Abstraction of Thermal Welding System based on Element-Description Method

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Thermal welding systems are widely used in industrial applications such as packaging machinery, food manufacturing machinery, injection molding machinery, and chemical plants. In these machines, the modeling of the thermal welding system is important to control the temperature with high accuracy. The actual thermal welding system is a distributed parameter system. When implementing the actual machine, it is generally used to approximate a lumped parameter system. However, the optimal approximation such as the selection of necessary and sufficient order to a lumped parameter system is difficult. This paper proposes an abstraction method for the thermal welding system based on an element-description method. The proposed method can abstract the necessary and sufficient model. Therefore, it is possible to design a highly accurate control system according to requirements.

Keywords: element description method, heat flow control, temperature control, welding system

1. Introduction

A thermal welding system has been widely used in various industrial applications such as packaging machinery, food manufacturing machinery, injection molding machinery, and chemical plants. In these machines, it is essential to model the thermal welding system to control the temperature with high accuracy. Proportional–integral–derivative (PID) control is one of the most common control methods of thermal control in industrial fields. There are many researches to control a thermal system with high precision. A 2nd-order linear observer and a fuzzy logic controller were used to achieving superior weld quality of thermoplastic composite materials. A recursive nonlinear autoregressive moving average model was used for modeling and identification of thermoelectric modules to achieve a highly accurate rendering of heat sensation. A heat inflow observer is a technology to estimate heat flow entering a system. By compensating the estimated heat flow, it became possible to perform robust temperature control that was not easily affected by disturbance. The actual thermal welding system is a distributed parameter system. When analyzing a distributed parameter system, a finite element method is often used. However, the method has a significant computational load, and it is difficult to divert the obtained model to a controller. Recently, some reports try to implement the distribution constant as it is. This makes it possible to perform highly precise control that does not require approximation. On the contrary, since modeling errors occur, highly accurate modeling is indispensable. From the above reasons, when implementing a controller for actual machinery, a lumped parameter system is generally used to approximate the system as shown in Fig. 1. Many studies preliminarily determine the structure of the mathematical expression and fit the parameters as mainstream. However, it is difficult to approximate the optimal order of a lumped parameter system. In other words, since the range of mathematical expressions is limited at the time of determining the formula structure such as the order of the model, high-precision modeling cannot be achieved if the structure is selected incorrectly.

This paper proposes an abstraction method of a thermal welding system based on an element-description method (EDM). The proposed method can abstract the necessary
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and sufficient model of a system. Therefore, it is possible to design highly accurate control according to requirements. The proposed method is evaluated in the thermal welding system of packaging machinery. In packaging machinery, the thermal welding system is used for sealing film. The sealing in the packaging machinery is one of the most important parts because it decides seal quality and easy opening property. A sealing system is required to reliably seal in a shorter time so that we can increase the number of baggage created per minute. However, when the sealing time becomes shorter, maintaining the quality of the sealing becomes harder. Therefore, highly accurate modeling and temperature control are indispensable.

This paper is organized as follows. In Section 2, the EDM is introduced. In Section 3, an abstraction method of the thermal welding system is proposed. In Section 4, the validity of the proposed method is confirmed by experiments using an actual industrial application. Section 5 describes the conclusions.

2. Basic Concept of EDM

This section gives the concept of EDM. In EDM, a system is expressed by an element matrix defined as a combination of simple elements. Figure 2 shows the element matrix. In Fig. 2, \( x \) expresses the signal flow of horizontal direction. The center area in Fig. 2 stands for the element matrix. \( n \) and \( m \) denote the column and row size of the element matrix, respectively. The matrix size is adjustable so that the number of row and column changes depending on the purpose. \( X \) and \( Y \) stand for the input and output signals from the system, respectively. Input and output terminals stand for the interface of the element matrix. \( X \) goes into the input terminal, while \( Y \) comes out from the output terminal. The calculation is conducted sequentially from the left top to the right bottom, using the input signal. Calculation of the \( i \)th row and \( j \)th column element is expressed as

\[
x_{i+1,j} = f_k(x_{i,j}), \quad (k = jn + i)
\]

where \( f_k \) stands for the calculation function. \( k \) denotes the address of each element. Each element is expressed as a single-input and single-output system. The output value of each element is used as an input value for the adjacent element. The calculation of each element is conducted based on the chromosome vector \( e_k \) expressed as

\[
e_k = (c_k, p_k)^T
\]

where \( c_k \) and \( p_k \) refer to the element code and element

![Image](https://example.com/fig2.png)

**Fig. 2.** Element matrix used for the EDM

![Image](https://example.com/fig3.png)

