

PROCESS MODELLING OF INDUCTION WELDING FOR THERMOPLASTIC COMPOSITE MATERIALS BY NEURAL NETWORKS

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ABSTRACT

Induction welding for thermoplastic composite materials uses an alternating current flowing through a coil to induce an electromagnetic field and generate eddy current inside laminate with various fiber orientations – the generated heat causes the laminate to heat up and melt the polymer. As a pressure is applied to the induction heating zones, cohesive bonding may occur during the melting of the polymer. The welding quality of the composite materials is highly influenced by the temperature varying inside the heating zones. Thus, it is beneficial for induction welding if temperature varying during heating can be acquired given a set of welding parameters, such as current, pressure, fiber orientations, etc. Conducting practical induction heating experiments for this purpose is laborious and time consuming given the large varying space of welding parameters. In this paper, we propose to address this problem by using machine learning techniques to model the relation between the welding parameters and the temperature varying inside the heating zones. We conduct two sets of induction heating experiments for laminate welding and the collected sample temperature varying data are used to train the neural networks with input of welding parameters and output of the predicted temperature varying. Testing of the models demonstrates that process modeling of induction welding with machine learning techniques is viable.

1. INTRODUCTION

This paper aims to model the process of induction welding for thermoplastic composite materials with machine learning technique by correlating induction welding parameters to temperature varying inside the heating zones. Induction welding for thermoplastic composite materials tries to weld two composite laminates together by heating up and melting the polymer in their overlapping regions. More specifically, when the overlapping regions are heated up and melted, a pressure is applied, and the laminates can contact each other. Once the heating zones stop to be heated up, the laminates will be welded together at the specific zones as polymer solidifies again due to temperature decreasing. Therefore, induction welding quality is highly dependent on temperature varying inside the overlapping regions, which is determined by the welding parameters such as current through coil, pressure applied on laminate overlap, etc. In this paper, we model the induction welding process by training neural networks which take the induction welding parameters as the inputs and can output the temperature varying inside the heating zones.

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Existing works treat the process of induction welding for thermoplastic composite materials as a multi-physics problem and address the problem based on finite element (FE) method [1][2][3]. These works mainly study the induction welding by subdividing the process into multiple smaller processes, such as electromagnetic field, heat transfer, etc. Given the model complexity, it is difficult for the FE method to consider all the factors that influence the induction welding in different experiment environments. In this paper, we propose to use machine learning techniques by treating the induction welding process as a black box with input of welding parameters and output of temperature varying – the neural network training is totally data-driven without considering any prior knowledge in physics. To the best of our knowledge, this is the first work trying to model the process of induction welding for thermoplastic composite materials with machine learning. Compared to previous FE methods, the proposed machine learning model can be easy to build for different experiment environments. Rebuilding an FE model to consider different factors in a new experiment environment can be very time-consuming and laborious. For the proposed machine learning method, all we need is to collect a set of training data consisting of sample induction welding parameters and their corresponding temperature varying in the new experiment environment, with which the neural network can be easily trained or tuned.

In the proposed method, the training data are sample-target pairs following the supervised learning strategy. The *sample* here means the induction welding parameters, while the *target* is the corresponding temperature varying. In this paper, to acquire training data, we design two sets of induction heating experiments for thermoplastic composite materials, one of which is conducted in vacuum bag, and the other is conducted in KVE Thermoplastic Assembly platform¹ (we denote it as KVE tool in the remainder of this paper), as detailed in the following sections. We process these training data and use them to train a neural network for predicting the temperature varying given a set of induction welding parameters.

1.1 Induction Welding

Induction welding is a non-contact heating process which can be used to bond thermoplastic composite materials. As reviewed in papers [4-6], induction heating/welding is not a new technology, and has been used for heating metals for a long time. From three decades ago, induction welding has also been applied to thermoplastic composites. Several studies on induction welding show its efficiency, e.g., it can weld fiber reinforced thermoplastic composite in very high speed [7 -10].

Based on electromagnetic induction discovered by Michael Faraday, induction starts from a coil of conductive materials (e.g., copper). Therefore, induction welding uses an induction coil to produce electromagnetic field. When an alternative current flow through the coil, a time-variable electromagnetic field, which has the same frequency as the alternating current, is induced. As the overlapping region of thermoplastic composite laminates with various fiber orientations is placed in the field, the eddy current is generated on both laminates, which results in laminates being heated up. Four heat mechanisms are discussed in [4]. Subsequently, the produced heating increases the temperature of heated zones on laminates. The polymer of the laminates melts when the temperature is above its melting point. Thus, as a pressure is applied on the overlapping region, the melted zones contact each other, which may introduce cohesive bonding during the melting of

¹ <https://www.kve.nl/application-groups/thermoplastic-assembly/>

polymer. After heating up for certain time, the induction heating is stopped, and the temperature decreases to room temperature. When the polymer solidifies, the laminates can be welded together. Note that the laminates used in this paper is Polyetherketoneketone (PEKK) laminates reinforced with carbon fibers.

