R&D of the KEK Linac Accelerator Tuning using Machine Learning

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1. Introduction

We have developed an operation tuning scheme for the KEK e-/e+ injector linac (Linac)

Figure 1: Accelerator placement at KEK.

100 beam position monitors (BPM),
200 steering magnets, 60 RF monitors.

To achieve the high luminosity,
though the precise beam tuning and high injection efficiency are required,
but, there exist several problems on the accelerator tuning.

1. A lot of parameters ~O(1000) should be tuned, and these parameters are intricately correlated with each other.
2. Continuous environmental change, due to temperature change, ground motion, tidal force, etc., affects to the operation tuning.

To solve the above problems, we have developed

1. Visualization of the accelerator parameters ~O(1000) based on the dimensionality reduction to two parameters.
2. Tuning of accelerators using deep neural networks that are continuously updated and adapt to continuous environmental changes

In this poster, we show the results on our R&D

We use the real operation e- beam data for SuperKEKB injection (2018 Nov. - 2021 Jun.)

- 500 operating params (Steering magnet)
- 732 environmental params
- Injection efficiency : Q_{ratio}

$$Q_{ratio} = \frac{Charge\ values\ at\ downstream\ of\ the\ accelerator\ (SP\_58\_0)}{Charge\ values\ at\ upstream\ of\ the\ accelerator\ (SP\_A1\_M)}$$

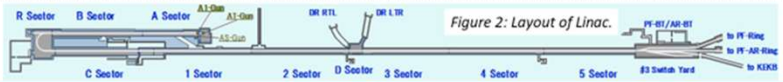

Figure 2: Layout of Linac.

2. Visualization of the accelerator parameters

Due to the large number of the control points ~O(1000), the operation system becomes much complicated.

We use dimensionality reduction to visualize the accelerator parameters in lower parameters, with Variational Auto Encoder (VAE) .

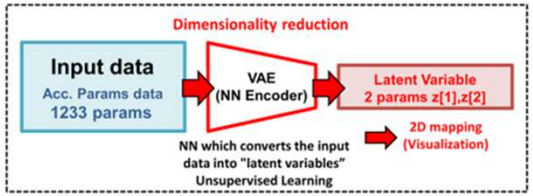

Figure 3: Outline of visualization using dimensionality reduction .

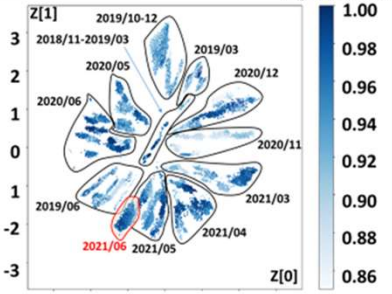

Figure 4: VAE output (two-dimensional Latent variables) from the 2018 Nov to 2021 June accelerator data.

Latent variables from the similar trend input data are closely distributed.
Using this property, we can visualize the accelerator parameters.

the Acc. Params. dataset containing 1232 parameters is visualized by VAE with dimensionality reduction to two dimensions.
The visualization results show that

1. **In the short term(~1month) , the accelerator trend does not drastically change, but**
2. **In the long term(>3month) , the accelerator trend vary over a wide range.**

3. Tuning using the Deep Neural Network

To adapt to the environmental changes , the environment driven DNN (Reinforcement ML) is a good candidate.

To apply the Reinforcement ML, we need

1. **Estimation of the Acc. Params. using DNN,**
2. **Realistic accelerator simulator.**

3-1. Estimation of the acc. params using DNN

we need the relationship btw injection eff. and acc. params. for the effective parameter optimization.

We designed a Regression-DNN with
Input : 1232 accelerator parameters (operating and env params)
Output : injection efficiency (Q_{ratio})

We prepare 3 datasets with different configurations.

Figure 5: overview of the datasets (1)-(3).

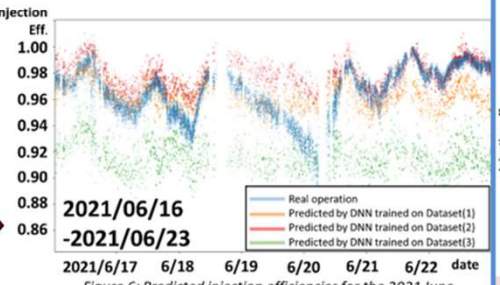

Figure 6: Predicted injection efficiencies for the 2021 June.

DNN trained with 2021 May data ; dataset (1,2), can predict 2021 Jun. injection eff.

