WAVEFORM PATTERN CONTROL OF THE PAINT BUMP POWER SUPPLY FOR THE J-PARC RCS USING NEURAL NETWORKS*

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Abstract

The J-PARC RCS uses four horizontal and two vertical painting magnets to generate a high-intensity beam through painting injection. Their IGBT-chopper power supplies can reproduce current waveforms with an accuracy better than 1%. By combining automatic generation of command voltage waveform with manual finetuning keeps the current deviation of the painting pattern within ±1.0% of the required accuracy. There are 90 waveform patterns in total, including two types: trapezoidal waveforms for low-beam-loss studies and decay waveforms for high-intensity beam production. As these patterns have different current demands and impose different loads on the power supplies, the tuning process becomes increasingly complex. Adjusting a single painting pattern takes approximately one hour and optimizing all 90 patterns takes several days; therefore, reducing the adjustment time is essential. To address this issue, we applied a neural network approach to generate optimized command voltage waveforms. After training the neural network using painting patterns generated by the actual machine, we achieved predictions with a deviation within ±0.2%. Furthermore, we were able to significantly reduce the time required for prediction to just a few seconds.

INTRODUCTION

The J-PARC [1] RCS [2] uses four horizontal and two vertical painting magnets to generate a high-intensity beam through painting injection [3]. The painting magnet power supplies [4] consist of rectifiers that uses an IGBT unit to generate currents with arbitrary waveforms, and an indirect conversion device comprising a chopper. These systems can generate and output trapezoidal or decay waveforms as required. In current operation, it achieves high-precision control, with the difference between the set-point and the output value falling within the required accuracy of ±1.0%. However, because the load impedance of the electromagnets exhibits nonlinearity with input waveforms, it takes about an hour to adjust a single waveform pattern. Furthermore, since 15 waveform patterns are used per unit during accelerator beam studies at the RCS, a total of 90 waveform patterns are required for the six painting magnets. As a result, it takes several days to adjust all the waveform patterns required for operation, and in the limited beam studies time available, there is a need to reduce the time required to adjust the waveform patterns for the painting magnets.

In this study, we used a neural network (NN) to model the nonlinear relationship between the command voltage waveforms and the output current waveforms, enabling the rapid determination of the appropriate command voltage waveform for a given output current waveform. The predictions for trapezoidal waveforms are as reported in IPAC'25[5]. This paper presents decay waveforms, the configuration of the NN, the waveform data employed for training, and the obtained results.

PAINTING MAGNET POWER SUPPLIES

The painting magnet power supplies require excitation waveforms of various shapes, such as trapezoidal waveforms used for low-beam-loss studies and decay waveforms used in painting injection. These waveforms are shown in Fig. 1. To generate these arbitrary waveforms, the painting magnet power supplies multiplex twelve IGBT unit assemblies operating at 54 kHz and outputs the required excitation waveforms through wave-form synthesis using high-speed switching at 648 kHz [6]. Figure 2 shows the basic configuration of the painting magnet power supplies. The output current of these is analog-controlled by an IGBT control signal converted from the command voltage waveform. This control signal is generated through current feedback and voltage feedforward. The response time constant of the current feedback is approximately 20 µs. Therefore, when the current value changes significantly and continuously over a short beam injection time of 500 µs, the command voltage waveform adjusted for voltage feedforward is directly applied. This ensures that the output current does not deviate from the reference current waveform. Furthermore, for the injection schemes in different paint areas required for the MLF [7] and MR [8], the command voltage waveforms for the respective excitation waveforms are applied.

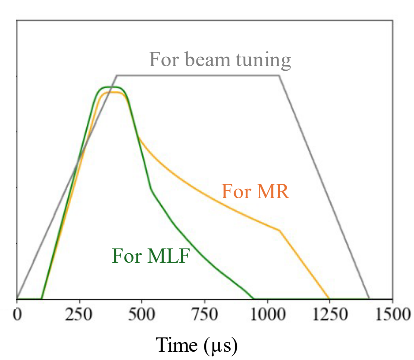

Figure 1: Examples of decay-type and trapezoidal waveforms for MLF and MR.

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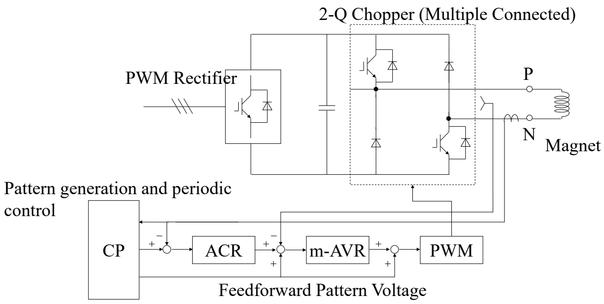

Figure 2: Basic configuration of the painting magnet power supply.