1.2 Neural Networks

In recent years, artificial intelligence (AI) has become a very important part of both research and our daily lives. As an important tool of AI, machine learning [11] tries to build a mathematical model for the *training data* in order to make predictions or decisions based on certain inputs. There are different machine learning models, such as Artificial Neural Network (ANN, or Neural Network, NN), Support Vector Machine (SVM), Bayesian Network, and Genetic Algorithm (GA). Due to the great successes of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) in tasks like computer vision [12][13] and natural language processing [14], we select Neural Network to model the process of induction welding for thermoplastic composite materials in this paper.

To be specific, we can treat machine learning model as a black box. It takes certain inputs, and outputs predicted results, as shown in Figure 1. For the case of modelling induction welding process for thermoplastic composite materials, the inputs of machine learning model are the induction welding parameters, while the desired outputs are the predicted temperature varying in laminate overlap during induction welding process. To train the machine learning model, a loss function is required to measure the deviation between predicted results (predicted temperature varying) and the ground truth (measured temperature varying in experiments) in the training data. The calculated loss value is used to update the weights of the model. Normally, this is achieved by Gradient Descent (SGD) algorithm. The training is repeated until the loss converges to a very small value.

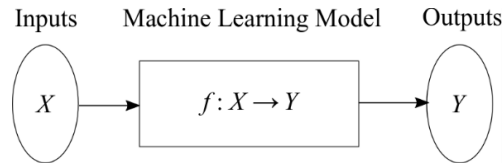


Figure 1. Machine learning model takes induction welding parameters as inputs and outputs predicted temperature varying in laminate overlap.

2. DATA ACQUISITION

Training data is one of the most important elements in machine learning. The first step to model the process of induction welding for thermoplastic composite materials is to acquire data. Therefore, we design two sets of induction heating experiments for thermoplastic composite laminates, which are the PEKK laminates reinforced with carbon fibers. One of the designs of experiments (DoE) is conducted in vacuum bag, while the other is conducted in KVE tool. The purpose of data acquisition is to collect sample-target pairs, each of which contains induction welding parameters as model input and corresponding temperature varying as desired model output. The steps for each set of induction heating experiments are:

- 1) Set up laminates with overlap and deploy temperature sensors in the overlap region;

- 2) Select and configure a set of induction welding parameters;
- 3) Conduct induction heating for desired time length and log the temperature varying captured by temperature sensors;
- 4) Wait for laminates cooling down to room temperature;
- 5) Repeat Steps 2) to 4) until all the desired sets of induction welding parameters are tested.

Note that we repeatedly use the same laminates for all experiments of one design without actually welding them. Therefore, the heating temperature is limited below 300°C during all experiments to avoid welding. As we want to model the process by correlating induction welding parameters and temperature varying, we do not have to weld the laminates in practice. All we need is the temperatures varying in the heated zones during induction heating in terms of each set of induction welding parameters.

2.1 Experiments in Vacuum Bag

2.1.1 Setting Up Laminates

The induction heating experiments in vacuum bag use air pressure to make laminates contact in the overlap region. First, we prepare two separate laminates of almost the same size – about 6 inches long and 3 inches wide. The overlap is 1-inch width along the long side of laminates. For induction heating experiments in vacuum bag, thermocouples (TCs) are used as temperature sensors. As shown in Figure 2, five thermocouples (TC-1~5) are placed inside the laminate overlap region, while two thermocouples (TC-6 and TC-7) are placed on the surface of the laminate overlap. TC-6 and TC-7 are on the surface centers of the top and bottom side of laminate overlap, respectively. TC-1~4 are placed on the center line along the length of laminate overlap, while TC-5 is placed on the center line along the width of laminate overlap a quarter inch away from overlap edge. As thermocouples are deployed in laminate overlap, the laminates are further placed on a heat sink and covered by a vacuum bag, as shown in Figure 3. The vacuum bag is sealed, and air is evacuated with a vacuum pump continually. Besides, the static coil is above the center of laminate overlap.

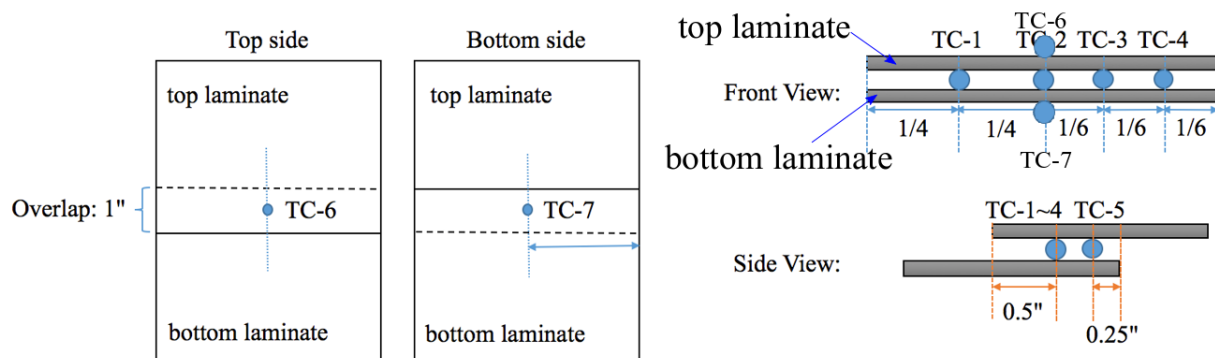


Figure 2. Thermocouple deployment in laminate overlap.