To predict the injection eff. of validation data with DNN, the training data must contain the data with the similar trend to the validation data.

3-2. Accelerator simulator based on GAN

To apply the reinforcement ML, realistic accelerator simulator is necessary for the pre-training.

We have develop a method using GAN (Generative Adversarial Network).

GAN learns to generate fake data that has the same function as the training set (real data).

GAN consists of two DNN:

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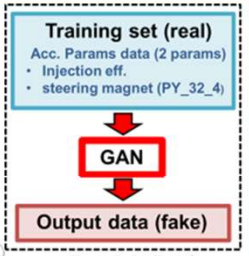

Figure 7: Outline of Accelerator simulator based on GAN

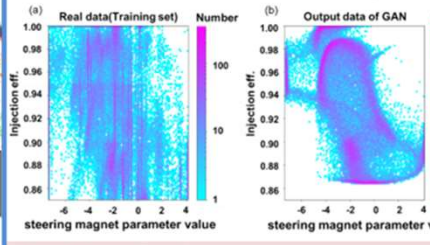

Figure 8: Two-dimensional histogram of real data(a) and generated data(b)

The results show that

- **GAN reproduces the two-parameter correlation trend.**
- **GAN output data has peaks that did not match the real data and does not cover the full range of the real data.**

"mode collapse"

4. Conclusion

We have developed an operation tuning scheme with ML

1. We visualize the 1232 params by dimensionality reduction using VAE
2. Injection efficiency is predicted using Regression-DNN
3. Acc. simulator based on GAN generates the parameters correlation trend. However, generated data dose not cover the full range of real data → "mode collapse"

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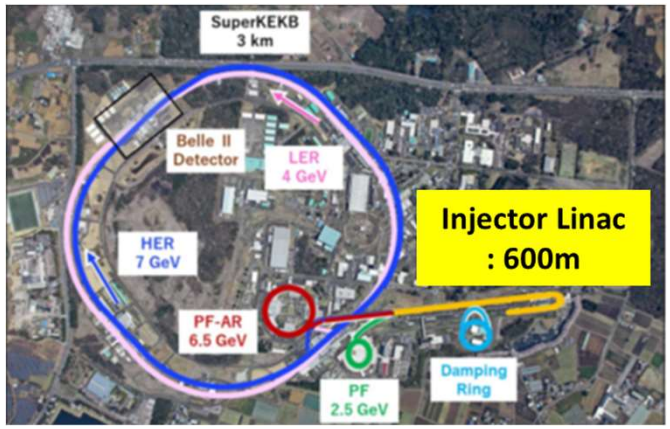

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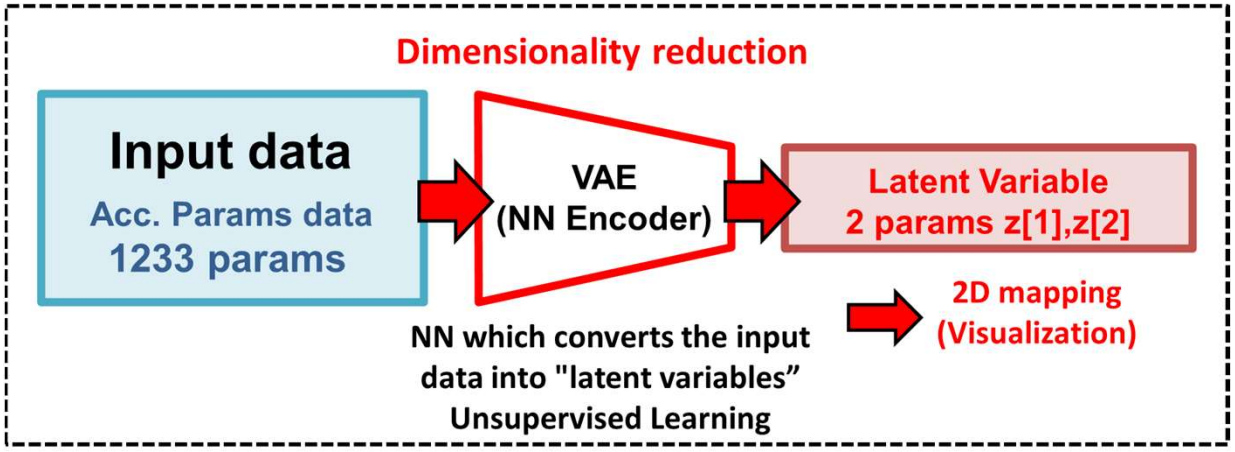

