APPLICATION OF LSTM AUTOENCODER TO THE 10 KHZ STORAGE RING ORBIT DATA*

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Abstract

In NSLS-II storage ring, the 10 kHz orbit data are always available and can be collected at any time interval. At this moment, they are being collected every 10 minutes to review the machine stability status or investigate orbit related issues impacting user satisfaction. To improve the machine performance, we are studying the machine learning techniques with which we can detect any orbit stability issue as early as possible. As one of the strong candidates, we are testing models constructed by the long short-term memory (LSTM) autoencoder from the orbit data. In this paper, we present the optimized LSTM autoencoder parameters and test results.

INTRODUCTION

The NSLS-II storage ring is the 3 GeV electron storage ring of the National Synchrotron Light Source II (NSLS-II) at Brookhaven National Laboratory. For the monitoring of the machine performance as well as to prepare the case of investigation, we continually collect the 10 kHz fast acquisition (FA) orbit data. They are very useful to review the machine stability status or investigate orbit related issues impacting user satisfaction. The available spectrum of the 10 kHz orbit data is from DC to 5 kHz, which is much higher than the typical spectrum of the slow orbit data (10 Hz) but we can also identify the low frequency information very clearly.

Many methods are available and applicable to analyze the 10 kHz orbit data in reviewing the past operation, but the traditional methods has limitations in detecting the orbit stability issue in real time. To overcome the limitations of the traditional methods, we are studying the machine learning techniques with which we can detect any orbit stability issue as early as possible with the trained model. As one of the strong candidates, we are testing models constructed by the long short-term memory (LSTM) autoencoder from the orbit data.

LSTM is a type of recurrent neural network (RNN) that is designed to handle sequential data and capture long-term dependencies. An autoencoder is a type of neural network that learns to encode input data into a lower-dimensional representation and then decode it back to the original input. By training an LSTM autoencoder on the 10 kHz orbit data, we can learn the normal patterns of the orbit and detect any deviations from the trained patterns, which may indicate stability issues.

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Data Collection

The 2026 user operation of NSLS-II started on January 20 and the schedule until the April shutdown is shown in Table 1.

Table 1: NSLS-II User Operation Schedule Until the April Shutdown.

01	2026-01-20 08:00:00	2026-01-27 06:00:00
02	2026-01-29 08:00:00	2026-02-06 08:00:00
03	2026-02-09 08:00:00	2026-02-17 06:00:00
04	2026-02-19 08:00:00	2026-02-27 08:00:00
05	2026-03-02 08:00:00	2026-03-10 06:00:00
06	2026-03-12 08:00:00	2026-03-20 08:00:00
07	2026-03-23 08:00:00	2026-03-31 06:00:00
08	2026-04-02 08:00:00	2026-04-10 08:00:00

During the 8 periods of the 2026 user operation, we collected FA orbit data every 10 minutes. The total file number of the collected data is 7344, and each file contains 2000 points for all the beam position monitors (BPM). Even though insertion device (ID) BPMs are also included in the collection, they are not used in the general analysis and used when specific investigation is needed. Therefore, the total number of BPMs in the analysis is 360, 180 for horizontal motion and 180 for vertical motion.

Data Analysis

As the usually review of the machine performance, we analyze the FA data with the singular value decomposition (SVD). Detailed analysis of singular vectors, spectrum analysis or pattern analysis are reserved for the specific investigation, but, instead, we focus on the variation analysis using singular values. The advantage is the method is very simple and fast while providing suitable information about the orbit stability.

Figure 1 shows the variation of the variation of SVD analysis parameters together with the beam properties collected together with FA data. The lifetime and injection efficiency, in the beam properties compared to the SVD analysis parameters are, usually considered as the most important indicators of the machine performance. And the beam size and emittance are also important indicators which impact the user satisfaction.

The total energy of the SVD analysis is the sum of the squares of the singular values, which represents the total variance in the orbit data. There are various ways to define the rank of the matrix using the singular values and three of them are shown in the figure, which are the number of singular values above 95 % of the total energy (Energy95), the hard threshold based on well-known algorithm

