previous work [54]. The following is an analysis of the method applied to the WALS BITL. Section 5.1 introduces the dynamic relationships in the WALS BITL and analyzes the mathematical relationships of the INN model applied to the WALS BITL. Section 5.2 provides a detailed description of the considerations for selecting the loss function in neural networks, with Table 8 summarizing the hyperparameters used in the final model. Section 5.3 introduces the R^2 metric and the steps for evaluating the model.

5.1 Dynamic relationships

The dynamic equations for the particle beam and the quadrupole magnet K -values at the WALS injection transfer line are

$$\hat{f} : D^{\vec{K}} \times D \rightarrow D^{\vec{\sigma}}, \quad (2)$$

$$\hat{f}(\vec{k}, d) = \hat{\sigma}(d), \quad (3)$$

where K represents the value of the quadrupole magnet, $d \in D$ represents the location in the beamline, function $\hat{f}$ represents the transfer line model, and $\hat{\sigma}$ represents the electron beam size at location d .

The INN model generally requires that the input and output data dimensions be equal. However, for the problem discussed in this study, the input data dimension is 30, whereas the output data dimension is 12, which are unequal; therefore, it is necessary to compensate for the data dimensions. Here, we define the total data dimension as A . Because the solution of the inverse problem is not unique, and there is a possibility of many-to-one solutions, when solving, it is not only mapped to the pre-designed values but also mapped to a prospective spatial distribution (I) that has been learned. By randomly sampling in I , the model constantly attempts to find the most suitable distribution value to complete the optimal solution of the inverse problem [54]. The total dimension A can be described as

$$A = \dim(K) + 1 + \dim(x_{\text{pad}}) = \dim(\sigma) + \dim(y_{\text{pad}}) + I, \quad (4)$$

where x_{pad} is the complementary dimension of the input data and y_{pad} is the complementary dimension of the output data. I is the potential spatial distribution dimension. For this paper, only the dimensionality of the output data is supplemented, so the mathematical expression of the forward prediction of the physical model for the transfer line is

$$\hat{f} : D^{\vec{K}} \times D \rightarrow D^{\vec{\sigma}} \times D^{\dim(y_{\text{pad}})} \times D^I, \quad (5)$$

$$\hat{f}(\vec{k}, d) = (\hat{\sigma}(d), \dim(y_{\text{pad}}), I). \quad (6)$$

The mathematical expression for the inverse prediction of the transfer line is

$$\hat{f}^{-1} : D^{\vec{\sigma}} \times D^{\dim(y_{\text{pad}})} \times D^I \rightarrow D^{\vec{K}} \times D, \quad (7)$$

$$\hat{f}^{-1}(\hat{\sigma}(d), \dim(y_{\text{pad}}), I) = (\vec{k}, d). \quad (8)$$

5.2 Loss function

The definition of the loss function during training consists of five components: the mean square error L_{MSE} between the predicted output and the true value of the model, the mean square error L of the complementary dimensions of the output data, the reconstruction error L_r to reduce the influence of small perturbations (δ) on the reverse prediction, L_k which is used to ensure that the sampled magnet K -values follow the same distribution as the dataset, and L_I which is used to ensure that the potential spatial distribution D^I follows the desired one. The expression for the loss function is

$$L_{\text{all}} = \omega_{\text{MSE}} L_{\text{MSE}} + \omega_r L_r + \omega_\alpha L_\alpha + \omega_k L_k + \omega_I L_I, \quad (9)$$

where ω_{MSE} , ω_r , ω_α , ω_k , and ω_I denote the weighting coefficients of the corresponding loss terms.

The mean square error (MSE) equation and the reconstruction error equation are given by

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2, \quad (10)$$

$$L_r = \sum_{i=1}^n (\hat{f}^{-1}(\hat{f}(k_i, d_i) + \delta) - k_i)^2. \quad (11)$$

In the above equations, n is the total number of adjustable quadrupole magnets in each sample, which is 30. Table 8 shows the other detailed data configurations corresponding to the INN model.

