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CNN-BASED SURROGATE MODEL AND TEMPERATURE PREDICTION METHOD USING SUPERPOSITION PRINCIPLE

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Abstract. A CNN-based surrogate model is being developed to accelerate CFD calculations. In order to use this surrogate model for design development, it is necessary to improve generalizability. One solution to this problem is to use the principle of superposition. For the multiple heating elements that make up the model, their temperatures are predicted by heating them individually. We devised a method to predict the temperature of the entire model by adding up these individually predicted temperature distributions. Radiation and convection phenomena, for which the superposition principle does not hold, were also considered.

1 INTRODUCTION

In the thermal design of product development, the use of CFD for pre-assessment before actual development is considered an essential part of the development design process. Furthermore, with the evolution of simulators and hardware, it is now possible to evaluate large-scale models that reproduce detailed structures, making CFD increasingly widely utilized.

However, in the models we are focusing on, the computational time ranges from several hours to dozens of hours, and faster computation is required to interactively respond to design changes.

To address this challenge, we have been working on accelerating computations using deep learning (CNN) for several years. We represent the input information for CFD (such as structure, physical properties, and heat generation) as image data and have developed a surrogate model to predict temperature distribution using a CNN-based network. This model is being implemented into our proprietary AI thermal design tool, making progress in its application to product development.

Figure 1 depicts the developed AI thermal design tool. Traditionally, thermal design of the board using CFD took several dozen minutes for computation. With the use of this tool, the computation can be completed in less than one second, leading to a significant improvement in efficiency in developmental design.

However, it became apparent that there are challenges in developing a surrogate model with generalization in mind to be incorporated into the tool. A surrogate model was developed targeting the temperature prediction of a specific product, board A. The training data for this surrogate model was created based on board A, with random variations in the shapes of heat sinks, positions of heat sources, heat generation rates, and so on. However, it is impossible to cover all possible variations, so parts with fixed positions in the design or those with low heat generation that are deemed to have minimal impact on thermal design were assigned fixed positions. This surrogate model provides sufficient accuracy for use in the design of board A; however, the prediction accuracy was not satisfactory when applied to board B, another product of the same type. It is expected that a surrogate model of the same accuracy as board A can be developed by creating and training data for board B in a similar way. However, developing surrogate models in a one-size-fits-all manner in this way would require creating a new surrogate model every time a different board or model needs to be predicted, which would be labor-intensive and make it difficult to apply to product development.

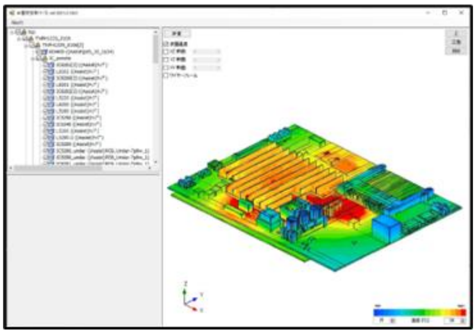

Figure1:AI Thermal Design Tool

In the field of image recognition, techniques such as transfer learning and fine-tuning can be utilized to create surrogate models with high generalization using a small amount of data. While we referred to these methods, it was challenging for us to create a surrogate model with high generalization.

Therefore, we devised a method using the principle of superposition, where the temperature distribution of multiple heat sources constituting the model is individually predicted and then added together to predict the overall temperature of the model. In addition, while there have been reported attempts to accelerate computations using CNN-based networks, such as the multi-analysis method combining CNN and domain decomposition techniques by Nishida et al. [2], the acceleration method using a Poisson solver with CNN as preprocessing by Suzuki et al. [3], and the application of autoencoder-type CNN to channel turbulent phenomena by Nakamura et al. [4], these differ from the application of CNN-based networks to temperature prediction targeted in this study.