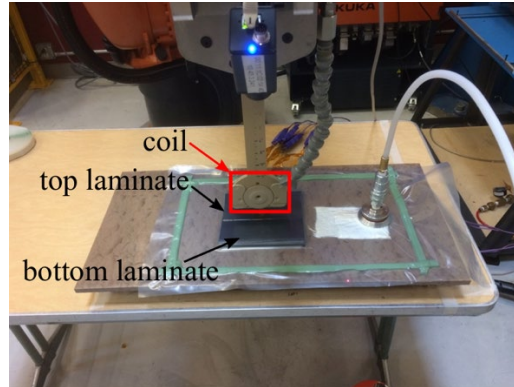


Figure 3. Induction heating experiments in vacuum bag.

2.1.2 Induction Welding Parameters

There are a lot of variables that may influence the induction welding for laminates. The considered parameters in the experiments include current value, vacuum pump level (determining pressure in vacuum bag), distance from coil to top surface of laminate overlap, air cooling height from the top surface of laminate overlap, air cooling angle, air cooling distance of coil and room temperature. Meanwhile, all other variables are kept constant in each induction heating experiments. In addition, the laminate overlap is heated up for five seconds based on each set of induction welding parameters. To reduce the deviations, we conduct induction heating three times for each set of induction welding parameters. The mean of the captured temperature values from each thermocouple at each time point is calculated as the final corresponding temperature data. Finally, we acquire 48 data samples.

2.2 Experiments in KVE Tool

The induction welding experiments in KVE tool rely on the pressure provided by the tool. Different from the experiments in vacuum bag, the experiments in KVE tool use fiber optic as temperature sensor to measure temperatures during induction heating for laminates. As shown in Figure 4, the fiber optic is deployed on the bottom, middle (inside) and top of the laminate overlap, by going through the middle twice. The fiber starts from the center line on bottom of the overlap. Then, it makes a loop and goes through the line $\frac{1}{4}$ inch away from overlap edge in the middle. Staying in the middle, it makes a second loop and goes through the center line inside the overlap. Finally, the fiber makes a third loop and goes through the center line on top of the overlap. Figure 5 shows the deployment of the fiber in the middle of the laminate overlap. The final laminate setting up is shown in Figure 6. Then, it can be placed in the KVE tool (Figure 7). During induction heating experiments, LUNA ODiSI-B System² is used to log the temperature measured by the fiber optic. Similar to experiments in vacuum bag, the coil is also static and placed above the center of laminate overlap.

The considered induction welding parameters include current value (range from 350 Amp to 540 Amp) and heating time (range from 2.5 seconds to 12.5 seconds), while all other variables that may influence induction heating are kept constant during experiments. To avoid melting the

² <http://lunainc.com/wp-content/uploads/2014/05/ODiSI-B-UGv3.0.pdf>

laminates, we stop heating experiments when peak temperature reaches about 300°C. Finally, 98 data samples are acquired from heating experiments.

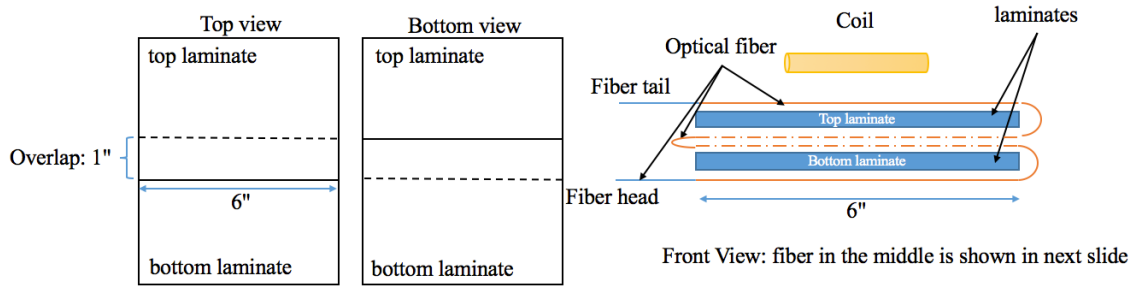


Figure 4. Fiber optic deployment in laminate overlap.

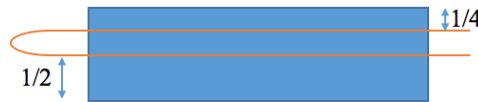


Figure 5. Fiber optic distribution between laminates (in the middle of laminate overlap).

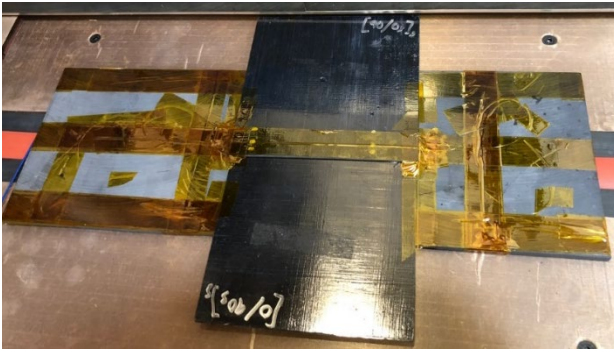


Figure 6. Laminate setting up for induction heating experiments.