5.3 Evaluation metrics

At the end of the transfer line, the beam size is determined by all the quadrupole magnets in the entire beamline (the dipoles also have an influence, which is ignored here); therefore, in the inverse prediction, simply comparing the predicted value with the true value cannot truly reflect the accuracy of the model. Therefore, R^2 was chosen as the evaluation metric. The value range of R^2 is between 0 and 1, and the closer it is to 1, the higher the prediction accuracy of the model is. R^2 is expressed as

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (\bar{y}_i - y_i)^2}, \quad (12)$$

where y_i is the true value, $\bar{y}_i$ is the mean of the true values, and $\hat{y}_i$ is the predicted value.

The steps for evaluating the model are as follows: (1) The model makes a forward prediction of the validation set and obtains the forward prediction σ value corresponding to the K -values of the quadrupole magnets (true K

values); (2) the true σ values and the forward predictions of σ are used to calculate the R^2 of the forward prediction; (3) the model makes an inverse prediction of the validation set and obtains the K -values of the quadrupole magnets predicted from the true σ s; (4) the model makes a forward prediction using the K -values of the quadrupole magnets obtained from the inverse prediction and obtains the σ values of the inverse prediction; (5) the true σ values and the σ values of the inverse prediction are used to calculate R^2 of the inverse prediction. Figure 13 shows the specific steps. Among them, the “Inverse prediction- σ ” obtained by the “Pending K -value” after the forward prediction represents the predicted σ value of the whole inverse prediction process.

After adequate testing, the value of R^2 can reach a maximum of approximately 0.96 for forward prediction and approximately 0.93 for inverse prediction. From both the corrected Twiss parameters and beam sizes and the R^2 value, the feasibility of this INN model for the beam correction study of the WALS BITL can be confirmed. Table 9 lists the R^2 data for one error seed. As shown in the table, the average forward prediction $\bar{R}^2$ reaches 0.9483, and for the inverse prediction, $\bar{R}^2$ reaches 0.9342.

6 Conclusion

An invertible neural network (INN) model was designed using a machine learning algorithm to optimize beam correction for the WALS BITL. The method was proved to be feasible, and the beam correction results were remarkable in the simulations. Owing to the unique “three-stage” design of the WALS BITL, the INN algorithm can solve the problem of simultaneous beam correction in both horizontal and vertical planes, as well as the beam correction difficulty caused by the lack of beam information under limited measurement points. The final design of the INN model not only realizes the forward prediction from the magnet K -values to the beam sizes σ , but also realizes the inverse prediction from the beam sizes σ to the K -values of the quadrupole magnets. The MATLAB AT toolbox was used to model the transfer line, collect beam-related data, verify the inverse prediction results of the INN model, and successfully demonstrate the commissioning optimization of the WALS BITL in the simulation. This method can provide practical guidance for the actual beam correction process. In the future, we will further explore the possibility of designing an appropriate INN model with a reduced number of beam profile monitoring systems in the beamline to reduce construction costs. This method will be applied in practice during the