The waveform patterns for the painting magnet power supplies are generated as 12-bit digital signals, with the command voltage and target current waveform created at a sampling rate of 500 kHz (every 2 μs). As long as the output current and voltage remain within the rated range, the power supplies can produce outputs with arbitrary waveform shapes. Currently, painting pattern adjustments are performed by combining software [9] with manual tuning, in which the command voltage waveform values are adjusted on a case-by-case basis while monitoring deviations in the output current.

APPLYING NN STUDY

MLF Decay Waveforms

Given that waveform pattern adjustment is time-consuming and there is a shortage of technicians, we designed a convolutional neural network (CNN) that learns the nonlinear relationship between the output current waveform and the command voltage waveform, enabling the system to generate the command voltage waveform when the output current waveform is input. As reported in IPAC25 [5], it is possible to predict trapezoidal waveforms with an accuracy of ±0.2% using a neural network. This paper reports on the prediction of decay waveforms for MLF and MR (MLF waveforms / MR waveforms), respectively.

First, we trained the NN on the MLF waveforms. Figure 3 shows the process. To generate training data, we applied command voltage waveforms to the painting magnet power supply and measured the resulting current waveform. The output current waveforms were used as the input data for the NN, and the command voltage waveforms were used as the output data. Details of the training data are described below.

Both the input and output data are one-dimensional and have been normalized to the range [0, 1]. In addition, the data length of the MLF waveform was set to t = 0–1190 μs (dim = 595), corresponding to the beam injection period. The number of training data for the MLF waveform was set to 444, and the number of validation data was set to 50. The command voltage waveform is a 12-bit digital signal that represents 0 V to 5 V with values from 0 to 2047, and -5 V to 0 V with values from 2048 to 4095. In other words, command values of 2048 or higher indicate a negative voltage. As shown in Fig. 4, when training the NN, the command voltage

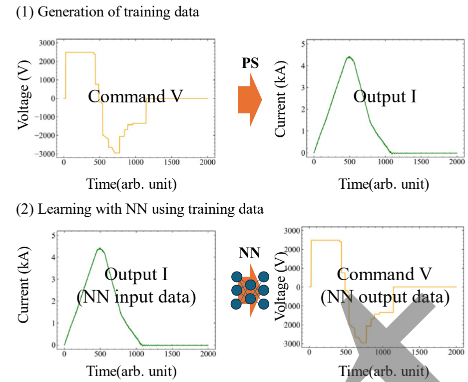

Figure 3: The process of the NN training.

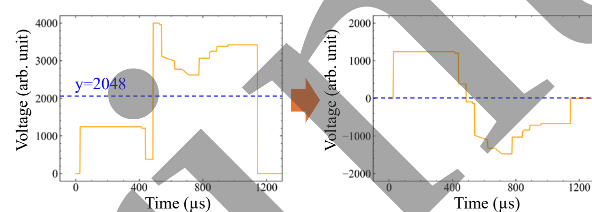

Figure 4: Conversion of command voltage waveforms.

waveforms were converted so that values greater than 2048 would be negative, ensuring a positive correlation between the command voltage and the output current waveforms. Figure 5 shows the prediction accuracy before and after conversion. Before conversion, there was an error of approximately 7% between the reference voltage waveform and the predicted voltage waveform around t=250; after conversion, this deviation was reduced to approximately 2%.

The NN was implemented using TensorFlow [10]. The network consists of eight layers, including two one-dimensional convolutional layers and one "Dropout" layer.

- "Dropout" was applied during prediction (Dropout rate: 0.05)
- The activation functions used are "tanh", 'ReLU', and "sigmoid"
- "Adam" was used as the optimizer, and "MSE" was used as the loss function.

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

- The number of epochs is set to 8000, and the batch size is set to 32

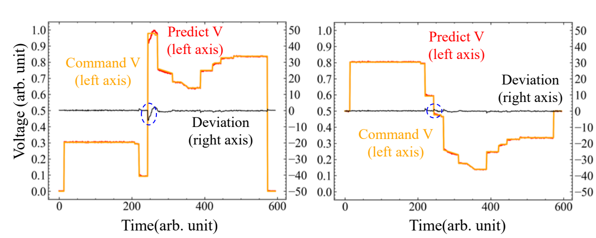

Figure 5: Prediction accuracy before and after command voltage waveform conversion. The graph on the left shows the data before conversion, and the one on the right shows the data after conversion.