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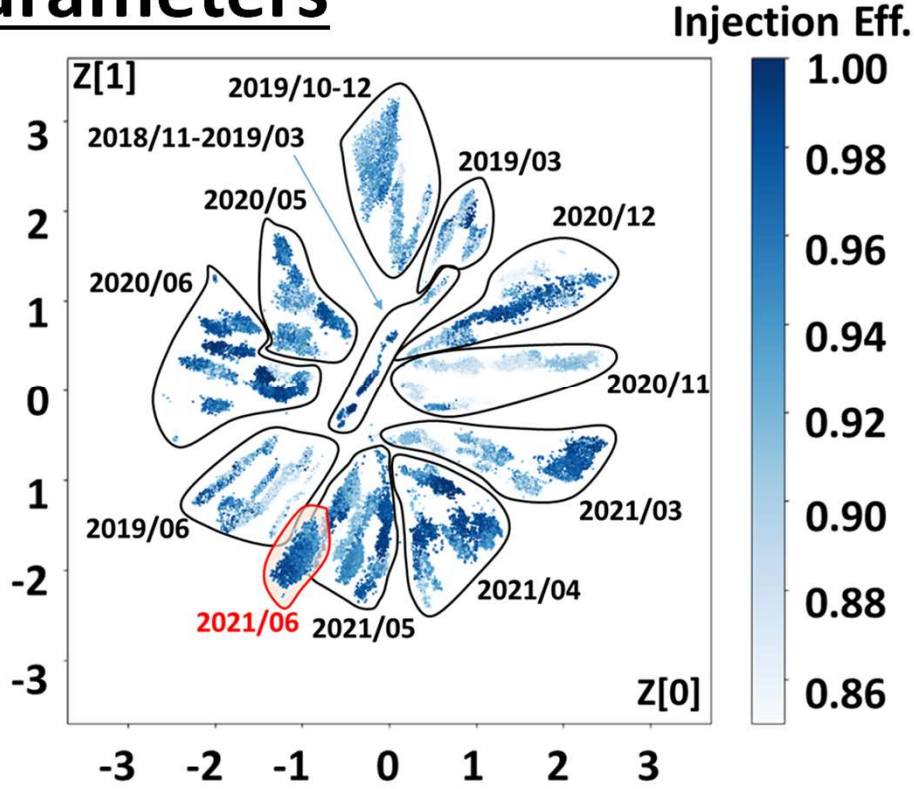

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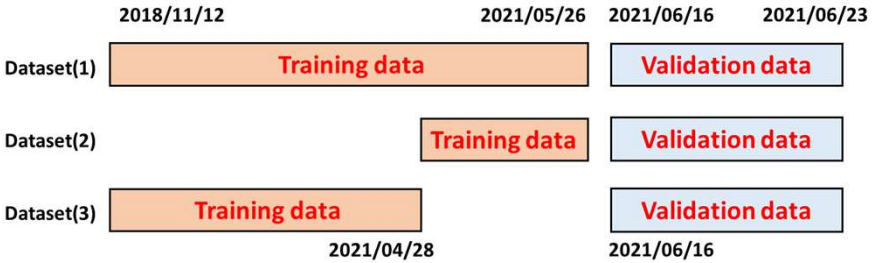