2 METHODS

2.1 CFD model

In this report, the calculation target is shown in Figure 2. The circuit board is composed of a simplified consisting of a substrate and a heating element. The heating element consists of one or more units (Figure 2 shows 10 heating elements), and the circuit board is made up of two types of substrates.

The sizes are as follows: the circuit board is 160mm in length, 160mm in width, and 1mm in height, while the heating element is 10mm in length, 10mm in width, and 1mm in height. The material properties are as follows: the circuit board uses substrate A (thermal conductivity of 36W/ m·K) and substrate B (4W/ m·K), while the heating element has a thermal conductivity of 36W/ m·K. The heating power ranges from 0.5 to 3.0W per heating element. Additionally, the grid size is 64 x 64 in the plane and 1 in the thickness direction of the circuit board.

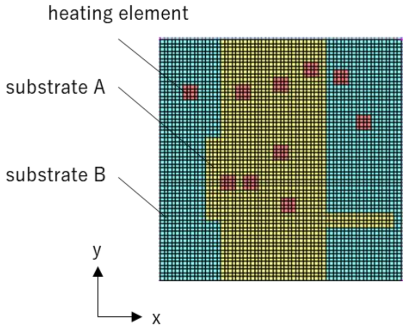

Figure 2: CFD model

2.2 Network

The surrogate model developed in this study is based on a CNN network known as U-Net. U-net was developed by Olaf and colleagues as a Semantic Segmentation technique for biomedical purposes, and it was presented at MICCAI (Medical Image Computing and Computer-Assisted Intervention)2015.

Figure 3 depicts the network diagram of U-Net, which consists of an encoder and a decoder. The encoder performs multiple convolutions on the input image to extract its features, while the decoder utilizes a process called deconvolution, which is the opposite of convolution, to generate an output image of the same size using the features extracted by the encoder. In the upsampling process using deconvolution to expand the feature maps, capturing the spatial information of objects can be challenging. To address this issue, U-Net resolves it by combining the feature maps from the encoder with those of the decoder at each layer.

The key feature of U-Net is the integration of the feature maps from the encoder with those from the decoder, known as skip connections. This operation enables high-precision pixel-level classification. Based on U-Net, a surrogate model has been developed to predict temperature distribution using structural information (heat generation, thermal conductivity in the plane and thickness directions, emissivity, and grid width in the x, y, and z axes) as input.

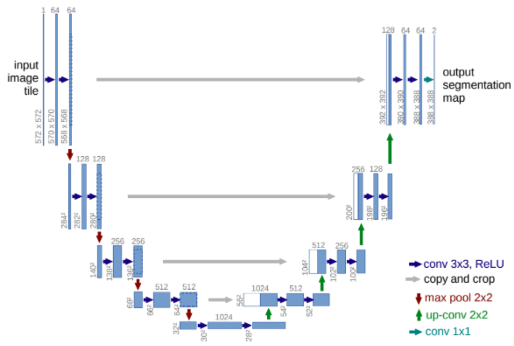

Figure 3: U-Net (Reference [1] Citation)

2.3 Method

In this report, we propose a method to predict the temperature of each heating element and sum the predictions using the principle of superposition. The rationale for this approach is the potential for improvement in generalization due to the principle of superposition, as well as the dominance of heat conduction phenomena in product development for high-density and dust-resistant designs.

Heat transfer is divided into three forms: conduction, radiation, and convection. For heat conduction, we utilize the principle of superposition, while for radiation and convection, we use a surrogate model for temperature correction.

