An Attempt to Identify Heat Transfer Coefficients in Casting CAE Using Cooling Curves

Kato Hiroto[1], Yasuhiro Maeda[2], *
1.Graduate Student, Dept. of Mechanical Engineering, Daido University
2.Professor, Dept. of Mechanical Engineering, Daido University
*Corresponding address: e-mail:y-maeda@daido-it.ac.jp

Abstract: The Casting CAE is used practically but is not almighty at all. There are some needs to improve the calculation accuracy of defect prediction, develop new functions, and be an easy operation. An efficient and accurate method for determining heat transfer coefficients (HTC) in heat transfer and solidification simulations is important. HTC is a physical property value that depends on the material properties and conditions at the interface. Still, it cannot be easily determined because HTC is influenced by many factors. Therefore, it is often used as a tuning parameter to control the accuracy of analysis.

Assume that we have the practical cooling curve in a simple experiment. In this case, one way to identify the HTC is to search for the HTC of simulation so that the cooling curves of the experiment and simulation match. Alternatively, there is a method to obtain the actual HTC using the inverse analysis of the measured cooling curve. In this study, as a new attempt, we constructed the inverse model of casting CAE by machine learning, using the cooling curve obtained by casting CAE as the input and the HTC as the output. Next, HTC was calculated by inputting the measured cooling curve into the constructed inverse model. The heat transfer and solidification simulation using the obtained HTC was carried out to confirm the cooling behavior between the experiment and the simulation.

Keywords: casting CAE; aluminum alloy; heat transfer coefficient; cooling curve

1 Introduction

Many researchers have studied how to identify the heat transfer coefficient (HTC) in the casting CAE[1-3]. HTC is influenced by many factors or conditions, such as pouring conditions, mold release agents, molten metal and mold material, repetition times, and so on.Further, HTC depends on time and temperature. Therefore, it is difficult to determine the actual value of HTC.

On the other hand, HTC is used as a tuning parameter in the reconciliation of experimental and simulation results.Some literature has reported how to determine the HTC from the cooling curve measured by experiments to identify the heat transfer coefficient between molten metal and mold [2,3]. Further, the HTC is identified by using data assimilation[4,5].

In this study, we propose a series of procedures, from measuring the cooling curve to determining physical properties other than HTC, and until to identifying HTC. In particular, the identification method using an inverse neural network (NN) model is proposed, and its results are compared to other methods.

2 Experimental setup

Figure 1 shows the schematic illustration of the experiment using the taper mold [3]. Assuming one-dimensional heat transfer, the temperatures of castings and mold(chill) measured in the experiment are stored in a recorder. Thermo-couples are located at 5, 10, and 15mm away from the interface. Their measurement points are named to MP1, MP2, MP3, CP4, CP5, CP6 from top, respectively. The pouring material is an aluminum alloy of JIS-AC4C(A360), and the chill material is a steel of JIS-S45C. As a mold release agent, the boron-nitride spray was applied to the interface between the castings and the chill. An example of the cooling curves measured a few times is shown in Figure 2. In addition to the above experiment, the cooling curve is also measured when the same material was slowly cooled in the crucible.

3 Analysis procedures

The results of two types of experiments identify the liquidus temperature, solidus temperature, and the relationship between temperature and solid fraction. Then, assuming one-dimensional heat transfer, the thermo-physical properties, such as thermal conductivity, etc., are also identified as constant values.