Fig. 13 Flowchart for evaluating the INN model of the WALS BITL

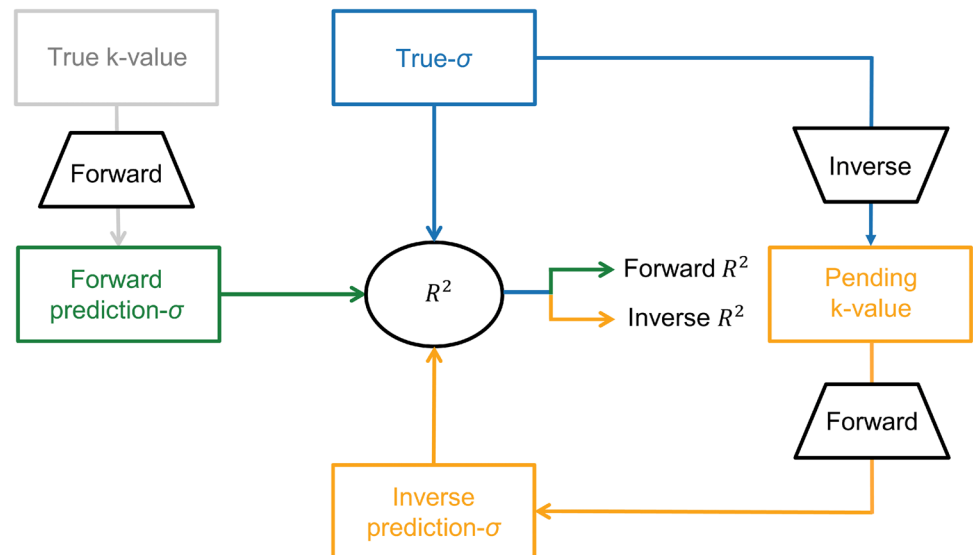


Table 9 R^2 values for the INN model predictions

	Direction	σ_1	σ_2	σ_3	σ_4	σ_5	σ_6	Average value
Forward	x	0.9637	0.9600	0.9006	0.9178	0.9613	0.9381	0.9403
	y	0.9761	0.9768	0.9099	0.9578	0.9581	0.9584	0.9562
Inverse	x	0.8618	0.9558	0.9730	0.9570	0.9594	0.8488	0.9260
	y	0.8803	0.9224	0.9584	0.9506	0.9631	0.9787	0.9423

construction and commissioning of the WALS BITL. In this study, a machine learning algorithm was used to correct the beam of the WALS BITL, and the strategy may be applied to similar accelerator physics problems in other facilities.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Hui Wang, Hao-Hu Li, Jia-Bao Guan, and Yuan-Cun Nie. The first draft of the manuscript was written by Hui Wang. Hao-Hu Li and Yuan-Cun Nie reviewed and edited the manuscript. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