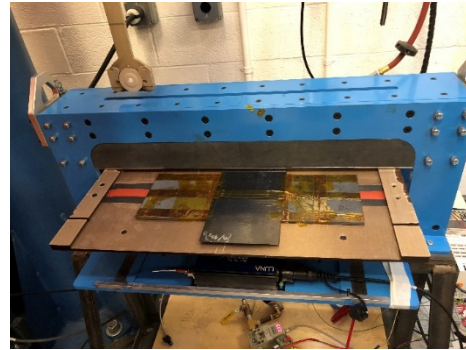


Figure 7. Laminates placed in KVE tool for induction heating experiments.

3. MACHINE LEARNING MODEL

To model the induction welding process with the acquired data, we process the data to the format that can be fed into neural network architecture.

3.1 Data Processing

3.1.1 Thermocouple Data

Induction heating experiments in vacuum bag use thermocouples to measure temperatures. As shown in Figure 8 (a), temperature values captured by each thermocouple increase for a certain time to reach the peak. Since the heating lasts for exactly 5 seconds, we suppose that the time for the temperature to reach the peak is 5 seconds from the start of heating. Therefore, we can extract

temperature varying data of each thermocouple after the start of heating, as shown in Figure 8(b). Note that the thermocouples measure temperatures during experiments at a sampling rate around 1Hz with deviations. An illustration of inconsistent sampling rate is shown in Table 1 for different trials of experiments based on same set of induction welding parameters. To align time points of all the temperature varying curves (after the start of heating), we interpolate the temperature values at time 0, 1, 2, 3, 4, and 5 seconds from the start of heating and an illustration is shown in Figure 8(c). Besides, as the heating is not started before time 0, the temperatures from a negative time to 0 should not change, ideally. Thus, we simply assign the temperature at time 0 with that of its nearest negative time point sampled in Figure 8(c).

Table 1. An illustration of inconsistent sampling rate of the same thermocouple. Time 5 is first confirmed by locating the peak temperature.

Experiment Trial 1		Experiment Trial 2	
Time (sec) from the start of heating	Temperature (°C) captured by TC-1	Time (sec) from the start of heating	Temperature (°C) captured by TC-1
-1.02	17.12	-1.40	16.00
0.34	29.77	0.33	24.13
1.12	37.89	1.65	40.25
1.96	50.80	2.57	48.70
2.99	58.92	3.23	56.89
4.41	71.04	4.00	64.62
5.00	71.70	5.00	69.54

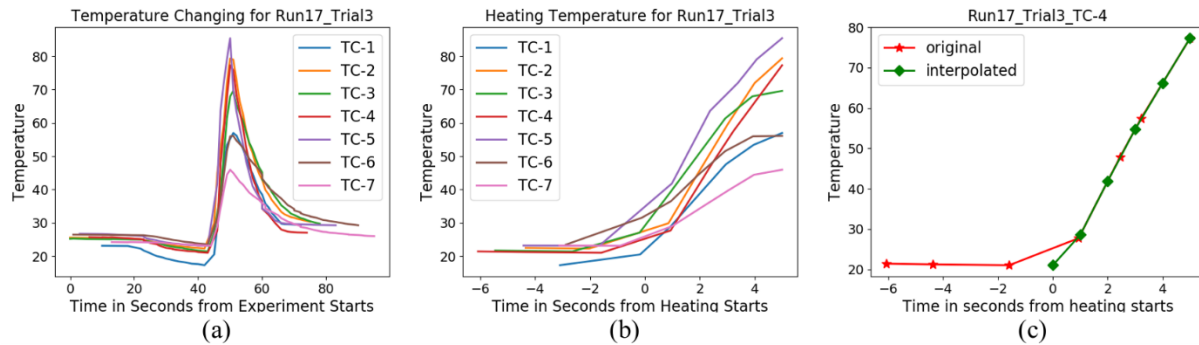


Figure 8. Thermocouple data processing.

3.1.2 Fiber Optic Data

Fiber optic is used to capture temperature varying during induction heating experiments in KVE tool. While each thermocouple captures temperature varying of one location in laminate overlap, a single fiber optic monitors temperature varying of multiple locations in laminate overlap. Each point of fiber optic can be regarded as a temperature sensor. Specifically, points are selected for every 2.59 mm on the fiber optic for measuring temperatures, as higher spatial resolution of sampling points results in lower measurement accuracy. The acquired temperature varying data can be recorded as a 2D matrix. Figure 9 shows an example of captured temperature varying during

an induction heating experiment. The horizontal axis indicates the points on fiber optic (one point per 2.59 mm from the fiber head), while the vertical axis represents the experiment time (in seconds), which is different from heating time, since the temperature monitoring starts earlier than the heating start. Colors in the matrix reflect the measured temperature ($^{\circ}\text{C}$) at certain points on the fiber optic at specific time. The white areas represent that the temperature value is missing or removed as obvious outliers, which result from noise or error due to strain in the fiber optic.