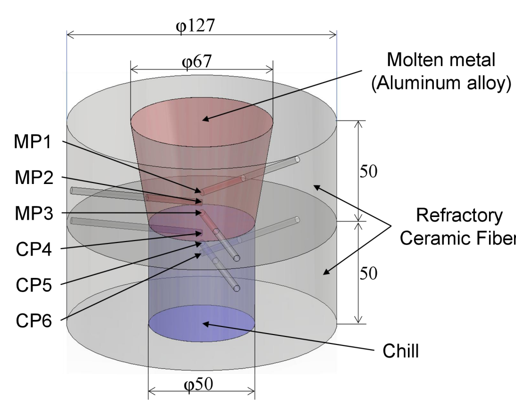

Figure 1 Schematic illustration of experiment using the taper-mold[3]

The above experimental results are simulated using the casting CAE software TopCAST™. We assume that the heat transfer and solidification processes can be constructed forward and inverse models using an NN. In this case, the inputs in the forward model include casting conditions, thermal properties, and heat transfer coefficients, and the outputs are the cooling curves. In this study, the heat transfer coefficient (HTC) is identified from the obtained cooling curve and the inverse model of the NN.

Figure 3 shows an overview of the NN model. It is a general all-coupled NN consisting of an input, hidden, and output layer. The open-source software "Jupyter Notebook" from "Project Jupyter" is used to create the NN. The total number of hidden layers and the number of nodes were considered in this study to determine the number of layers and nodes with higher accuracy.

4 Results and discussion

As a machine learning example, which uses the sigmoid function as the activation function, and Adam as the optimization method, the learning results using 10 data sets and 1 hidden layer are shown in Figure 3 and Figure 4.Figure 4shows the relationship between mean squared error (MSE) and the number of trials. The normalized input and output data are used in machine learning. From the figure, it is clear overlearning occurs when the number of trials is about 300. The NN model constructed in this study can calculate the error with an accuracy of approximately 150W/m^2·K.The results of the simulation using the HTC identified by the inverse model are affected by a convergenceerror and did not show a good agreement. Then, in the future study, it may be necessary to modify the NN structure or increase the number of data sets.

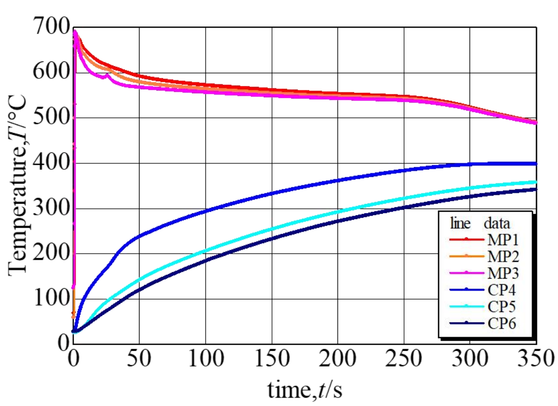

Figure 2 Cooling curves

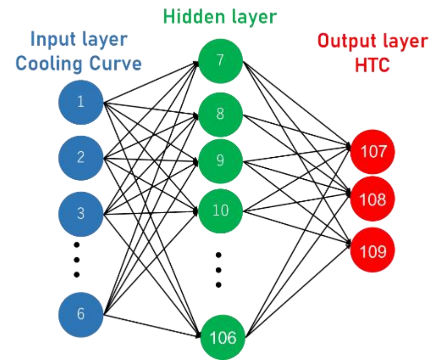

Figure 3 Overview of the NN model

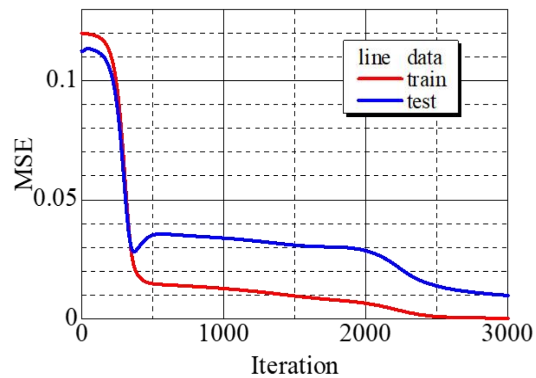

Figure 4 Relationship between mean squared error (MSE) and the number of trials in the case of 10 data sets

5 Conclusion

A method for identifying heat transfer coefficient (HTC) using NNs is investigated in the present study. Although the identification accuracy is still insufficient, it is thought that it can be improved by reconsidering the number of data sets, etc.

References

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