1. H.N. Chapman, Fourth-generation light sources. *IUCrJ* **10**, 246 (2023). <https://doi.org/10.1107/S2052252523003585>
2. P.F. Tavares, E. Al-Dmour, A. Andersson et al., Commissioning and first-year operational results of the MAX IV 3 GeV ring. *J. Synchrotron Rad.* **25**, 1291 (2018). <https://doi.org/10.1107/S1600577518008111>
3. V.S. Dyubkov, SYLA storage ring status. *Nucl. Instrum. Methods Phys. Res. A* **1075**, 170413 (2025). <https://doi.org/10.1016/j.nima.2025.170413>
4. L. Valle, T. Brochard, N. Carmignani et al., Off-energy operation for the Extremely Brilliant Source at the European Synchrotron Radiation Facility. *Phys. Rev. Accel. Beams* **27**, 051601 (2024). <https://doi.org/10.1103/PhysRevAccelBeams.27.051601>
5. J. Yi, X. Gang, X.H. Cui et al., The HEPS project. *J. Synchrotron Rad.* **25**, 1611 (2018). <https://doi.org/10.1107/S1600577518012110>
6. Z.H. Bai, G.W. Liu, T.L. He et al., A Modified Hybrid 6BA Lattice for the HALF Storage Ring. Paper Presented at the IPAC 2021, Campinas, SP, Brazil, pp. 407–409 (2021). <https://doi.org/10.18429/JACOW-IPAC2021-MOPAB112>
7. F.C. Li, R.Z. Liu, W.J. Li et al., Synchrotron radiation: A key tool for drug discovery. *Bioorg. Med. Chem. Lett.* **144**, 129990 (2024). <https://doi.org/10.1016/j.bmcl.2024.129990>
8. Z.Y. Dai, Y.C. Nie, Z. Hui et al., Design of S-band photoinjector with high bunch charge and low emittance based on multi-objective genetic algorithm. *Nucl. Sci. Tech.* **34**, 41 (2023). <https://doi.org/10.1007/s41365-023-01183-6>
9. H.H. Li, J. Wang, L. Tang et al., Project of Wuhan photon source. Paper Presented at the IPAC 2021, Campinas, SP, Brazil, pp. 346–349 (2021). <https://doi.org/10.18429/JACOW-IPAC2021-MOPAB092>
10. Y. Zou, H.H. Li, Y. Chen et al., Studies on beam injection system for Wuhan advanced light source storage ring. Paper Presented at the IPAC 2023, Venice, Italy, pp. 1176–1179 (2023). <https://doi.org/10.18429/JACoW-IPAC2023-MOPM086>
11. Z.Y. Dai, Y.C. Nie, J.H. Zhong et al., Beam dynamics study of the photoinjector at Wuhan advanced light source. *Radiat. Detect. Technol. Meth.* **8**, 1319 (2024). <https://doi.org/10.1007/s41605-024-00455-y>
12. H.H. Li, J. Li, G. Wei et al., Beam transfer line of Wuhan advanced light source. Paper Presented at the IPAC 2023, Venice, Italy, pp. 1082–1084 (2023). <https://doi.org/10.18429/JACoW-IPAC2023-MOPM040>
13. A.G. Akritas, G.I. Malaschonok, Applications of singular-value decomposition (SVD). *Math. Comput. Simulat.* **67**, 15 (2004). <https://doi.org/10.1016/j.matcom.2004.05.005>
14. S.H. Mirza, R. Singh, P. Forck et al., Closed orbit correction at synchrotrons for symmetric and near-symmetric lattices. *Phys. Rev. Accel. Beams* **22**, 072804 (2019). <https://doi.org/10.1103/PhysRevAccelBeams.22.072804>
15. A.M. Cox, J.F. Benesch, R.M. Bodenstein et al., Beam correction for multi-pass arcs in FFA @ CEBAF: status update. Paper Presented at the IPAC 2024, Nashville, TN, pp.1054 (2024). <https://doi.org/10.18429/JACoW-IPAC2024-TUPC23>