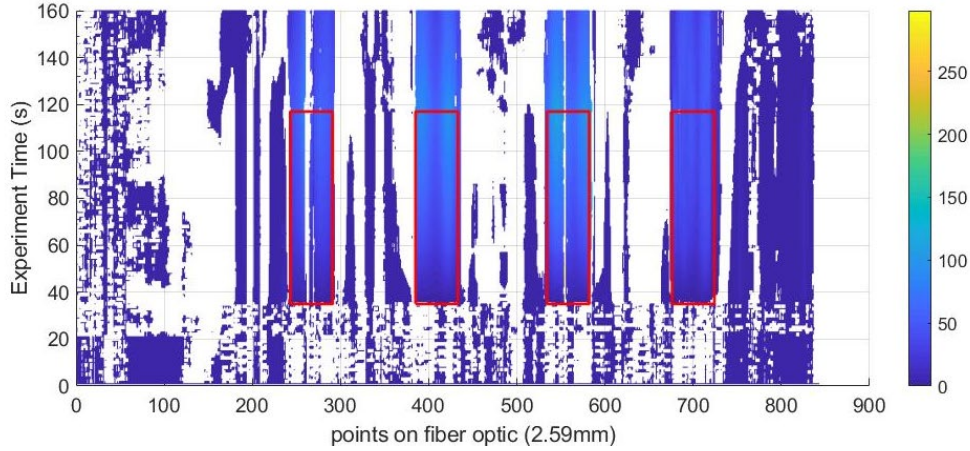


Figure 9. An illustration of the collected temperature matrix based on a set of induction welding parameters.

As in processing the thermocouple data, we also need to extract heating segment of temperature varying, i.e., only the data after the start of the heating, during induction heating for each location monitored by fiber optic in laminate overlap. As described in Figure 4, there are four sections of fiber optic contacting with laminate overlap. Therefore, the heating segments are extracted for temperature varying of points in these fiber optic sections. As manifested in Figure 9, four sub-matrices are indicated in red boxes. Each sub-matrix is with 32 columns, while number of its rows is determined by the heating time. When the heating time is 2.5, 5.0, 7.5, 10.0 and 12.5 seconds, the number of rows is 21, 42, 63, 84 and 105, respectively. In fact, we set the temporal sampling of fiber optic as 10Hz. Therefore, deviation exists for fiber optic sampling. Note that 32 consecutive points in fiber optic leads to a length that shorter than the overlap length (also the length of a fiber optic section in laminate overlap region), because the unexpected strain on the fiber optic at the edges of laminate overlap makes the temperature value measured by points in these sections not reliable.

Figure 10 shows an illustration of the extracted temperature matrices based on a set of induction welding parameters. We can notice that temperature values at some matrix coordinates are missing, which means temperature at a certain location and a specific time is not measured successfully. Without the ground-truth temperature values, supervised machine learning model cannot be trained to predict temperature at this location and this specific moment. Therefore, we use a masking matrix for each sub-matrix to specify the matrix coordinates where temperature values are missing. The missing values are not used during model training. The masking matrices are calculated by an “OR” operation of temperature sub-matrices for the same fiber section based on different induction welding parameters to indicate if the value is missing at the certain matrix

location, as shown in Figure 11. The yellow color represents the coordinates without missing value, while blue color indicates that temperature value missing occurs on these coordinates.

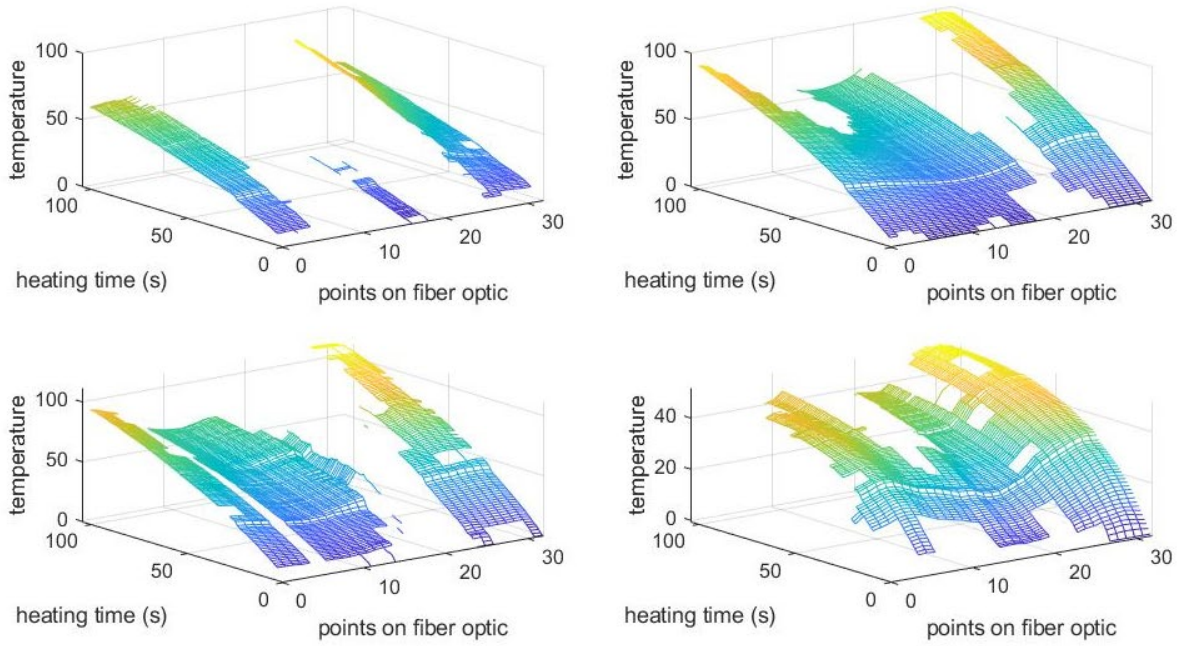


Figure 10. An illustration of extracted temperature sub-matrices based on a set of induction welding parameters, each of which corresponds to a section of fiber optic.