The principle of superposition is a characteristic principle that generally holds for linear systems, wherein the response of the system when two or more inputs are simultaneously applied is the sum of the responses returned when each input is applied individually, as in Equation (1). This principle can be applied to linear differential equations.

$$F(x_1 + x_2) = F(x_1) + F(x_2) \tag{1}$$

The heat conduction is described by the heat conduction equation (Equation (2)). Since the heat conduction equation related to heat transfer is a linear partial differential equation with respect to temperature, the principle of superposition holds true, allowing for the superposition of temperatures.

$$\frac{\partial T}{\partial t} = \alpha\left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2}\right) + \frac{q}{\rho c} \tag{2}$$

T:temperature t :time α :thermal conductivity x、y、z : Coordinates

ρ :density c : specific heat q: heat generation per unit volume

However, the principle of superposition does not hold for convection and radiation. The reason is as follows: Convection is represented by the Navier-Stokes equation (Equation 3). This equation is a second-order nonlinear partial differential equation for fluid flow, and therefore, superposition for fluid flow is not possible. Consequently, the heat (temperature) transferred by fluid flow cannot be superimposed.

$$\rho\left\{\frac{\partial v}{\partial t} + (v \cdot \nabla)v\right\} = -\nabla p + \mu\nabla^2 v + \rho f \tag{3}$$

ρ: density μ: viscosity coefficient v: flow velocity p: pressure acting on the fluid

f: external force acting per unit volume of fluid

Radiation is represented by Stefan-Boltzmann's law (Equation (4)). From this equation, as radiation energy is proportional to the fourth power of the absolute temperature, superposition with respect to temperature is not possible.

$$E = \varepsilon\sigma T^4 \tag{4}$$

E:radiation energy ε:emissivity(0～1)

T:absolute temperature(surface temperature of the object)

A:5.67E-8(Stefan-Boltzmann constant)

All the training data is created using Computational Fluid Dynamics (CFD), and the correct temperatures are obtained from the results of the CFD calculations.

2.4 Temperature prediction methods

We will explain the temperature prediction method of the proposed approach. For temperature prediction, surrogate models 1, 2, and 3 are used, and we will describe each of these surrogate models later.

1. Summation of Temperatures (Figure 4)

Prepare the substrate for prediction. In this example, we prepared a substrate with five heat sources installed. First, data with each of these five heat sources installed separately on the substrate is prepared, and the temperature of each substrate was predicted using surrogate model 1. Subsequently, the predicted temperatures of the five substrates are summed up.

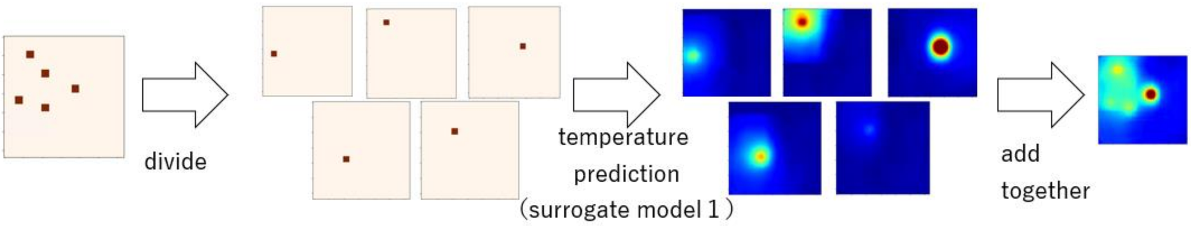

Figure 4: Add the temperatures together

2. Correction of added temperatures

We input the average temperature of the added temperatures from Figure5(left) and the temperatures of the five individual substrates before summation into Surrogate Model 2 to perform temperature correction. The predicted results are shown in the graph in Figure6. The closer the graph is to the 45-degree line, the better the accuracy. While the prediction angle in Figure5(center) is greater than 45 degrees, the thickness of the prediction line is thinner than that in Figure5(left), indicating a reduction in the variability of the prediction. Next, we input the mean and variability of the predicted temperatures of each pixel of the substrate into Surrogate Model 3 and calculate the angle of the graph. We then correct the temperatures to ensure that the angle matches 45 degrees. The corrected result is shown in Figure5(right).

