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

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Abstract

The Japan proton accelerator research complex (J-PARC) rapid cycling synchrotron (RCS) uses four horizontal and two vertical painting magnets to generate a high-intensity beam through painting injection. Their insulated gate bipolar transistor (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 (NN) approach to generate optimized command voltage waveforms. After training the NN using painting patterns generated by the actual machine, we achieved predictions with a deviation within ±0.3%. Furthermore, we were able to significantly reduce the time required for prediction to just a few seconds.

INTRODUCTION

The Japan proton accelerator research complex (J-PARC) [1] rapid cycling synchrotron (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, which use insulated gate bipolar transistor (IGBT) units to generate currents with arbitrary waveforms, and an indirect conversion device comprising a chopper. These systems can output arbitrary 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 describes the results obtained regarding the prediction of decaying waveforms, while explicitly detailing the neural network architecture and the waveform data used for training.

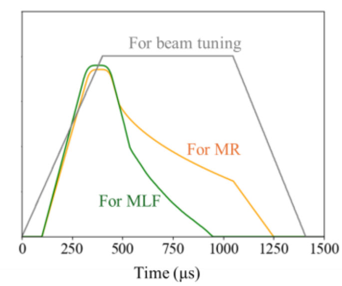

Figure 1: Examples of decay-type and trapezoidal waveforms for MLF and MR.

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. Furthermore, for the injection schemes in different paint areas required for the materials & life science experimental facility (MLF) [7] and main ring (MR) [8], the command voltage waveforms for the respective excitation waveforms are applied. 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. 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

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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.

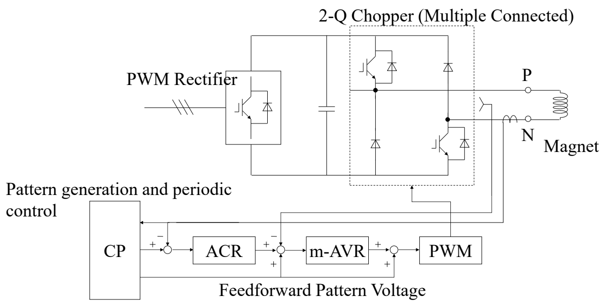

Figure 2: Basic configuration of the painting magnet power supply.

APPLYING NN STUDY

NN model and Closed-Loop Validation

To rigorously evaluate the prediction accuracy, we performed a closed-loop validation using the actual power supply system. First, the ideal current waveform was input into the trained NN to predict the command voltage waveform. Figure 3 shows the process. Next, this predicted waveform was applied to the real painting magnet power supply to measure the resulting output current waveform. This end-to-end protocol ensures that the validation accounts for physical model mismatches and operational non-linearities that cannot be captured by synthetic data alone.

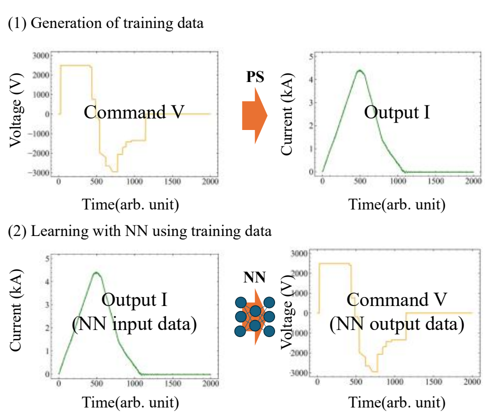

Figure 3: The process of the NN training.

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. The NN architecture adopted in this study is identical to those previously employed for trapezoidal waveforms [5]. The specific configuration and training parameters are detailed below (see Fig. 4). The NN based on TensorFlow [10] comprises eight layers: two 1D convolutional layers (8 filters, kernel 3, stride 2, tanh), MaxPooling (pool 4, stride 2), and a dense layer (ReLU). A Dropout layer (0.05, active during prediction) evaluates output uncertainty, while a 'sigmoid' output layer ensures optimal accuracy. Using the Adam optimizer (LR 0.001) and MSE loss, training used a batch size of 32 for 8,000 (individual) or 5,000 (combined) epochs.

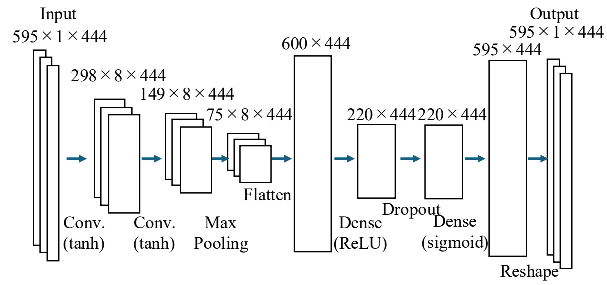

Figure 4: Block Diagram of the Neural Network

MLF Decay Waveforms

First, we trained the NN on the MLF waveforms. To generate training data, we applied command voltage waveforms to the painting magnet power supply and measured the resulting current waveform. Parametric perturbations around operating points were employed to generate the training data. Specifically, the command voltage waveforms were created by varying the values of existing waveforms within a range of ±10%. The output current waveforms were used as the input data for the NN, and the command voltage waveforms were used as the output data. 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 12-bit command data were converted to voltage by interpreting values of 2048 or higher as negative values, following the signed representation used in the control system. 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%. Figure 6 shows the training and validation loss curves, which demonstrate that overfitting did not occur.