16. H. Jin, D.O. Jeon, J.H. Jang, Results of on-line orbit correction at the medium energy beam transport section of the RAON accelerator. *J. Korean Phys. Soc.* **83**, 854 (2023). <https://doi.org/10.1007/s40042-023-00919-2>
17. J. Arthur, G. Materlik, R. Tatchyn et al., The LCLS: A fourth generation light source using the SLAC linac. *Rev. Sci. Instrum.* **66**, 1987 (1995). <https://doi.org/10.1063/1.1145778>
18. J.N. Galayda, The LCLS-II: A high power upgrade to the LCLS. Paper Presented at the IPAC 2018, Vancouver, BC, Canada, pp. 18–23 (2018). <https://doi.org/10.18429/JACoW-IPAC2018-MOYGB2>
19. C. Emma, A. Edelen, M.J. Hogan et al., Machine learning-based longitudinal phase space prediction of particle accelerators. *Phys. Rev. Accel. Beams* **22**, 112802 (2018). <https://doi.org/10.1103/PhysRevAccelBeams.21.112802>
20. H.J. Xu, Z.T. Zhao, Current status and progresses of SSRF project. *Nucl. Sci. Tech.* **19**, 1 (2008). [https://doi.org/10.1016/S1001-8042\(08\)60013-5](https://doi.org/10.1016/S1001-8042(08)60013-5)
21. T.Y. Yang, W. Wen, G.Z. Yin et al., Introduction of the X-ray diffraction beamline of SSRF. *Nucl. Sci. Tech.* **26**, 020101 (2015). <https://doi.org/10.13538/j.1001-8042/nst.26.020101>
22. Z.L. Li, Y.C. Fan, L. Xue et al., The design of the test beamline at SSRF. *AIP Conf. Proc.* **2054**, 060040 (2019). <https://doi.org/10.1063/1.5084671>
23. J.H. He, X.Y. Gao, Status of the crystallography beamlines at SSRF. *Eur. Phys. J. Plus* **130**, 32 (2015). <https://doi.org/10.1140/epjp/i2015-15032-6>
24. R.C. Li, Q.L. Zhang, Q.R. Mi et al., Application of machine learning in orbital correction of storage ring. *High Power Laser and Particle Beams* **33**, 034007 (2021). <https://doi.org/10.11884/HPLPB202133.200318> (in Chinese)
25. T. Kattenborn, J. Leitloff, F. Schiefer et al., Review on Convolutional Neural Networks (CNN) in vegetation remote sensing. *ISPRS. J. Photogramm. Remote Sens.* **173**, 24 (2021). <https://doi.org/10.1016/j.isprsjprs.2020.12.010>
26. L. Alzubaidi, J.L. Zhang, A.J. Humaidi et al., Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *J. Big Data.* **8**, 53 (2021). <https://doi.org/10.1186/s40537-021-00444-8>
27. W.C. Zhu, Z.Y. Wei, C.J. Xie et al., Development of the NFTHz accelerator beam profile measurement system. *High Power Laser and Particle Beams* **36**, 034004 (2024). <https://doi.org/10.11884/HPLPB202436.230361> (in Chinese)
28. H. Zou, The adaptive lasso and its oracle properties. *J. Am. Stat. Assoc.* **101**, 1418 (2006). <https://doi.org/10.1198/01621450600000735>
29. J. Ransam, J.A. Cook, LASSO regression. *Brit. J. Surg.* **105**, 1348 (2018). <https://doi.org/10.1002/bjs.10895>
30. Y.B. Yu, W.B. Ni, G.F. Liu et al., Initial Application of Machine Learning for Beam Parameter Optimization at the Hefei Light

