Study on the State Prediction of a Pool-Cooled Large Superconducting Coil Using Machine Learning

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***Abstract*—For the LHD subcooling system composed of pool-cooled large superconducting coils wound with NbTi superconductors, a machine learning technique was introduced to increase the reliability of the system. The machine learning model for the state prediction of the system was developed using the technique, together with the data accumulated in the LHD plasma experimental campaign. Regarding the temperature changes in the system due to coil excitation and discharging, it is possible to make predictions using the model. Especially for the usual coil current waveform in a helical coil operation, which is a trapezoidal waveform, the model achieved high prediction accuracy.**

***Index Terms*—Machine learning, state prediction, pool-cooled superconducting coil, NbTi superconductor, helical coil, subcooled helium, long short-term memory (LSTM).**

I. Introduction

IN THE superconducting magnet system, which is the core equipment of a fusion experimental device, a large number of measurement sensors are installed in the system for its operation and monitoring. Although each measurement sensor is inspected and repaired during the maintenance period of the experimental device, there is a concern that trouble may occur in a sensor that has been used for a long period of time. If trouble occurs in a sensor that is important for system operation, it is necessary to stop the plasma experiment, raise the temperature of the superconducting magnet system to room temperature, and repair or replace the measurement sensor.

In this study, the development of a machine learning model was conducted to predict the state of the superconducting magnet system, based on the measurement data accumulated during system operation. By using the model, even if trouble occurs in the measurement sensor, the system operation is continued. Namely, the reliability of the superconducting magnet system is increased with the machine learning model. For example, the ITER superconducting magnet system, which is currently under construction, is also being modeled using machine learning technology [1], [2].

The object of model development in this study is the subcooling system for the Large Helical Device (LHD) [3], [4]. This system is suitable for the model development because an amount of measurement data, which is used as training data for the modeling, has already been accumulated through the LHD plasma experimental campaign.

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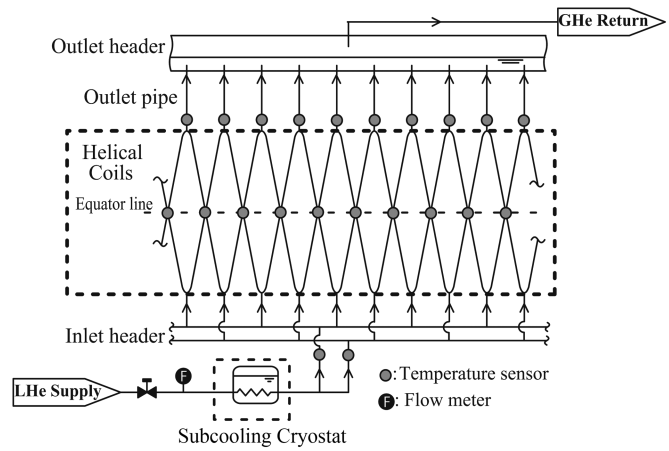

Fig. 1. Flow diagram of the LHD subcooling system.

This paper describes the details of the modeling and the validity of the machine learning model, while comparing predicted values from the model with the measurement results in the subcooling system. Additionally, the difference between the machine learning model and the physics model, which have been developed in a previous study, is discussed.

II. LHD Subcooling System for Helical Coils

The LHD is a plasma experimental device composed of superconducting helical coils [5], [6]. The helical coils are a pair of pool-cooled superconducting coils wound with superconductors which consist of NbTi/Cu strands, a pure aluminum stabilizer and a copper housing [7], [8]. Also, the coils are composed of three coil winding blocks called H-I, H-M and H-O from the inner side. Details of the helical coils are described in the References [3], [5].