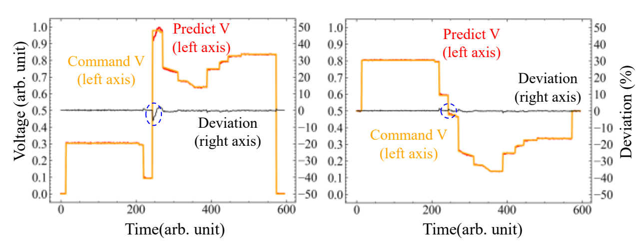

Figure 5: Prediction accuracy before and after command voltage waveform conversion. The graph on the left shows the data before conversion, and the one on the right shows the data after conversion.

Figure 7 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.

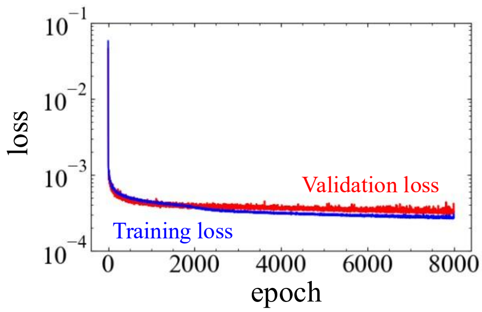

Figure 6: Training and validation loss of the NN

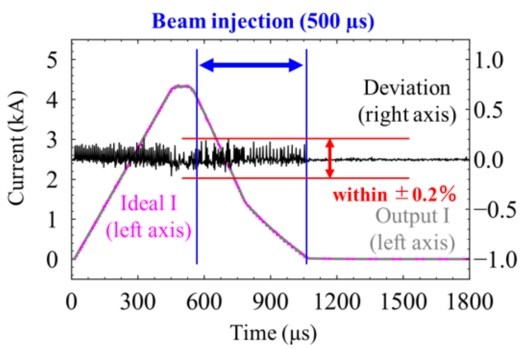

Figure 7: Results of the MLF waveform verification.

MR Decay Waveforms

Second, we trained the NN on the MR waveforms. The primary differences in the configuration for MR waveforms involve the data length, which was set to t=0–1620 μs (dim =810), and the dataset sizes, consisting of 444 training data and 50 validation data. The verification results are shown in Fig. 8. During the beam injection period, the deviation between the target current waveform and the output current waveform was kept within ±0.2%.

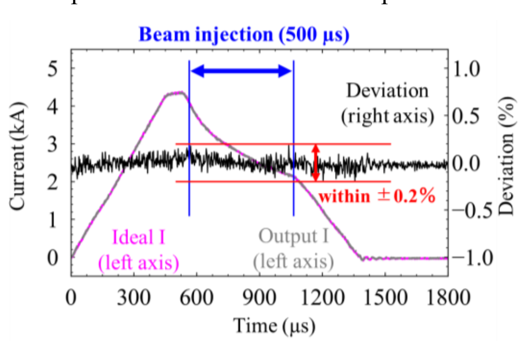

Figure 8: Results of the MR waveform verification.

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. Consequently, we trained a combined model using a unified data length of t=0–1620 μs (dim =810). This training involved 900 training samples and 75 validation samples, and the model was optimized over 5,000 epochs with a batch size of 32. The results are shown in Fig. 9, where the MR waveform was evaluated as a representative case. When the predicted voltage was applied to the power supply, the current deviation between the target current and the output current was found to be a maximum of ±0.3% during the beam injection period. This result demonstrates the successful training of a single neural network capable of learning both the MLF and MR waveforms.

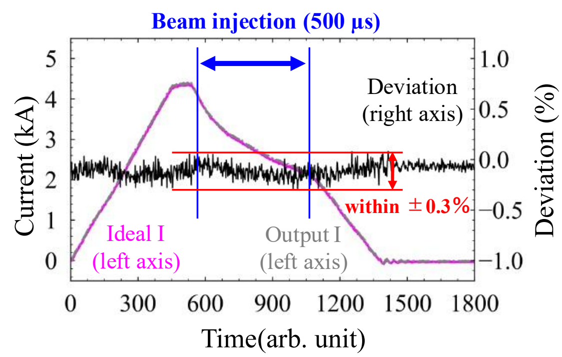

Figure 9: Results of the MR waveform verification when training a single neural network on MLF and MR waveforms.

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 ±0.2-0.3% against a target accuracy of ±1.0%.

In the future, incorporating weighted losses or one-hot encoding aims to achieve further improvements in accuracy. 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. 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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