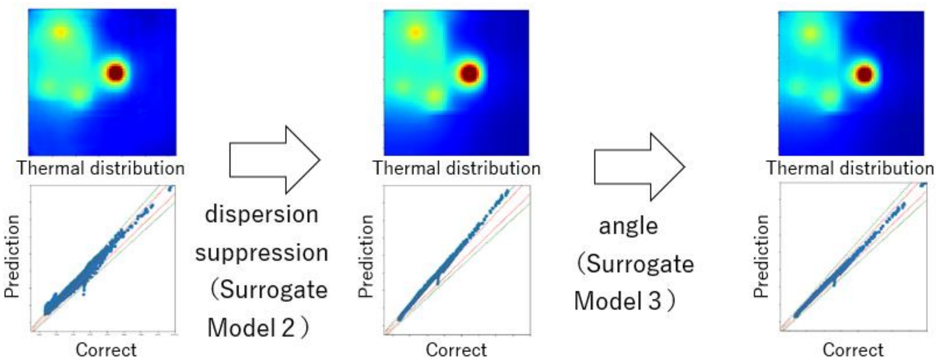

Figure 5: left: added temperatures center: dispersion suppression right: Predicting angles, correcting temperatures

2.5 Surrogate Model

Explaining the training methods of surrogate models 1,2,3.

1.Surrogate Model 1

Create training data with only one heat source installed on the circuit board. An example of the training data is shown in Figure 6. The size is the same as in Figure 2. The positions and heat generation rates of the heat source, as well as the sizes and positions of different parts of the substrate material, are randomly varied. Train using this training data. The input information consists of the heat generation rate, thermal conductivity(in-plane/through-thickness), emissivity, and the grid widths in the xyz directions over 7 layers, with the output information being the temperature distribution. (Figure7)

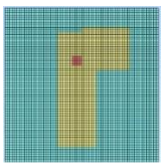

Figure 6: An example of training data

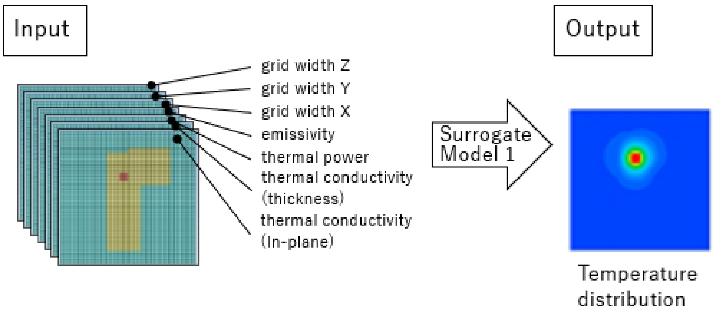

Figure 7: Data structure

The structure of the network considered in this study is shown in Figure8, based on 3D Convolution, MaxPooling, and 3D Convolution Transpose. It includes two Skip Connections to transfer information. The input data to the network is subjected to standardization. This pretrained network is referred to as Surrogate Model 1.