To generate higher magnetic fields for improving the performance of plasma experiments, the cooling system for the helical coils was upgraded in 2006-2007 [6], [7], [8]. The upgraded system is called the "subcooling system". Fig. 1 shows the cooling flow path diagram of the helical coils. Saturated helium at a temperature of 4.4 K is supplied from the liquid helium storage tank, which is the starting point of the flow. Next, the saturated helium is cooled from 4.4 K at a constant pressure by a subcooling cryostat equipped with a two-stage low-temperature exhaust compressor and a heat exchanger, to generate subcooled

TABLE I
DAYS OF TRAINING DATA FOR THE MACHINE LEARNING MODEL

*Campaign	Year	Month	Day
20	2018	Oct.	23, 24, 25, 30, 31
		Nov.	1, 6, 7, 8, 13, 14, 15, 20, 21, 27, 28, 29
		Dec.	4, 5, 6, 11, 12, 13, 18, 19, 20, 25
	2019	Jan.	8, 9, 10, 16, 17, 22, 23, 24, 29, 30
		Feb.	5, 6, 7, 13, 14, 19, 20
21		Oct.	9
		Nov.	14, 19, 20, 21
		Dec.	3, 4, 5, 11, 17, 18, 19, 20, 24, 25,26
	2020	Jan.	7, 8, 10, 15, 17, 21, 22, 23,28, 29, 30
		Feb.	4, 5

*Campaign: LHD experiment campaign

helium. After that, the subcooled helium is branched into two flow paths, and is supplied to the helical coil from the coil inlets (bottom) at ten points via the inlet header. Further, since the flow path branches from the coil inlet portion toward the outlet portion (uppermost) to the coil inner and outer peripheral sides, the coil portion has 20 parallel flow paths. After cooling the helical coil, the subcooled helium that comes out of the coil portion is returned to saturated helium by heating with film heaters installed in each of the ten outlet pipes, and is collected in the outlet header.

As shown in Fig. 1, temperature sensors are installed at two locations on the coil inlet piping, ten locations on the coil outlet piping, and ten locations on the outer peripheral side of the coil container and on the equatorial plane on the plasma vacuum vessel side.

III. MACHINE LEARNING MODEL

A machine learning model was developed to predict temperature changes in the outlet pipe and coil case during coil excitation and demagnetization. The model is composed of a network structure consisting of input, middle, and output layers. The middle layer is composed of the long short-term memory (LSTM) network [9], and the output layer consists of activation and error functions. The LSTM is a type of recurrent neural network which prevails in learning the nonlinear features of time series data [10]. The LSTM has its own memory capability and is used in the middle layer to go back in time for longer periods [11].

The model was developed using the Neural Network Console of Sony Network Communications Inc., which is an application for a machine learning mode [12]. The input and output parameters of the model are the current values of the three coil windings (H-I, H-M, H-O) in the helical coil, the mass flow rate of subcooled He, and the temperatures of the outlet pipe and the coil case. Fig. 2 illustrates the schematic view of the network structure for the model.

IV. TRAINING DATA

The measurement results obtained in the 20th and 21st cycles of the LHD plasma experiment were used as training data for the machine learning model described in Section III. Details of the experimental days used as training data are listed in Table I. Each example of the training data consists of the measurement results which are the data of temperature, coil current, and mass flow rate for 22 hours every minute, including coil excitation and demagnetization.

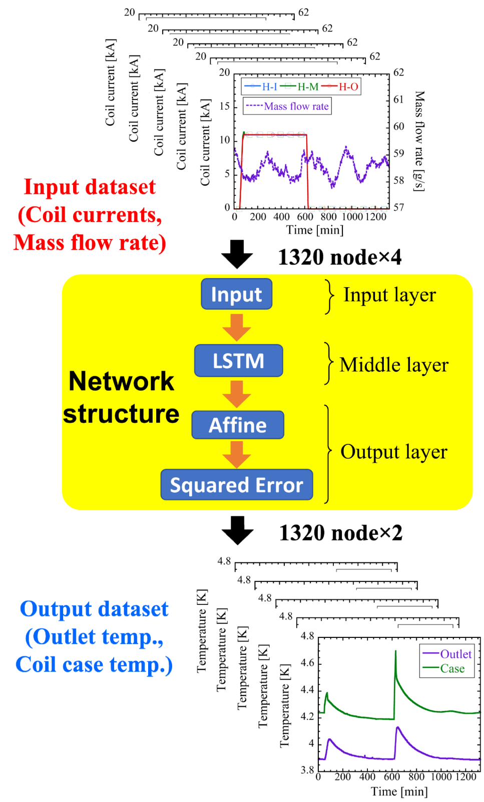

Fig. 2. Schematic view of the network structure for the model.