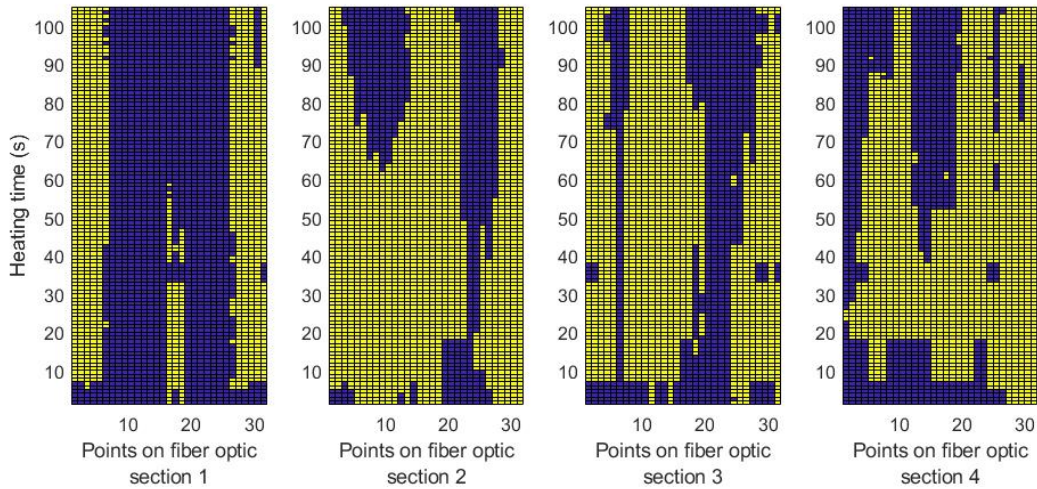


Figure 11. Extracted masks for temperatures collected by each fiber section in laminate overlap.

3.2 Model Training

For the two designs of induction heating experiments, we train separate models based on two acquired datasets, respectively. There are 48 data samples acquired from induction welding experiments in vacuum bag with thermocouples as temperature sensors and 98 data samples acquired from experiments in KVE tool with fiber optic as temperature sensors. As machine

learning, especially deep learning, requires as many data as possible to train a robust model, we use most of data samples in each dataset for model training and the remaining data samples for model testing to validate the trained model. To model the induction welding process in vacuum bag, we randomly select 43 of 48 data samples for training and use the remaining 5 data samples for testing. Similarly, to model the induction welding process in KVE tool, we randomly pick 80 of 98 data samples for model training and the remaining 18 data samples for model testing.

3.2.1 Neural Network Model

We use neural network as machine learning framework to model the induction welding process due to the great success of its extension, deep learning, in many research areas, such as computer vision, natural language processing, etc. We construct two individual neural networks with similar architecture for induction welding processes in vacuum bag and KVE tool, respectively. Neural network is a layered machine learning model structure. It normally consists of input layer, hidden layers and output layer. The input layer feeds inputs into the model. Then, hidden layers receive inputs and generate outputs depending on inputs and activation functions. Each hidden layer consists of a number of neurons. Each neuron receives the inputs and produce the outputs, which are also taken as the inputs to the neurons of subsequent hidden layer.

Both our designed models are mainly composed of linear layers and Rectified Linear Units (ReLU) activation. Suppose $\mathbf{X}_i = [x_{i,1}, x_{i,2}, \dots, x_{i,n}]$ is the input of a linear layer i (also the output of its predecessor layer $i - 1$), the output of this layer $\mathbf{Y}_i = [y_{i,1}, y_{i,2}, \dots, y_{i,m}]$ should be

$$y_{i,j} = \mathbf{W}_j^T \mathbf{X}_i + \mathbf{b}_j, \quad [1]$$

where $\mathbf{W}_j$ and $\mathbf{b}_j$ are the weights and biases of neuron j in linear layer i , and $j = \{1, 2, \dots, m\}$ with m being the number of neurons. With ReLU as the activation function, non-linearity is introduced to the designed models since linear model may not able to fit the practical process, as shown below:

$$x_{i+1,j} = \max(0, y_{i,j}). \quad [2]$$

Besides, min-max normalization is performed on each input before being fed into the network for model training.