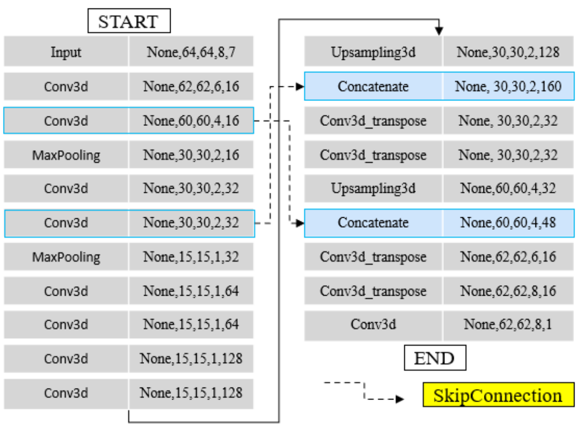

Figure 8: Network structure

2.Surrogate Model 2

The result of adding up temperatures yields a temperature distribution that follows the same trend as the ground truth, but with differing absolute values. This is due to the influence of radiation and convection, and to correct this deviation, a surrogate model was created to reduce the variability in temperature prediction. I analyzed the summation temperature of boards equipped with various numbers of heat sources and found that even if the temperature rise at a specific point is the same, the thermal influence differs there, i.e., the summation temperature varies depending on the number of installed heat sources. An example is shown in Figure 9 and 10. The temperatures of the central heating elements in Figures 9 and 10 are almost the same. Figure 9 is equipped with two heating elements. When each heating element is heated separately and the temperatures are calculated, the overlaid temperature (blue line in the figure) are the correct temperature (orange line in the figure) are almost the same. Figure 10 is equipped with five heating elements, and when the temperatures are calculated for each heating element heated separately, the overlaid temperature (blue line in the figure) and the correct temperature (orange line in the figure) diverge. It is understood that as the number of heating elements increases, the difference between the correct temperature and the temperature when each heating element is heated separately (gray line) becomes larger. It is considered that this temperature difference will have a significant impact on radiation and convection, and therefore it was decided to include it in the input data.

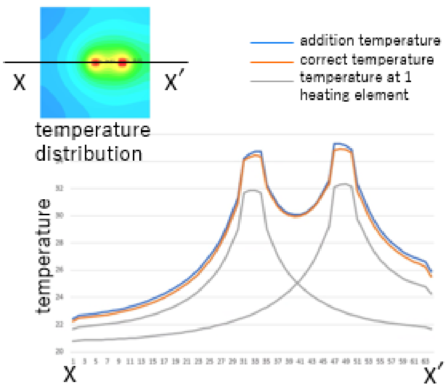

Figure 9: Temperature distribution in cross section

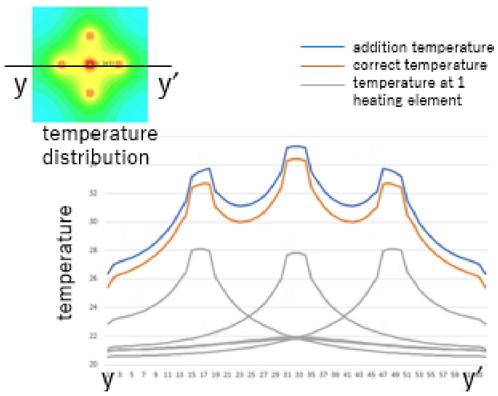

Figure 10: Temperature distribution in cross section

I trained 100 instances of a circuit with three heat sources, each with their own temperature distribution, as shown in the figure 11. I predict the temperature of each heat source separately and then sum them together. From the combined temperature, I subtract the temperature of each individual heat source. (Figure 12) The Surrogate Model 2, as depicted in the figure 13, is trained to learn the correct temperature as an output, taking this combined temperature and the overlapping temperature as input. The network used for the Surrogate Model 2 is also a U-net, like Surrogate Model 1.

3.Surrogate Model 3

The prediction variability in Surrogate Model 2 has decreased, and the graph of the correct temperature on the horizontal axis versus the predicted temperature on the vertical axis forms almost a straight line, but deviates from the 45-degree line where the error is zero. Upon analysis, it was found that there is a relationship between the temperature variability of pixels within a single substrate and the average temperature of the substrate. Figure 14 shows the plots for substrate and the average temperature of the substrate. Figure 14 shows the plots for substrates with 3, 5, 7, 10, 12, 15, and 20 heat sources, each consisting of 100 instances. The x-axis represents the temperature variability of each substrate's pixels, which is the variability of the temperature of 64x64x8pixels. Similarly, the y-axis represents the average predicted temperature of each substrate's pixels, and the z-axis represents the angle of prediction at that time. Surrogate Model 3 was trained with data from substrates with 3, 5, 7, 10, 12, 15, and 20 heat sources, with 15 instances for each, totaling 105 instances. It takes the temperature variability between pixels of the substrate to be predicted and the predicted average temperature as input, and learns the angle of the graph. The network used is fully connected.