**Fig. 3.** Genetic structure for the EDM

![Image](https://example.com/fig4.png)

**Fig. 4.** Kind of elements

![Image](https://example.com/fig5.png)

**Fig. 5.** A feedback element
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Parameter, respectively. In EDM, the element matrix is optimized by a genetic algorithm (GA) \(^{(15)–(17)}\). Figure 3 stands for chromosome structure used in EDM. There are two chromosomes; one is the element code chromosome, and the other is the parameter chromosome. The element code chromosome denotes the kind of elements. The type of selectable element can be arbitrarily determined according to the objective. The parameter chromosome stands for the numerical value for calculation. This type of chromosome exists because some elements use the parameters for their calculation. The parameter of each element is limited within arbitrarily range. Examples of the elements are shown in Figs. 4 and 5. The subscripts in and out stand for the input and output value of the element, respectively. Elements I in Fig. 4 shows structure definition elements. These elements define the structure of the system. Elements II represents linear operation elements. These elements are operators of linear systems. Elements III depicts nonlinear operation elements. These elements perform nonlinear calculations. Figure 5 refers to a feedback element. This element uses the parameter as the address of the feedback target element. In a target element, the feedback value is added to the input value before calculation, as shown in Fig. 5. The elements shown in this figure are merely examples. Various elements can be prepared according to necessity. For example, an element of 1st-order low-pass filter is calculated as follows:

\[
x_{\text{out}} = \frac{a_{\text{lpf}}}{s + a_{\text{lpf}}} x_{\text{in}} \tag{3}
\]

where \(a_{\text{lpf}}\) denotes the cut-off frequency of the low-pass filter. \(a\) is calculated by

\[
a_{\text{lpf}} = (p_{\text{max}}^{\text{lpf}} - p_{\text{min}}^{\text{lpf}}) P_k + p_{\text{min}}^{\text{lpf}}, \tag{4}
\]

where \(p_{\text{max}}^{\text{lpf}}\) and \(p_{\text{min}}^{\text{lpf}}\) refer to the maximum value used for the low-pass filter element, the minimum value used for the low-pass filter element, and a random value ranged by 0 to 1, respectively. \(p_{\text{max}}^{\text{lpf}}\) and \(p_{\text{min}}^{\text{lpf}}\) can be designed arbitrarily according to the kind of elements. Moreover, when the element affects the calculation logarithmically, \(a_{\text{lpf}}\) is set logarithmically by

\[
a_{\text{lpf}} = 10^\left(\frac{p_{\text{max}}^{\text{lpf}} - p_{\text{min}}^{\text{lpf}}}{\log_{10}(P_k + P_{\text{min}}^{\text{lpf}})}\right) \tag{5}
\]

The optimization procedure of EDM is based on the general procedure of GA. Algorithm 1 shows the flow of the calculation. Since element code \(c_k\) and element parameters \(p_k\) are optimized by GA, engineers only need to design element code choices, parameter ranges and initial values. The evolution continues until the result satisfies the termination condition. The evolutionary process consists of four parts: selection, crossover, mutation, and parameter shift. In the selection process, individuals to be considered in the next generation are selected. In the crossover process, whether to perform an intersection is determined probabilistically for every individual based on a crossover rate. Figure 6 shows an overview of the crossover process. In the mutation process, the chromosomes are stochastically rewritten based on the mutation rate. In the parameter shift process, parameters selected probabilistically slightly increases or decreases. Figure 7 depicts an overview of the parameter shift and mutation process. When the result meets the termination conditions,
3. Modeling of Thermal Welding System

An example of the thermal welding system of packaging machinery is shown in Fig. 8. The system consists of a heater, heat pipe, thermocouple, and metal block. This is a sealing system that melts and welds the film. The films stick together heat pipe, thermocouple, and metal block. This is a sealing system which melts and welds the film. The films stick together and making the sealant layer melt. This sealing system requires highly accurate temperature control because the seal strength and appearance quality change due to temperature variation. In the conventional PID control, the system is treated as a simple 1st order lag system or a 1st order system with dead time. However, when trying to implement high-level control such as HIOB, this model cannot achieve highly accurate control with significant errors. Therefore, in this research, we propose a highly precise modeling method based on EDM. The distributed parameter system is abstracted into a suitable lumped constant model by EDM.

