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MACHINE LEARNING FOR BEAM ORBIT CORRECTION AT KOMAC ACCELERATOR

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Abstract

There are approaches to apply machine learning (ML) techniques to efficiently operate and optimize particle accelerators. Deep neural networks-based model is applied to experiments, correcting beam orbit through the low energy beam transport at the proton injector test stand. For more complex applications, time-series analysis model is studied to predict beam orbit in the 100-MeV beamline at KOMAC. This paper describes experimental data to train neural networks model, and presents the performance of the machine learning models.

INTRODUCTION

KOrea Multi-purpose Accelerator Complex (KOMAC) has been providing 100-MeV proton beams to users since 2013 [1,2]. In order to make facility operation more stable and reduce the time required for beam tuning, an automatic scan program has been developed and utilized. However, it is not a systematic method due to lack of linkage between data and physics model. Advanced control techniques are applied only to specific areas such as feedback control to compensate for transient beam loading in low level RF systems [3].

Machine learning, which has recently been in the spotlight again with the rapid increase in computing power and the development of new algorithms, is showing various applications and good results in the field of accelerator control [4,5]. In the low energy beam transport (LEBT) section of high-power linear accelerator like KOMAC, beam orbit correction is important for beam matching with the subsequent RFQ to minimize beam loss. MYYRHA and IPHI develops neural networks algorithm for LEBT tuning of proton injectors. The collimator position and vacuum pressure were set as input nodes, and the output nodes were trained on beam transmission data [6].

In KOMAC, there was a previous study verifying the practicality of a machine learning model trained with beam dynamics simulation data in LEBT. The model made with more than 700,000 computational data showed a similar level of accuracy while running more than 10 times faster than the traditional simplex algorithm [7]. Here, this study shows the results of developing a trained neural networks model which performs beam orbit correction based on beam measurement data so that beam control can be automated and advanced.

In addition, we present a preliminary study to develop an effective machine learning model in medium or high energy beam transport with more complexity. To overcome the finite number of beam diagnostics and beam correctors, time series analysis is applied to the transverse dynamics of a bunched beam with time-sequence. It shows the results of applying the long short term memory (LSTM) model and a transformer model.

METHOD

Beam dynamics simulation and beam experiments are carried out to develop deep neural networks model for beam orbit correction at the proton injector test stand and time-series analysis model for beam orbit prediction at the KOMAC.

Deep Neural Networks Model for Beam Orbit Correction at the KOMAC Proton Injector Test Stand

Beam orbit correction has been studied in proton injector test stand at the KOMAC by developing deep neural network model. Proton injector has very simple structure to adapt machine learning model with just a few number of control variables and measured beam parameters as shown in Fig. 1.

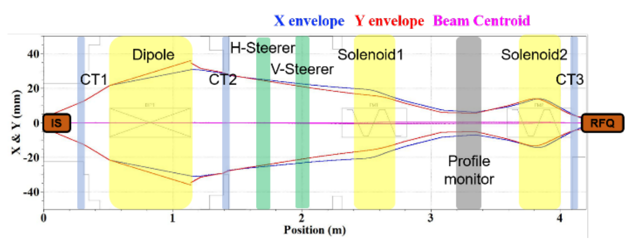

Figure 1: Layout and calculated beam dynamics of proton injector test stand at the KOMAC.

Low energy beamline consists of three focusing magnets including a dipole and two solenoids and two steering magnets. Transverse beam profiles are measured at the beam profile monitor installed at the diagnostics chamber located between two solenoids.

The initial beam properties change according to the operating parameters of the ion source, which affects the beam dynamics in the low energy beamline. As demonstrated in Fig. 2, we collect beam experimental data and train deep neural networks to make low energy beam orbit correction model for various operating variables.

Adjustable variables include absorbed power and ion source solenoid strength in microwave ion source part, and magnetic field strengths of dipole, solenoid#1, horizontal steerer, and vertical steerer magnets in the low energy beamline. As shown in Fig. 2(b), the neural networks

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model is composed of an input layer with 6 nodes, three hidden layers with 32 nodes each, and an output layer with 4 nodes which are beam measurement data.

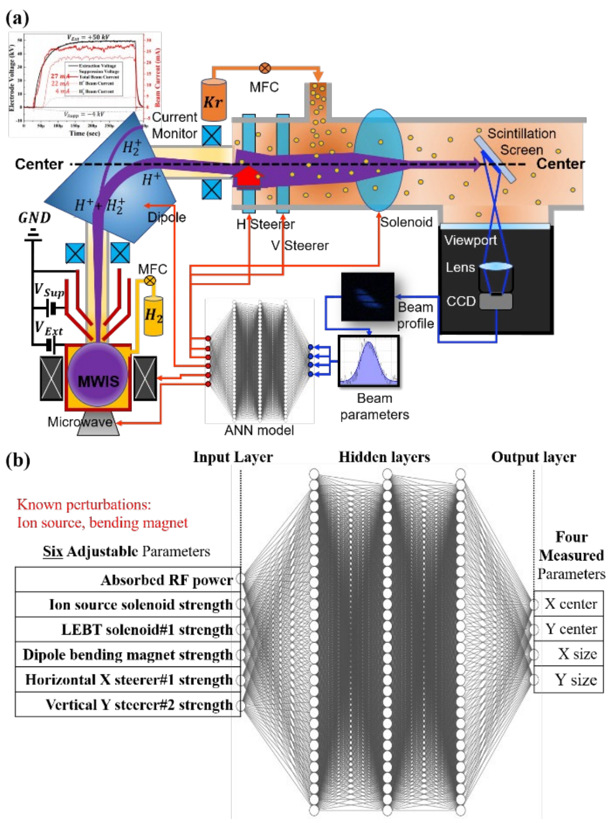

Figure 2: (a) Overview of beam experiments and flow of data to train deep neural networks model. (b) Layout of neural networks model for the low energy beam orbit correction.