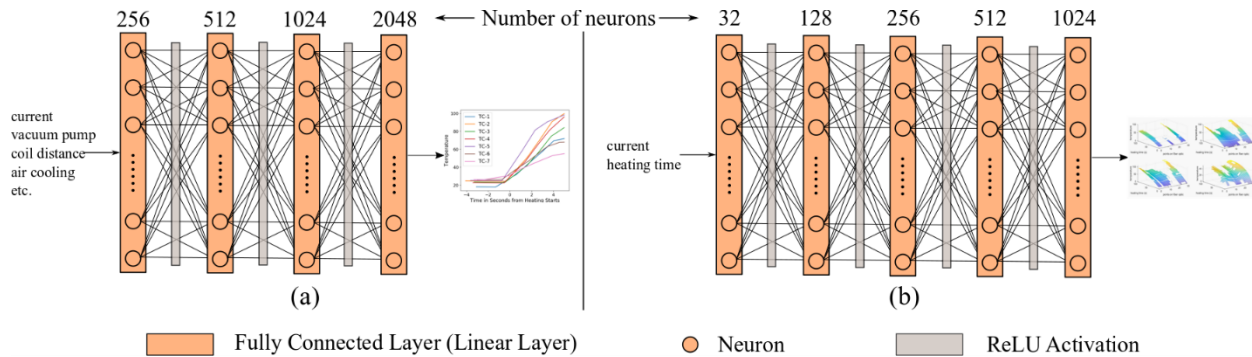


Figure 12. The designed neural networks for modelling induction welding process.

The designed networks are shown in Figure 12. To model induction welding process in vacuum bag, the designed network includes linear layers with the number of neurons as (256 – 512 – 1024 – 2048) as shown in Figure 12 (a). To model induction welding process in KVE tool, the designed network includes linear layers with the number of neurons as (32 – 128 – 256 – 512 – 1024) in Figure 12 (b).

3.2.2 Loss Functions

When induction welding parameters is fed to the above machine learning models, the models predict temperature varying as outputs. To measure the reliability of the model during training, a cost function is required for comparing the predicted temperature varying and the true temperature varying acquired by temperature sensors.

For modelling the induction welding process in vacuum bag, the cost function is defined as

$$loss = \max\left(\left|\frac{p-t}{t}\right|\right) + \max(\text{sigmoid}\left(\frac{p-t}{t}\right) - 0.5, 0), \quad [3]$$

$$\text{sigmoid}(u) = \frac{1}{1+e^{-u}}, \quad [4]$$

where p denotes a predicted temperature value, while t denotes the measured ground-truth temperature value. It is known that the temperatures inside the laminate overlap need to be higher than a certain threshold to melt the polymer. Therefore, if the predicted temperatures are much higher than the ground truth, it may occur that the predicted temperatures have already reached the threshold, while the real temperatures based on the same set of induction welding parameters have not. This may result in not enough time of heating to melt the laminate polymer, which impairs welding quality. Thus, the first term of the loss function in Equation (3) is to measure the overall prediction error, while the second term is for the extra penalty to high prediction error, as shown in Figure 13. By minimizing the loss value, the model is optimized to make the predicted temperature values to be as close to the ground-truth temperature values as possible based on induction welding parameters.

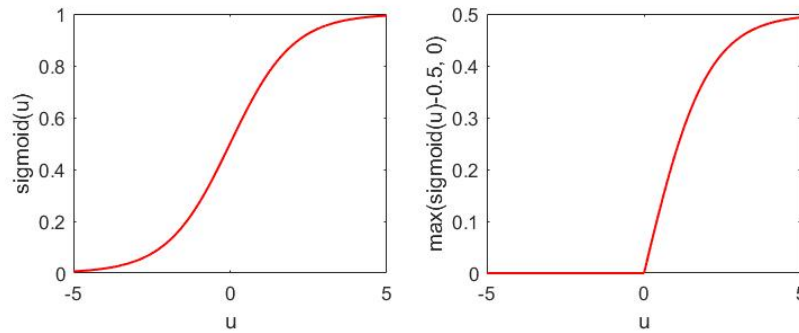


Figure 13. The extra penalty for high prediction error.

Similarly, a loss function for training the model of induction welding process in KVE tool is defined as

$$loss = \frac{1}{N} \sum_{i=1}^N (t_i - p_i)^2 + \max(|\mathbf{P} - \mathbf{T}|) + \max(\mathbf{P} - \mathbf{T}), \quad [5]$$

where $\mathbf{P}$ and $\mathbf{T}$ are the predicted temperature values and ground truth temperature values, respectively, and $t_i \in \mathbf{T}$, $p_i \in \mathbf{P}$.

To minimize the loss functions, Gradient Descent (GD) [15] algorithms, such as Stochastic Gradient Decent, RMSprop [16], Adam [17], etc., are usually used. In this paper, we adopt an extension of GD – Adam – as the optimizer to train the model. When the losses converge to small values, we assume that the model training is completed.

3.3 Model Testing

To evaluate the effectiveness of the trained models, we define the *prediction error* as the absolute differences between predicted temperatures and ground-truth temperatures. We consider four evaluation metrics to estimate the performance of the trained models: 1) maximum high prediction error – the maximum prediction error of the predicted temperatures which are higher than the ground-truth temperatures; 2) maximum low prediction error – the maximum prediction error of the predicted temperatures that are lower than the ground-truth temperatures; 3) mean value of the prediction errors; 4) standard deviation of the prediction errors.

3.3.1 Modelling based on Thermocouple Data

We conduct four runs of training and testing based on temperature data collected by thermocouples to model the induction welding. The results are shown in Table 2. It shows that the prediction errors are tolerable since the maximum prediction errors are smaller than 30°C for all runs of model training and testing. Besides, we also compare the predicted temperature varying and measured temperature varying captured by each thermocouple based on a set of induction welding parameters (in testing subset). As shown in Figure 14, the predicted temperature varying is quite close to the corresponding ground truth. This means that the trained models are capable of modelling induction welding process in vacuum bag.