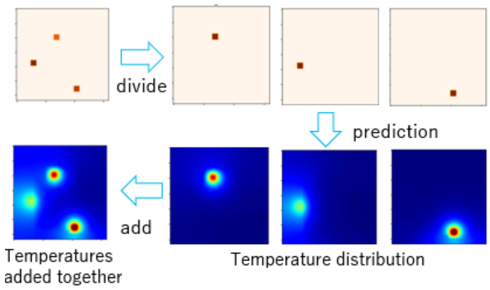

Figure 11: Diagram of a board with three heating elements, divided into one heating

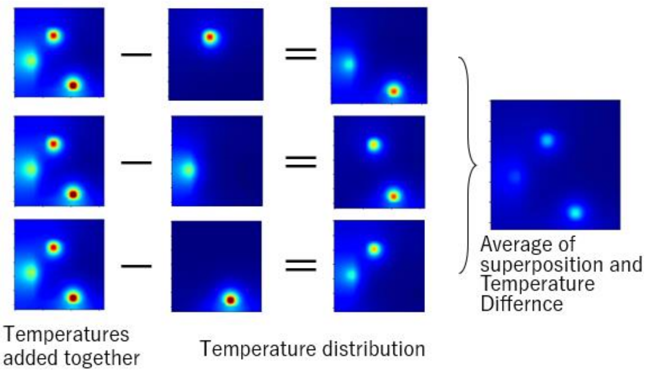

Figure 12: Average of superposition temperature minus temperature of each heating element

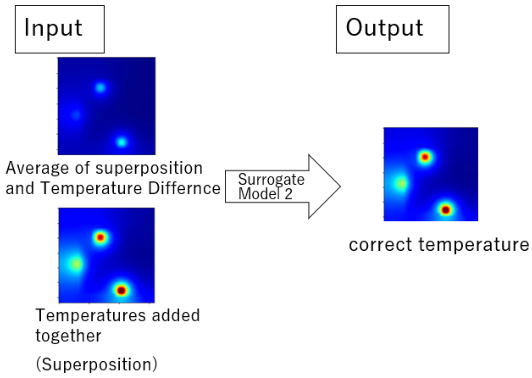

Figure 13: Surrogate Model 2 Input and Output

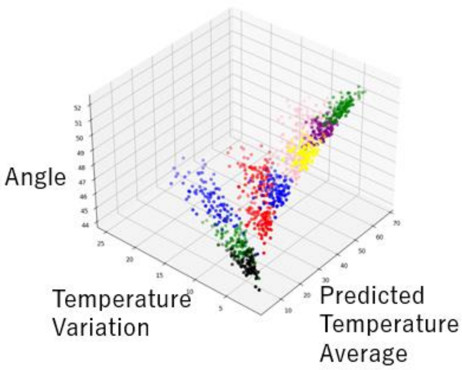

Figure 14: Graph of temperature variation vs. Predicted temperature average vs. angle

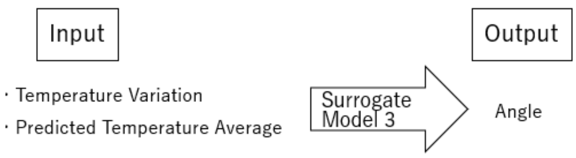

Figure 15: Surrogate Model 3 Input and Output

3 RESULTS AND DISCUSSION

Using the method described in this report, we prepared 100 instances of data for substrates with 5, 10, 15, and 20 heat sources randomly placed, and predicted the temperature for each, confirming their accuracy. The results are shown in Table 1. The top section of Table 1, labeled "Surrogate Model 1," presents the data where the temperatures is predicted separately for each heat source and then combined. The x-axis represents the actual temperature, and the y-axis shows the predicted temperature for each pixel. The middle section, labeled "Surrogate Model 2," represents the data input to Surrogate Model 2, consisting of the combined data (from the upper section) and the average difference between the combined temperature and the temperature when each heat source is activated, which was used for prediction. The lower section represents the data input to Surrogate Model 3, consisting of the temperature average and the temperature variability of each pixel. This was used to predict the angle of the graph in the middle section and to correct the temperature prediction. The data in the bottom section represents the final predicted temperatures. It is evident from this data that very accurate predictions can be made.