Time-series Analysis Model for Beam Orbit Prediction at the KOMAC Linear Accelerator

For systems with such a small number of control knobs, it is easy to build a data-driven neural network model using parameter scan. However, there are numerous beam optics elements for the entire accelerator, and it is almost impossible to accumulate data by scanning each of them. The number of beam position monitors and the number of controlling magnets are usually limited. In particular, when the number of beam diagnostics is greater than or equal to the number of FODO lattices, beam orbit errors mainly caused by misalignment or field errors can be re-constructed.

Virtual diagnostics are needed to overcome the lack of measurement data. The beam propagates in the longitudinal z direction, which is also a function of time t for a beam bunch. Therefore, the beam has the characteristics of time sequence data. Time series analysis can be used when a variable at one point in time is affected by previous variables and by past errors.

According to the analysis method, finite data may be interpolated to reconstruct continuous trends. And it is also possible to extrapolate beam trajectories in the future or downstream that have not been measured. In this context, beam orbit is predicted by using the informer model that showed state-of-the-art performance among transformer-based models [8], and it was compared with the seq2seq model which is composed of long short-term memory(LSTM)-based encoder and decoder.

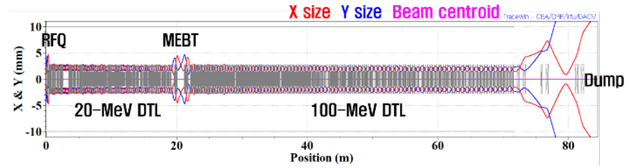

Figure 3: Calculated beam dynamics from 3-MeV RFQ to 100-MeV proton beam dump.

The beam orbit data on a horizontal plane is collected from beam dynamics simulation data on the KOMAC 100-MeV dump beamline as plotted in Fig. 3. From 3-MeV RFQ exit to 100-MeV beam dump, beam dynamics is calculated on accelerator cavities and beamlines with a total length of 80-m. A beam orbit is computed at over 1700 points divided by accelerating gaps and beamline element positions. The time series data is analysed by models that can predict the beam orbit near the end of beamline or beam dump.

RESULTS

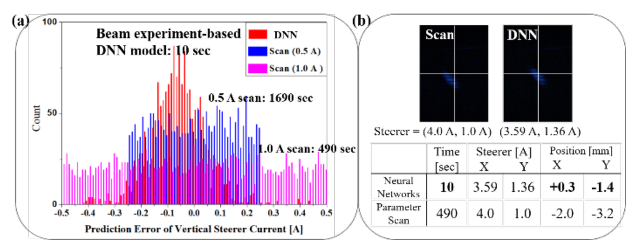

Figure 4: Comparison of prediction errors and consumed time between the DNN model and parameter scan method.

Low energy beam orbit correction methods are compared in terms of prediction errors and consumed time as illustrated in Fig. 4. The deep neural networks (DNN) model shows a prediction error distribution close to Gaussian, and the mean and standard deviation for horizontal(H) steerer and vertical(V) steerer are (-0.05±0.10 A, -0.06±0.10 A). On the other hand, parameter scan method shows a relatively flat error distribution due to a truncation of discrete setting value.

The measurement was repeated 10 times under one operating condition, and the pulse beam repetition rate was 1 Hz. It takes 10 seconds to obtain the data on the average of beam center and prediction error when the DNN model is utilized to correct beam orbit. On the other hand, when scanning current values from -3 A to +3 A for two steering magnets, it takes 1690 sec at 0.5 A interval and 490 sec at 1.0 A interval. Combining and comparing the above results,

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the DNN model produces accurate results in terms of prediction error compared to the parametric scan method, and consumes much shorter tuning time.

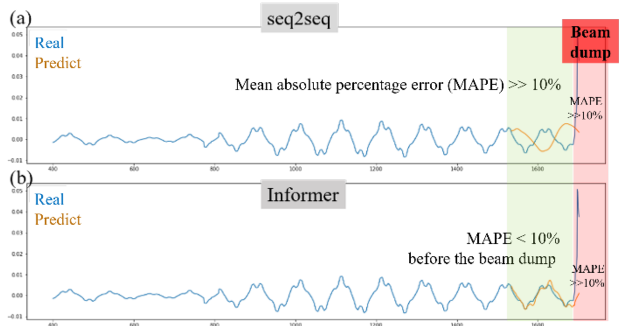

Figure 5: Comparison of the prediction models for beam orbit on a horizontal plane - (a) seq2seq (b) Informer.

Time-series analysis is performed on the beam orbit data from beam dynamics calculation on the 100-MeV dump beamline. As shown in Fig. 5, informer model overally produces better prediction than seq2seq model. Transformer-based informer model seems to be more robust to a sudden change in beam trajectories near the beam dump than seq2seq model. Mean absolute percentage error (MAPE) of informer model is estimated to be under the 10% right before the beam dump. However, the prediction error sharply increases at the beam dump in both models. Instead, this attribute could be utilized for anomaly detection to predict uncontrollable beam loss or severe damage on machine beforehand.

CONCLUSION

In the proton injector test stand at the KOMAC, deep neural networks model is deployed to control low energy beam orbits under various operating conditions. The machine learning model shows faster and more accurate orbit correction than the traditional parameter scan method.

The beam orbit prediction model is constructed using the long short-term memory-based seq2seq model and the transformer-based informer model. The transformer-based model infers 100-MeV proton beam orbit better. The technique covered in the study will be utilized to develop a machine learning-based beam orbit correction model or anomaly detection model for more efficient beam operation.

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