- Source II. J. Phys. Conf. Ser. **2687**, 072002 (2024). <https://doi.org/10.1088/1742-6596/2687/7/072002>
31. Z.M. Chu, D.J. Xiao, Y.S. Qiao et al., Machine learning applications for particle accelerators. *Front. Data Comput.* **1**, 110 (2019). <https://doi.org/10.11871/jfcd.issn.2096-742X.2019.02.010>
 32. Y.B. Yu, G.F. Liu, W. Xu et al., Research on tune feedback of the Hefei Light Source II based on machine learning. *Nucl. Sci. Tech.* **33**, 28 (2022). <https://doi.org/10.1007/s41365-022-01018-w>
 33. L. Ardizzone, J. Kruse, S.J. Wirkert et al., Analyzing inverse problems with invertible neural networks. Paper Presented at the ICLR 2019, Ernest N. Morial Convention Center, New Orleans, LA (2019). <https://doi.org/10.48550/arXiv.1808.04730>
 34. O. Moran, P. Caramazza, D. Faccio et al., Deep, complex, invertible networks for inversion of transmission effects in multimode optical fibres. Paper Presented at NeurIPS 2018, Montreal, Canada (2018). <https://doi.org/10.5555/3327144.3327248>
 35. D.P. Kingma, P. Dhariwal, Glow: Generative flow with invertible 1x1 convolutions. Paper Presented at NeurIPS 2018, Montreal, Canada, pp. 10236–10245 (2018). <https://doi.org/10.5555/3327546.3327685>
 36. D. Yarotsky, Error bounds for approximations with deep ReLU networks. *Neural Netw.* **94**, 103 (2017). <https://doi.org/10.1016/j.neunet.2017.07.002>
 37. J.C. He, L. Lin, J.C. Xu et al., ReLU deep neural networks and linear finite elements. *J. Comput. Math.* **38**, 502 (2020). <https://doi.org/10.4208/jcm.1901-m2018-0160>
 38. D.P. Kingma, J. Ba, Adam: A method for stochastic optimization. Paper Presented at ICLR 2015, San Diego (2015). <https://doi.org/10.48550/arXiv.1412.6980>
 39. D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning representations by back-propagating errors. *Nature* **323**, 533 (1986). <https://doi.org/10.1038/323533a0>
 40. J. Li, J.H. Cheng, J.Y. Shi et al., Brief introduction of back propagation (BP) neural network algorithm and its improvement. *Advances in Computer Science and Information Engineering: Volume 2*. (Springer, Berlin Heidelberg, 2012), pp. 553–558
 41. S. Walston, S. Boogert, C. Chung et al., Performance of a high resolution cavity beam position monitor system. *Nucl. Instrum. Methods Phys. Res. A* **578**, 1 (2007). <https://doi.org/10.1016/j.nima.2007.04.162>
 42. Y.C. Wu, J.W. Feng, Development and application of artificial neural network. *Wirel. Pers. Commun.* **102**, 1645 (2018). <https://doi.org/10.1007/s11277-017-5224-x>
 43. B.C. Wang, C.X. Tang, M.T. Qiu et al., A machine learning approach to TCAD model calibration for MOSFET. *Nucl. Sci. Tech.* **34**, 192 (2023). <https://doi.org/10.1007/s41365-023-01340-x>
 44. Y.J. Ma, Y. Ren, P. Feng et al., Sinogram denoising via attention residual dense convolutional neural network for low-dose computed tomography. *Nucl. Sci. Tech.* **32**, 41 (2021). <https://doi.org/10.1007/s41365-021-00874-2>
 45. X.D. Guo, P. He, X.J. Lv et al., Material decomposition of spectral CT images via attention-based global convolutional generative adversarial network. *Nucl. Sci. Tech.* **34**, 45 (2023). <https://doi.org/10.1007/s41365-023-01184-5>
 46. G.X. Wei, S.X. Zhang, Z. Li et al., Multi-modality measurement and comprehensive analysis of hepatocellular carcinoma using synchrotron-based microscopy and spectroscopy. *Nucl. Sci. Tech.* **32**, 102 (2021). <https://doi.org/10.1007/s41365-021-00927-6>
 47. H.Y. Yang, D. Wang, D.D. Wang, An overview of the application of neural network algorithm in the nuclear field of China. *Nucl. Sci. Technol.* **8**, 19–34 (2020). <https://doi.org/10.12677/NST.2020.81003> (in Chinese)
 48. W.B. He, Y.G. Ma, L.G. Pang et al., High-energy nuclear physics meets machine learning. *Nucl. Sci. Tech.* **34**, 88 (2023). <https://doi.org/10.1007/s41365-023-01233-z>
 49. Z.P. Gao, Y.J. Wang, H.L. Lü et al., Machine learning the nuclear mass. *Nucl. Sci. Tech.* **32**, 109 (2021). <https://doi.org/10.1007/s41365-021-00956-1>
 50. Y. Zou, Q.Z. Xing, B.C. Wang et al., Application of the asynchronous advantage actor-critic machine learning algorithm to real-time accelerator tuning. *Nucl. Sci. Tech.* **30**, 158 (2019). <https://doi.org/10.1007/s41365-019-0668-1>
 51. K. Deb, A. Pratap, S. Agarwal et al., A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* **6**, 182 (2002). <https://doi.org/10.1109/4235.996017>
 52. H.X. Yin, J.B. Guan, S.Q. Tian et al., Design and optimization of diffraction-limited storage ring lattices based on many-objective evolutionary algorithms. *Nucl. Sci. Tech.* **34**, 147 (2023). <https://doi.org/10.1007/s41365-023-01284-2>
 53. R. McGill, J.W. Tukey, W.A. Larsen, Variations of box plots. *Am. Stat.* **32**, 12 (1978). <https://doi.org/10.1080/00031305.1978.10479236>
 54. R. Bellotti, R. Boiger, A. Adelmann, Fast, efficient and flexible particle accelerator optimisation using densely connected and invertible neural networks. *Information* **12**, 351 (2021). <https://doi.org/10.3390/info12090351>

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