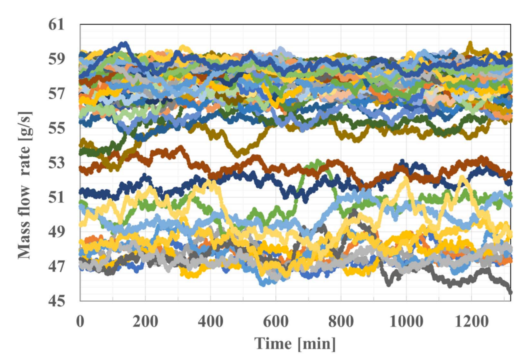

Fig. 3. Training data of the mass flow rate of subcooled He.

The training data of the mass flow rate in the subcooling system is shown in Fig. 3. Since the mass flow rate has relatively large fluctuations for each measurement time, an average value for every ten minutes was used as the training data of the mass flow rate. The training data of the helical coil (H-I, H-M, and H-O) currents are shown in Fig. 4. These three coil currents in the LHD plasma experiment are almost all the same current waveform, except for some plasma experiments requiring a unique magnetic field configuration. Figs. 5 and 6 show the training data of the temperatures of the coil outlet and the coil case, respectively. Each temperature increases rapidly due to AC losses incurred during the excitation and discharging of the

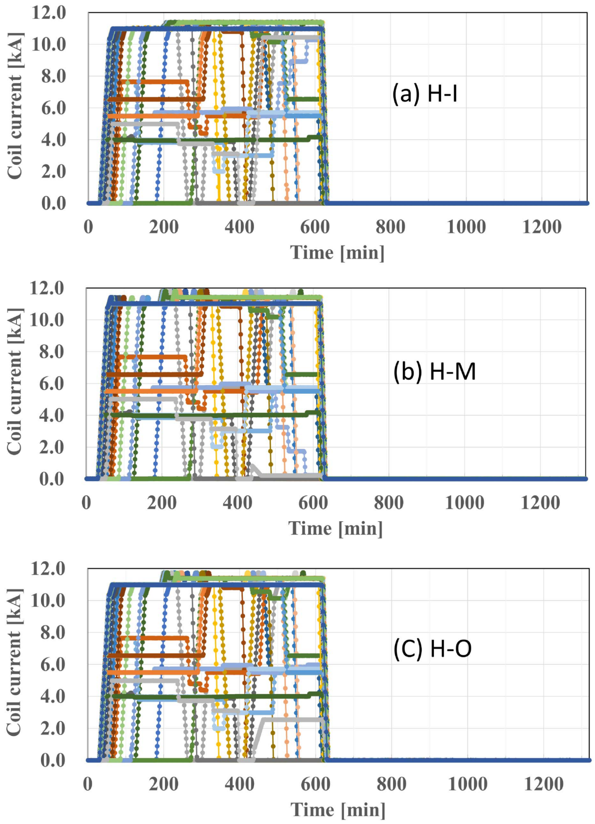

Fig. 4. Training data of current values of the helical coil windings (a) H-I, (b) H-M, and (C) H-O.

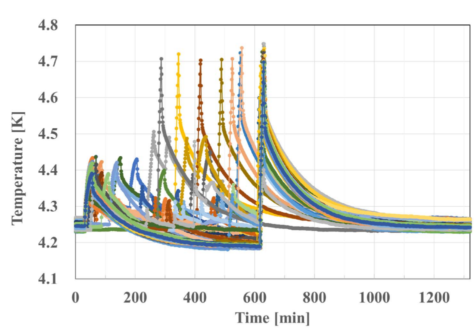

Fig. 5. Training data of the temperatures at the coil case.