3.1 Modeling based on ARX Model

An Auto-Regressive eXogenous (ARX) model is one of the most famous models used for system identification. It is a method for deriving a lumped parameter model. The general expression of the ARX model using the difference equation is given as

\[ y[k] = -\sum_{i=1}^{n} a_i y[k-i] + \sum_{j=0}^{m} b_j u[k-j] + w[k]. \]  

(6)

where \( u, y, a, b, \) and \( w \) stand for the input, output, coefficients for the input and output values, and white noise, respectively. The model assumes that the output is affected by previous values of both the input and output. The values \( n \) and \( m \) determines the order of the model. By setting the values large, a high order model can be derived, while when they are set as small value, a simplified model can be derived. In general, coefficients \( a \) and \( b \) are derived by using the batch least squares method. It gives the combination of the coefficients that minimizes the error between the actual output and the output from the model. When deriving the parameters, it is able to insert a weighting matrix to further reduce the error; however, since the main proposal of the paper is not deriving the most suitable ARX model, the matrix was not used in this paper. For the simplicity, the paper assumed that the effect of the white noise is small enough so that it can be ignored, and that \( n \) and \( m \) to be the same order. The model can also be used when there is an input delay in a system. In this case, the equation becomes as follows:

\[ y[k] = -\sum_{i=1}^{n} a_i y[k-i] + \sum_{j=0}^{m} b_j u[k-j - T_d] + w[k]. \]  

(7)

where \( T_d \) represents the delay element.

3.2 Modeling based on Thermal Network Method

The thermal welding system is often modeled as a lumped parameter system based on thermal network method (TNM). Figure 9 represents an example of lumped constant modeling by TNM. In Fig. 9, \( R_C, R_L, \) and \( C \) stand for thermal resistance of contact, thermal resistance of heat loss, and heat capacity of object, respectively. In this way, the system can be expressed by expressing the thermal system with an equivalent electric system. Figure 10 depicts a block diagram of Fig. 9. In Fig. 10, \( P_{ref}, T_{ref}, \) and \( q_d \) refer to power reference, input heat flow to the \( n \)-th thermal capacitor, and the temperature of the \( n \)-th thermal capacitor, respectively. The order of the system can be defined by the number of thermal capacitors. As the order of the system increases, the accuracy of the calculation improves, but the calculation becomes complicated. Therefore, it is important to select suitable order of the model.

3.3 Abstraction based on EDM

Then, abstraction method of the thermal welding system based on EDM is
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Fig. 11. Block diagram of abstraction of a thermal welding system based on EDM.

A thermal welding system

Heat pipe Thermocouple Cartridge heater

Fig. 12. Experimental setup

Fig. 13. Input response of identification data explained. Figure 11 represents the block diagram of abstraction of a thermal welding system based on EDM. In Fig. 11, \( T_{\text{res}} \) refers to temperature response. The superscript \( \hat{\text{•}} \) and \( \tilde{\text{•}} \) stand for estimated value and error value, respectively. The fitness function is designed as

\[
\Gamma = \frac{1}{N_{\text{sum}}} \sum_{q=1}^{N_{\text{sum}}} \Lambda(q) \cdot (T_{\text{res}}[q] - \hat{T}_{\text{res}}[q])^2, \quad \cdots \cdot (8)
\]

where \( \Gamma \), \( N_{\text{sum}} \), and \( \Lambda(q) \) stand for the fitness value, number of data, and window function, respectively. The window function in fitness function is used for arbitrarily designing a section to be emphasized in the optimization. Evolution processing is performed so that this fitness function is minimized.

4. Experiments

In order to confirm the validity of the proposed method, experiments are conducted. Figure 12 depicts the experimental setup. The area indicated by the green dashed line represents a thermal welding system used in the experiments. In the experiments, the accuracy of the identification result by the TNM, the ARX modeling, and EDM are compared.

4.1 Abstraction Phase

Initially, the step response of a thermal welding system was measured as data to use in the abstraction of the system. Figure 13 shows experimental input data used for model estimation. The data for identification is a step response of 10 s. The following shows the abstraction procedure by EDM. In the beginning, learning is performed with a small number of elements in order to derive important elements with a higher abstraction level. For the above reason, we set the number of row to 1 and increase only the number of columns (Step 1). The abstraction by EDM is tried 20,000 evolutions 100 times for each number of columns. In the learning of the 1st row, a window function
is designed as follows in order to prevent an error before applying power.