Check the prediction accuracy of the NN. First, the ideal current waveform is input into the trained NN to predict the command voltage waveform. Next, apply the predicted command voltage waveform to the painting magnet power supply and verify the output current waveform. Figure 6 shows the results of feeding the voltage predicted by the trained NN into the painting magnet power supply. The deviation between the ideal current waveform and the output current waveform during the beam injection period was within ±0.2%. Furthermore, while it used to take about an hour to adjust a single waveform pattern, it can now be done in just a few seconds.

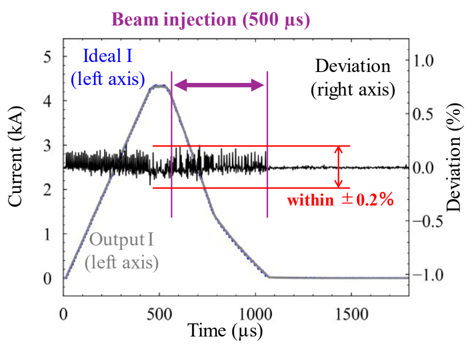

Figure 6: Results of the MLF waveform verification.

MR Decay Waveforms

A NN for MR waveforms was created using the same layer structure as the NN built during the training of attenuated MLF waveforms, and it was then trained. Describe only the points that differ from the NN of the MLF waveforms.

- ·The data length was set to t = 0–1620 µs (dim = 810)
- ·The number of training data was set to 444, and the number of validation data was set to 50

The verification results are shown in Fig. 7. During the beam injection period, the deviation between the target current waveform and the output current waveform was kept within ±0.2%.

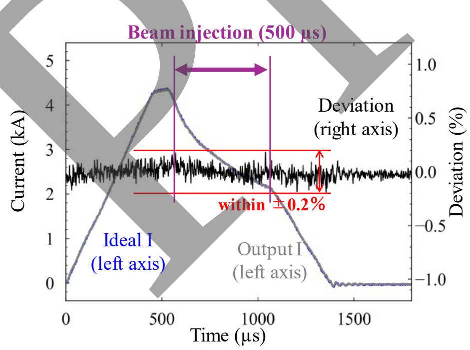

Figure 7: Results of the MR waveform verification.

Learning Two Types of Waveforms

Up to this point, we have trained separate NN for the MLF and MR waveforms; however, to reduce adjustment time and improve operational efficiency, it is desirable in actual operation to be able to make predictions using the same NN regardless of the waveform shape. Therefore, we trained a single NN on MLF and MR waveforms and verified its prediction accuracy. The differences in the training data are listed below.

- The data length was set to t = 0–1620 µs (dim = 810),
- The number of training data was set to 900, and the number of validation data was set to 75
- ·The number of epochs is set to 5000, and the batch size is set to 32

The results are shown in Fig. 8. Since the deviation between the target voltage waveform and the predicted voltage waveform was within ±1%, we were able to train a single neural network to learn both the MLF waveform and the MR waveform.

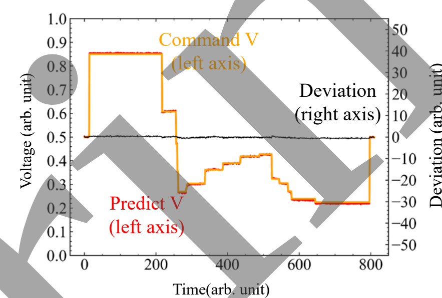

Figure 8: Ideal voltage waveforms and predicted voltage waveforms when training a single neural network on MLF and MR waveforms.

SUMMARY

A waveform pattern control system for the J-PARC RCS painting magnet power supplies, utilizing machine learning, was developed. After conducting an analysis of the trapezoidal waveform and the decay waveform used in beam adjustment, we were able to demonstrate that by training a NN to learn the model between the command voltage and the output current, it is possible to predict the command voltage waveform from the output current waveform for both the MLF and MR waveforms. For both waveforms, we were able to reduce the adjustment time from one hour to a few seconds and achieve an accuracy of ±0.2% against a target accuracy of ±1.0%.

In this report, the painting magnet power supply was used offline. There may be slight variations between individual power supplies. In the future, similar verification tests are planned to be conducted on the four horizontal and two vertical painting magnets that have been installed in the J-PARC RCS. This makes it possible to verify the prediction accuracy of the NN. Furthermore, we intend to apply waveform adjustment using the NN to not only the power supplies for the painting magnets, but also to all pattern power supplies in the J-PARC.

ACKNOWLEDGEMENTS

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