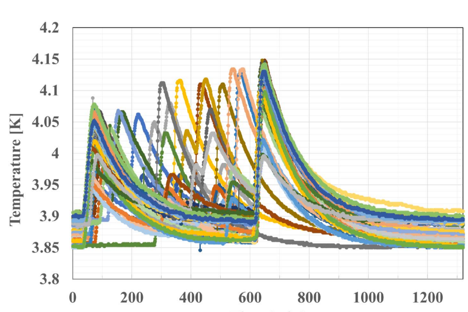

Fig. 6. Training data of temperatures at the coil outlet.

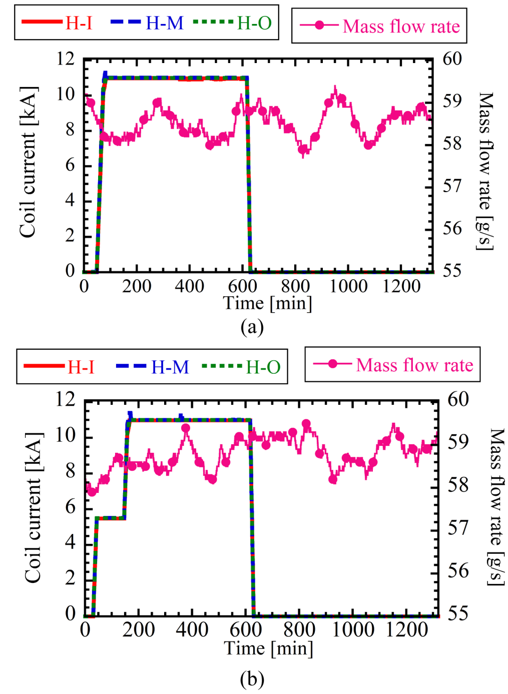

Fig. 7. Input data for the model. (a) Trapezoidal current waveform and (b) staircase current waveform.

helical coil. After the increase of the temperatures, they decrease gradually with a decay time constant.

V. Evaluation of the Model

To evaluate the validation of the developed machine learning model, the predicted values obtained from the model were compared with the measurements during the LHD experimental campaign. As data for the comparison, two types of the helical coil current waveforms were used. One is the trapezoidal waveform, which is the usual current waveform in the LHD plasma experiments, and the other is the staircase waveform. Fig. 7 shows the input data for the model, which are the coil currents and the mass flow rate of the subcooling He. In the case of the trapezoidal current waveform, the outlet pipe and the coil case temperatures in the prediction and the measurement are shown in Fig. 8. The predicted values are in good agreement with the measurement results. Regarding the outlet pipe temperature, the maximum difference between the prediction and measurement was only 0.029 K. Using the model, hence, it is possible to predict accurately the temperature changes due to AC losses incurred by the helical coil with the trapezoidal current waveform.

Fig. 9 shows the temperatures of the outlet pipe and the coil case in the prediction and measurement under the staircase current waveform. There is a slight difference between the prediction and measurement during coil excitation. After the coil discharging, on the other hand, the predicted values agree fairly well with the measurement results. Compared with the prediction accuracy in the trapezoidal current waveform, that in the staircase current waveform is lower. The difference of the

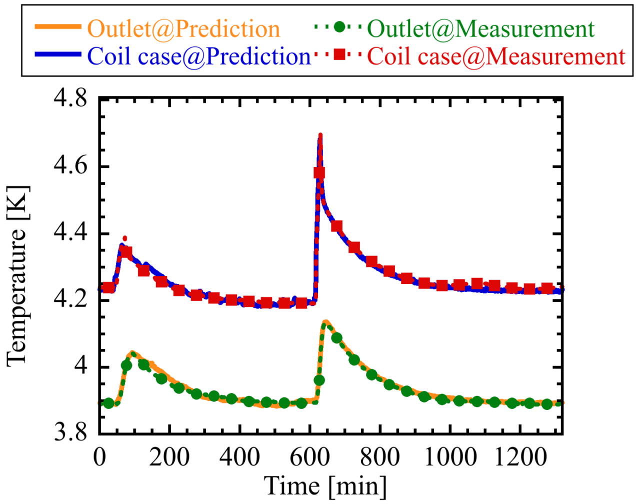

Fig. 8. Comparison between the prediction and measurement results for each set of input data, which is on 24/1/2020, including the trapezoidal current waveform.