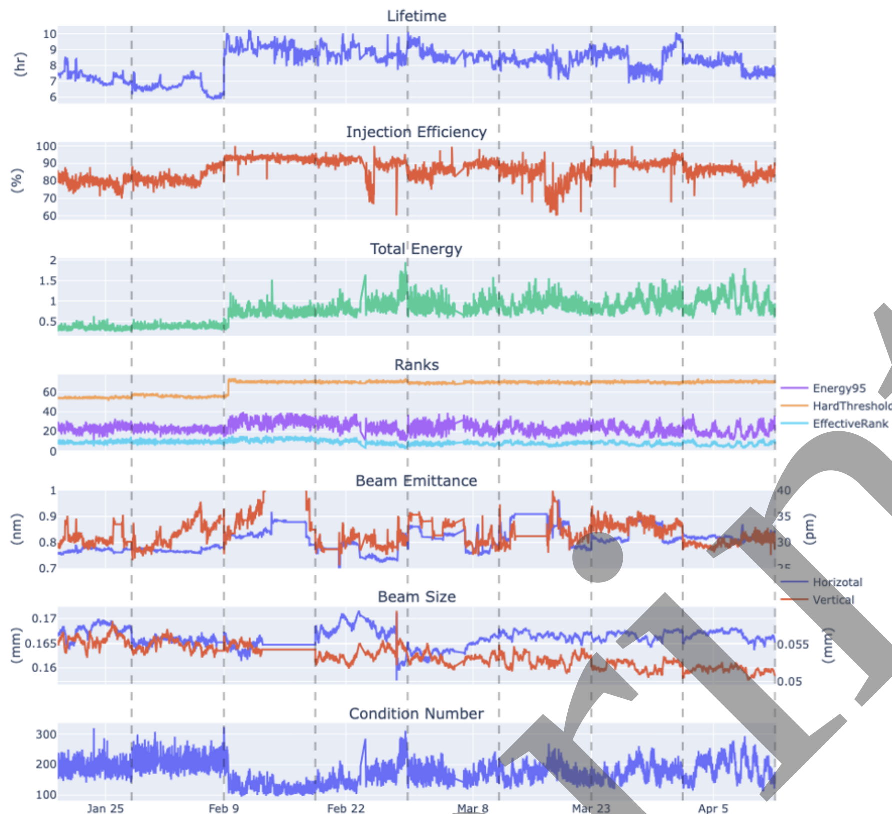

Figure 1: The variation of the singular value analysis parameters together with the beam properties during the 2026 user operation. The dashed vertical lines indicate the start and end of the user operation periods.

(HardThresold) [1] and the exponential of the Shannon spectrum entropy of the singular value distribution (EffectiveRank). The condition number is the ratio of the largest singular value to the smallest singular value, which represents the sensitivity of the orbit data to perturbations.

From Fig. 1, we can see the possible correlation of the variation of the SVD analysis parameters to the lifetime and injection efficiency while the correlation to the beam size or emittance is less clear. In fact, the beam size and emittances measurements are not so reliable and furthermore, they are manipulated time to time by users' requests. Thus, we will focus on the correlations of the SVD analysis parameters to the beam size and emittance as well as between themselves.

LSTM AUTOENCODER

Even though the SVD analysis can be used to detect the change in orbit stability which can be related to the beam properties, no more detailed information is provided. To overcome the VD analysis limitations, we are testing the LSTM autoencoder model to analyze the 10 kHz orbit data whether it also has correlation to the beam properties and whether it can provide more detailed information about the orbit pattern. That is SVD analysis based on the singular value magnitudes and distribution while the LSTM autoencoder analysis is based on the pattern of the orbit data itself.

Conventionally, the LSTM autoencoder model is trained to learn the normal patterns of the data, and then it is used to detect any deviations from the trained patterns, which may indicate some issues. In our case, we need to train the model at the start of the operation even we cannot say the FA data pattern is standard because we are interested in detecting change. Then we need another models if beam properties are changed beyond some threshold, which should be defined based on the correlation analysis and the experiences. That means we cannot use files as the training dataset because them model needs to be trained fast enough to be used as additional model, practically within several hours at least, while the machine is stable.

In this paper, as the feasibility study of the LSTM autoencoder model, we are training the LSTM autoencoder model with the files collected at the arbitrary period of user operation where the beam properties are considered to be relatively stable.

For the training dataset, files are selected from the period of the user operation where the lifetime is relatively high and stable, which is from March 2 10:37 to March 3 09:07. We also impose the condition of the lifetime to be higher than 9.5 hours, which is considered as the threshold for the good machine performance, which makes the number of selected files to be 56. For the effective LSTM model training, we need to select the number of BPMs and the number of points in each file, which are the two main parameters for the model training. As for the BPMs, the horizontal readings at the dispersive regions are selected because they are more likely to have more information about the beam properties. In the NSLS-II storage ring, each cell has 2 BPMs, BPM3

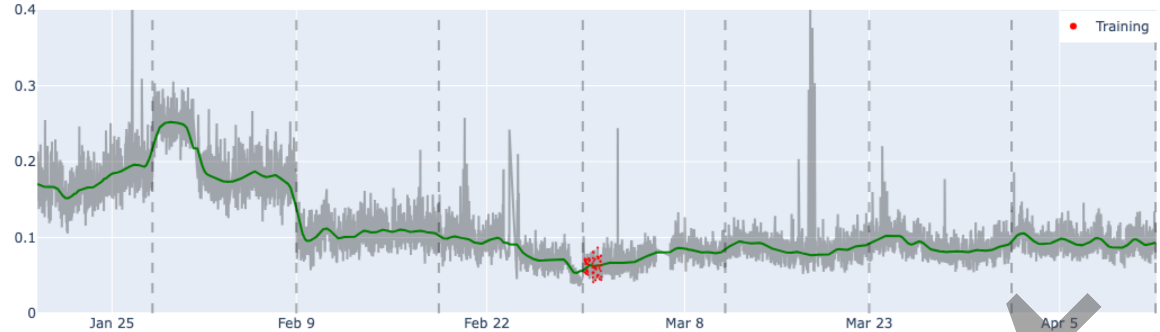

Figure 2: Deviations from the LSTM model predictions. The red dots represent the training data sets.