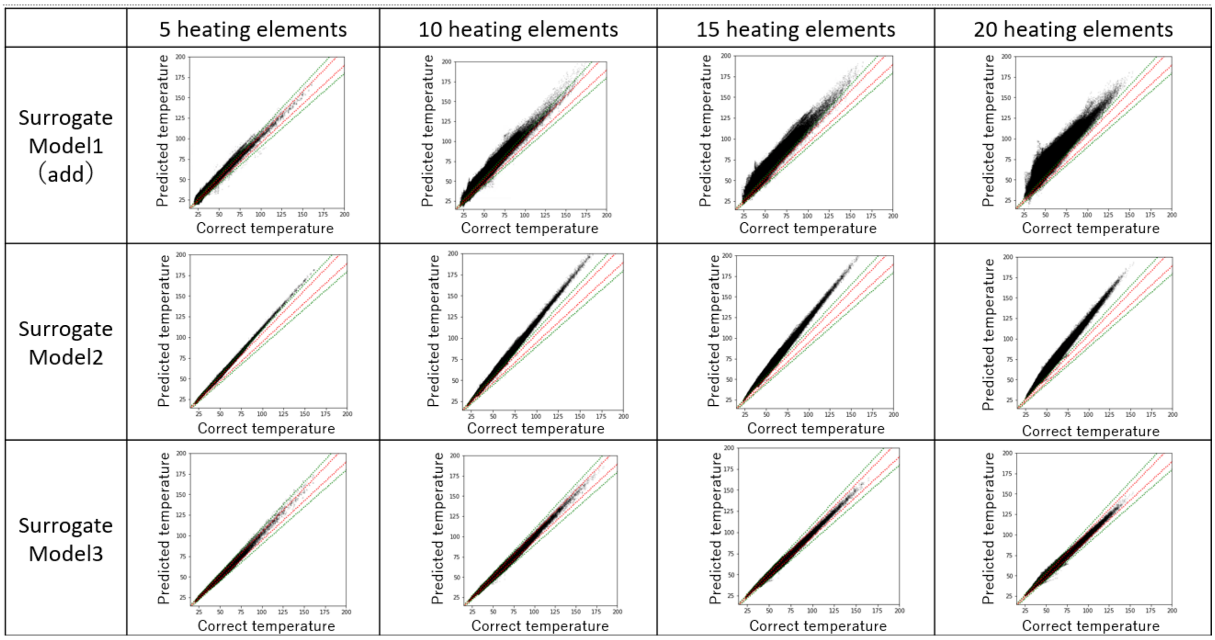

Table 1: Prediction results

4 CONCLUSION

Using the principle of superposition, we proposed a method to individually predict the temperature distribution of multiple heat sources comprising a circuit board and combining these to predict the temperature of the entire circuit board. We were able to demonstrate the efficacy of this approach in a simplified model.

Furthermore, even for phenomena such as radiation and convention where the principle of superposition does not hold, we were able to create surrogate models with limited data. By predicting the temperature fore each individual heat source using Surrogate Model 1, and then correcting the combined results using Surrogate Model 2 and 3, we significantly improved the accuracy of temperature predictions.

Previously, when creating training data by determining the component placement and heat generation randomly based on a target substrate, there were challenges such as reduced prediction accuracy for patterns not included in the data. However, with the proposed method in this study, it is no longer necessary to create surrogate models for various substrates, indicating the potential for a highly generalizable approach.

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