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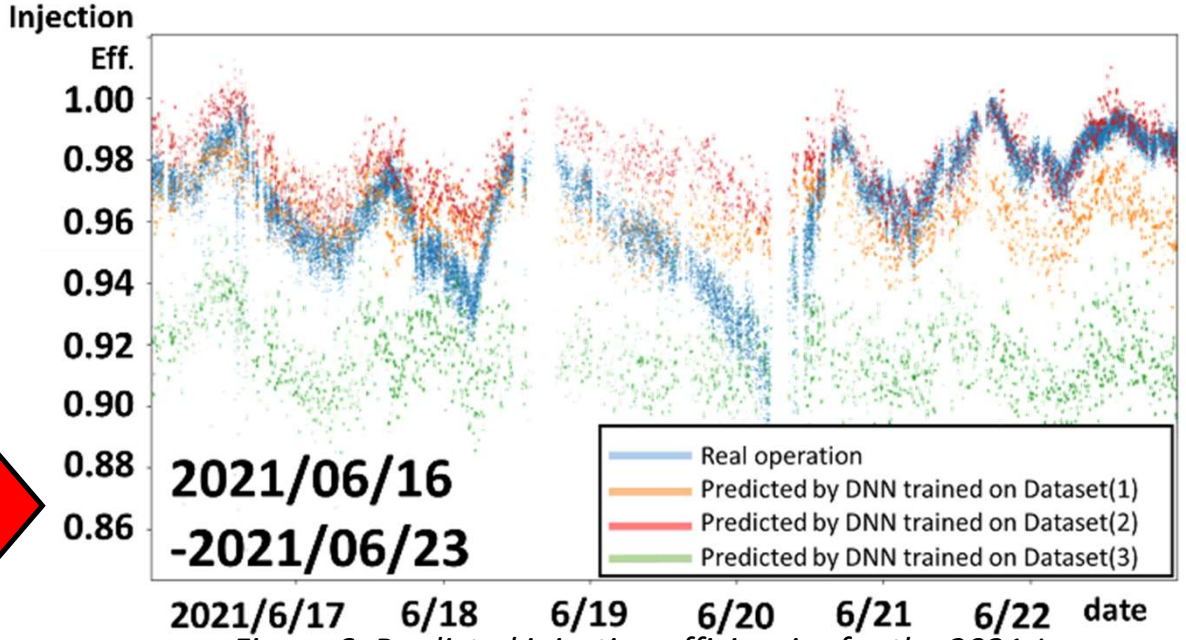

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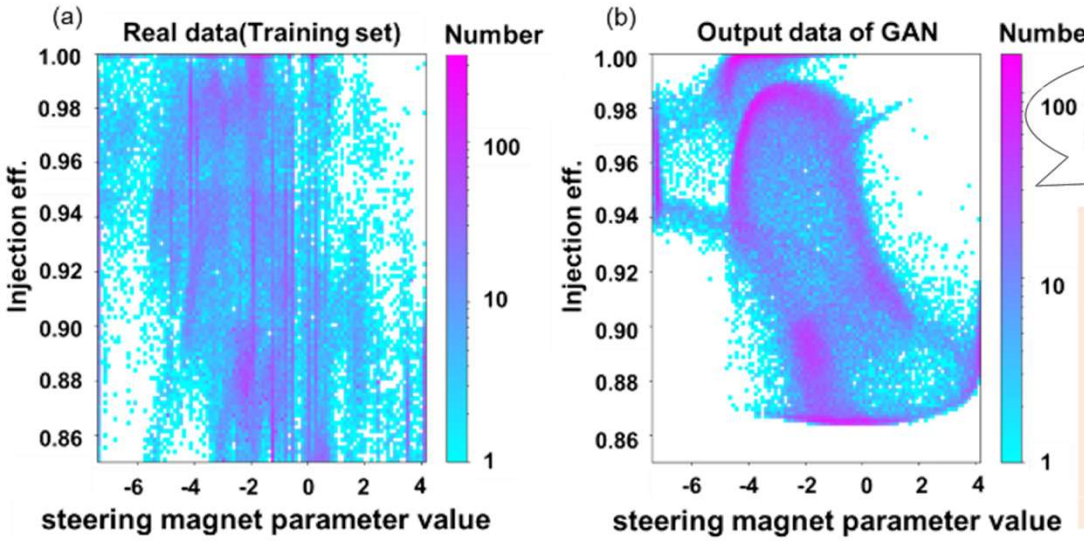

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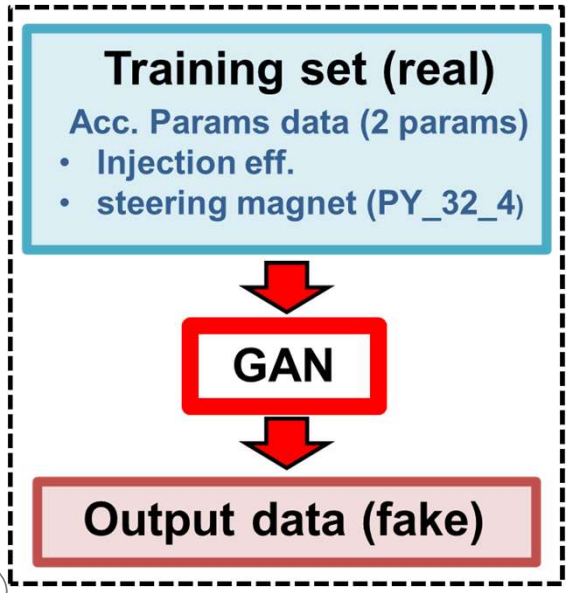

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