Table 2. Prediction results: four runs of training and testing procedures.

Prediction errors (°C)	Run 1	Run 2	Run 3	Run 4
Maximum high prediction error	5.52	5.61	9.42	9.73
Maximum low prediction error	14.05	17.79	16.29	11.69
MEAN	2.66	5.14	3.34	3.52
STD	2.07	3.74	2.69	2.44

3.3.2 Modelling based on Fiber Optic Data

Similarly, we test the model trained for induction welding process in KEE tool with the test samples. The prediction results include: 1) maximum high prediction error is 14°C; 2) maximum low prediction error is 23°C; 3) mean value of prediction errors is 1.4°C; 4) standard deviation of prediction errors is 2.0°C. The results show that the trained model can predict the temperature

varying very close to the ground truth. This also indicates that the designed machine learning model can model the induction welding process in KVE tool.

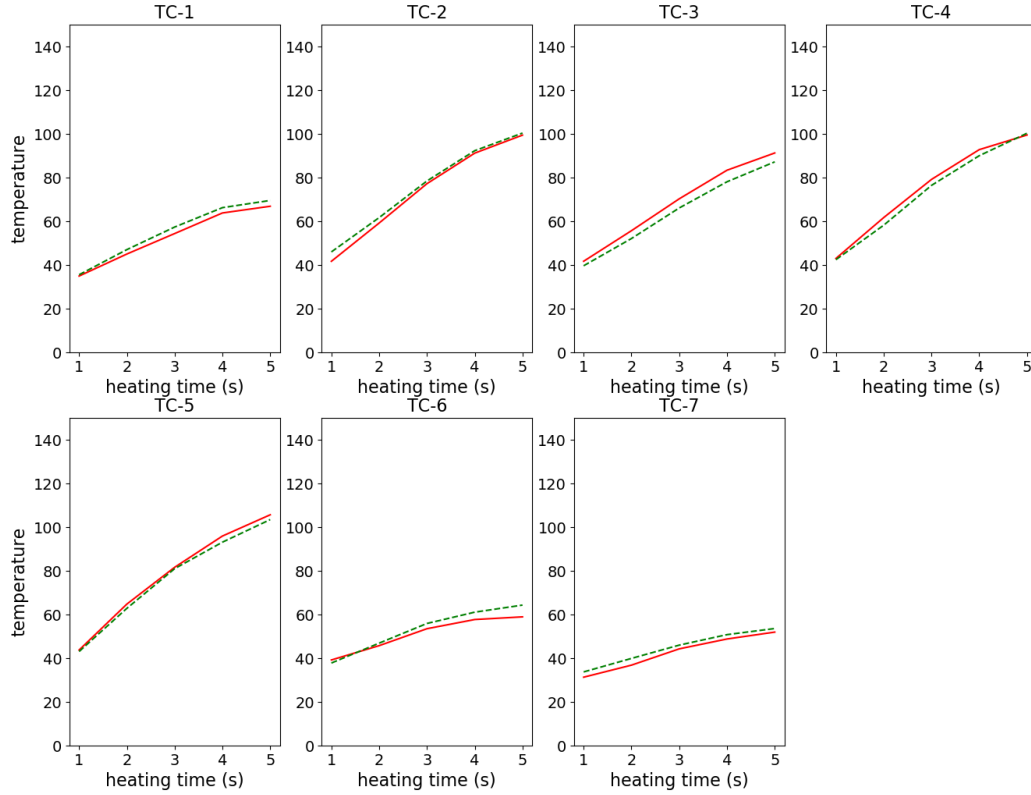


Figure 14. An illustration of the comparison between the predicted temperature varying during induction heating (red) and the ground truth temperature varying (green).

4. CONCLUSIONS

4.1 Conclusion

This paper proposed to use machine learning techniques to model the induction welding process for thermoplastic composite materials. To achieve this goal, we correlate induction welding parameters to temperature varying in laminate overlap by training neural networks. We collect two sets of induction welding data, which consist of induction welding parameters and the corresponding temperature varying, from induction heating experiments for PEKK laminates in vacuum bag and KVE tool, respectively. Based on the collected data, we designed two individual neural networks to model the induction welding processes. The testing results of the trained models demonstrate that the designed models can predict temperature varying based on induction welding parameters quite close to ground truth. This suggests that machine learning models can be used for modelling induction welding process for thermoplastic composite materials.

4.2 Discussion

To our best knowledge, this is the first study on modelling induction welding process for thermoplastic composite materials using machine learning techniques. Our models correlate induction welding parameters to temperature varying in laminate overlap during induction heating. Many further works can be explored to enhance this study. For example, to simplify the modelling, the induction welding experiments designed to acquire training data cover only limited variables that may influence the welding quality, while all other variables are kept constant in each experiment environment. In practice, there may be more complex variables to be considered during induction welding. Moreover, during all our induction heating experiments, the coil is relatively static to the laminate overlap, while the continuous induction welding has not been explored yet. We believe these works could be studied in the future work.

5. ACKNOWLEDGEMENT

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