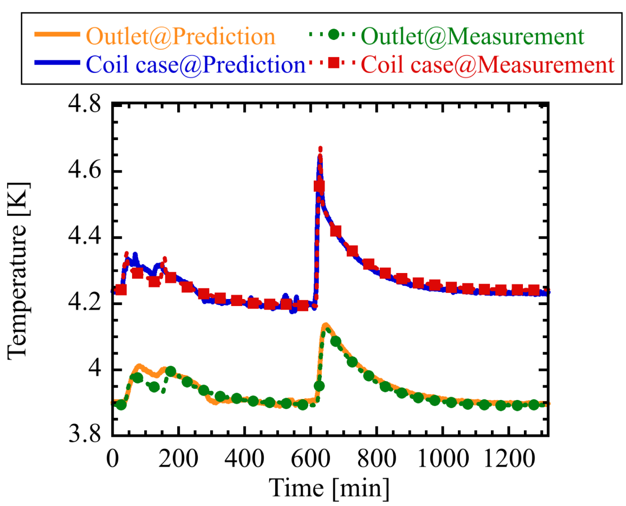

Fig. 9. Comparison between the prediction and measurement results for each set of input data, which is on 16/1/2020, including the staircase current waveform.

prediction accuracy for each current waveform is discussed in Section VI.

VI. Discussion

A. The Different Prediction Accuracy for Each Coil Current Waveform

Using the developed machine learning model, there is a different prediction accuracy of the temperature changes in the coil outlet and the coil case for each coil current waveform. As a cause of the difference, the bias of the training data for the model is considered. Compared to the training data for the trapezoidal current waveform, there is much less training data for the staircase current waveform. To increase the general versatility of the machine learning model, it is necessary to use the training data for various current waveforms.

B. The Difference Between the Machine Learning Model and the Physics Model for the LHD Subcooling System

In the previous study [7], [8], modeling the LHD subcooling system has been conducted to predict the temperatures of the coil outlet and coil case under coil excitation, using the physics model based on heat conduction equations. In this study, meanwhile, the prediction of the temperatures in the subcooling system was carried out using the machine learning model with the measurement results accumulated in the LHD experimental campaign. Based on these studies, the differences between the physics model and the machine learning model are discussed.

In the machine learning model, a large amount of training data is necessary to develop it with high prediction accuracy. On the other hand, the physics model is developed without the measurement results, provided that some of them might be required to adjust a fitting parameter used in the model.

As for the development of the physics model, there are the following difficulties. To reduce the calculation time, simplifying the complicated configuration of a modeling object such as the LHD helical coil is needed, while keeping the physical phenomenon of the object. In addition, it is necessary to demonstrate the validity of unsteady calculations that reproduce time-varying temperature changes due to AC losses in the coil. Regarding the development of the machine learning model, it is difficult to design the structure of a neural network for the model which realizes high prediction accuracy.

As mentioned above, the machine learning model and the physics model each have unique characteristics. It is hard to say which of these two is better. They are both useful for the LHD subcooling system. Using not only the physics model but also the machine learning model, the reliability of the LHD subcooling system is significantly increased.

VII. Conclusion

A machine learning model was introduced for the state prediction of the LHD subcooling system, composed of helical coil windings which are pool-cooled large superconducting coils. To develop the machine learning model for the state prediction, regarding temperature changes in the system, the measurement results of the LHD experimental campaign were used as training data. Additionally, the structure of a neural network including the LSTM was designed for the model. As a result, the predicted value of the model was in good agreement with the measurement result when the coil current waveform was a trapezoidal wave, which was a usual current waveform in the LHD experiment. In cases where the current waveform was a staircase wave, however, there was a slight difference between the predicted value and the measurement result. The bias of the training data for the model is considered as a cause of the difference.

Regarding the state prediction of the LHD subcooling system, the machine learning model developed in this study was compared with the physics model which had already been developed in the previous study. As a result, the reliability of the subcooling system is significantly increased, using these models together.

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