\[ \Lambda(q) = \begin{cases} 10 & (0 \leq qT_s < 10) \\ 2 & (80 \leq qT_s) \\ 1 & \text{otherwise} \end{cases} \quad (9) \]

where \( T_s \) denotes the sampling time. Table 1 represents the root means square (RMS) values for each trial and its statistical results in Step 1. Figure 14 is a graph showing statistical values. Focusing on the minimum RMS in the number of columns in Table 1, while the minimum value decreases greatly when the number of columns increased up to three columns, there is not much change when the number increased beyond three columns. Therefore, the results of the three columns are considered to be excellent models with a high level of abstraction. Figure 15 shows the temperature response of the abstracted system by EDM. It shows the best result response among trials of each matrix size. Figure 16 gives the temperature error of the abstracted system by EDM. Then, the result of row 1, column 3 is inherited, and the abstraction of row 2 is implemented (Step 2). In EDM, it is possible to improve the accuracy of the model in a hierarchical manner by increasing the number of rows. In the 2nd row, the parts that the 1st column could not express are abstracted. From Fig. 15, since the model using the 1st row cannot represent the overshoot and slow temperature drop, the 2nd row is expected to extract models that represent them. In the learning of the 2nd row, a window function \( \Lambda(q) \) is designed as 1 in order to improve overall accuracy. In this step, 20,000 evolutions are performed 100 times in 2 rows and 3 columns. The temperature response of the abstracted system by EDM is shown in Fig. 17 which shows the best result response in Step 2. Also, the temperature error in Step 2 depicts in Fig. 18. As can be seen from Fig. 17, a model representing overshoot and slow temperature drop was extracted in the 2nd column. Table 2 represents the RMS values for each trial and its statistics in Step 2. Although it is possible to proceed with the steps on the third line, this study ends EDM abstraction here to keep the model simple. Table 3 stands for RMS of the conventional methods in abstraction phase. The parameter of the ARX model and the TNM are optimized by least squares here to keep the model simple. Table 3 represents RMS values for each trial and its statistics in Step 2. Although it is possible to proceed with the steps on the third line, this study ends EDM abstraction here to keep the model simple. Table 3 represents RMS values for each trial and its statistics in Step 2. Although it is possible to proceed with the steps on the third line, this study ends EDM abstraction here to keep the model simple. Table 3 stands for RMS of the conventional methods in abstraction phase. The parameter of the ARX model and the TNM are optimized by least squares here to keep the model simple.
Table 5. RMS of 5 s step response in evaluation phase by ARX and TNM

| Order | 1   | 2   | 3   | 4   | 8   |
|-------|-----|-----|-----|-----|-----|
| RMS of ARX (conv. 1) | 0.096 | 0.097 | 0.097 | 0.096 | 0.115 |
| RMS of TNM (conv. 2) | 0.197 | 0.086 | 0.061 | –   | –   |

Table 6. RMS of 30 s step response in evaluation phase by ARX and TNM

| Order | 1   | 2   | 3   | 4   | 8   |
|-------|-----|-----|-----|-----|-----|
| RMS of ARX (conv. 1) | 0.259 | 0.253 | 0.259 | 0.288 | 0.373 |
| RMS of TNM (conv. 2) | 0.669 | 0.166 | 0.151 | –   | –   |

Table 7. Comparison of conventional methods and EDM

| Method | 10 s (abst. phase) | 5 s (evaluation 1) | 30 s (evaluation 2) |
|--------|-------------------|-------------------|--------------------|
| ARX (conv. 1) | 0.127 | 0.097 | 0.259 |
| TNM (conv. 2) | 0.059 | 0.062 | 0.151 |
| EDM (prop.) | 0.033 | 0.050 | 0.133 |

Fig. 21. Comparison of the temperature response in evaluation phase (5 s step response)

Fig. 22. Comparison of the temperature response in evaluation phase (30 s step response)

Fig. 23. Comparison of the temperature error in evaluation phase (5 s and 30 s step response)

The model is an abstracted thermal welding system by EDM. The EDM can order the importance of each model, which means the 1st row is the most important model. The green dotted line in Fig. 17 corresponds to the model in the 1st row. The 2nd line is the next important model, which is the model corresponding to the difference between the green dotted line and the red line in Fig. 17. As the learning step progresses to the 3rd line, it is expected that the accuracy of the model will be further improved. At the expense of higher accuracy, the simplicity of the model decreases. Therefore, learning should stop when the model has sufficient accuracy.

5. Conclusions

This paper proposed the abstraction method of the thermal welding system based on EDM. Both the model structure and parameters were simultaneously abstracted by using the proposed method. Therefore, determining the model in advance is not needed when the target system is identified. This property makes it possible to abstract a model of the target system even if the system model is unknown. Moreover, it can express nonlinear elements by preparing nonlinear selectable elements. In addition, the abstraction result is understandable because it is expressed by a combination of the simple elements shown in Fig. 4. Hence, abstracted results can be used for controller design. It is also possible to inherit the obtained result to other target system abstractions. Therefore, learning can be finished arbitrarily at the time when sufficient accuracy is obtained. In this paper, EDM was applied to a thermal welding system, and its effectiveness was demonstrated. The EDM can be expected to develop as a machine learning method that is highly cooperative with humans.

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