Table 2: Correlation Matrix of the SVD Analysis Parameters, Beam Properties and LSTM Deviation

	Lifetime	**Injection Efficiency**	**Total Energy**	**Hard Threshold Rank**	**Condition Number**	**Hor. Emittance**	**Ver. Emittance**	**Hor. Beam Size**	**Ver. Beam Size**	**LSTM Deviation**
Lifetime	1	0.51	0.49	0.72	-0.52	0.24	0.28	-0.10	-0.24	-0.64
Injection Efficiency	0.51	1	0.26	0.49	-0.42	0.16	0.28	-0.14	-0.16	-0.37
Total Energy	0.49	0.26	1	0.79	0.15	0.34	-0.03	-0.05	-0.63	-0.77
Hard Thres. Rank	0.72	0.49	0.79	1	-0.41	0.40	0.15	-0.12	-0.63	-0.80
Condition Number	-0.52	-0.42	0.15	-0.41	1	-0.16	-0.37	0.08	0.04	0.21
Hor. Emittance	0.24	0.16	0.34	0.40	-0.16	1	0.39	-0.22	-0.33	-0.33
Ver. Emittance	0.28	0.28	-0.03	0.15	-0.37	0.39	1	-0.28	0.13	-0.04
Hor. Beam Size	-0.10	-0.14	-0.05	-0.12	0.08	-0.22	-0.28	1	-0.05	0.10
Ver. Beam Size	-0.24	-0.16	-0.63	-0.63	0.04	-0.33	0.13	-0.05	1	0.53
LSTM Deviation	-0.64	-0.37	-0.77	-0.80	0.21	-0.33	-0.04	0.10	0.53	1

and BPM4, at the dispersive regions, therefore, there are 3 ways to select the BPMs, which are BPM3 only, BPM4 only and both BPM3 and BPM4. As for the number of points, 50 points are selected because the number is sufficient to capture the orbit pattern and also short to train the model fast enough. The total number of time sequences for the training dataset obtained from the 56 files is 10,976, which is enough for the model training. Among them, 65 % of the time sequences are used for the training and the rest of them are used for the validation.

As for the feature numbers, it is determined by the number of selected BPMs, which are 30 for BPM3 or BPM4 only and 60 for both BPM3 and BPM4. We use the PyTorch framework for the model, with one layer used for the LSTM and the hidden size of the LSTM given as 300. The model is trained for 150 ~ 300 epochs with the decreasing learning rate starting from 0.001 and the batch size of 64, which are determined based on the training time and the training performance.

The deviation of the trained model is calculated as the mean squared error (MSE) between the input and the output of the model, which represents how well the model can reconstruct the input data. The deviations of the all files from the model prediction are calculated in the same way, and the results are shown in Fig. 2.

CONCLUSION

In this paper, we present the application of the LSTM autoencoder model to the 10 kHz orbit data collected during the NSLS-II user operation. From SVD analysis, we can see the possible correlation of the variation of the SVD analysis parameters to the lifetime and injection efficiency while the correlation to the beam size or emittance is less clear. Between the SVD analysis parameters, the total energy and the hard threshold rank have strong correlation to each other while the condition number has weak correlation to the other two parameters.

The SVD parameters have some correlations to the beam properties like lifetime, injection efficiency, and vertical beam size. The LSTM deviation has also some correlation to the beam properties as well as to the SVD parameters.

The difference is that LSTM model is trained with the regularized data, therefore, the model is capturing the patterns while the SVD analysis is based on the singular value magnitudes and distribution. That means the similar correlations are not trivial and need to have background mechanism connecting the pattern and the amplitude of the orbit data.

In fact, in SVD analysis case, even the strong correlation is identified, it is quite limited to study and obtain the detailed information. On the other hand, the LSTM model can provide more detailed information about the orbit pattern, which can be used to detect any deviations from the trained patterns, which may indicate some issues. Therefore, the LSTM autoencoder model not only can be used to detect the orbit stability issue as early as possible but also can provide more detailed information about the orbit pattern, which can be used for the improvement of the machine performance.

REFERENCES

[1] M. Gavish and D. L. Donoho, “The optimal hard threshold for singular values is $4/\sqrt{3}$”, in *IEEE Trans. Inf. Theory*, vol. 60, no. 8, p. 5040–5053, 2014. doi:10.48550/arXiv.1305.5870