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Hybrid modelling of the contact gap conductance heat transfer in welding process

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ABSTRACT

One of the difficulties encountered in thermal modelling of welding processes is the determination of the input parameters and in particular the thermal boundary conditions. This paper describes a novel method of determining these values using an artificial neural network to solve the Inverse Heat Conduction Problem using the thermal history as input data. The method has been successfully applied to models that represent the heat transfer to the backing bar with a contact gap conductance heat transfer. Both constant and temperature dependent values of the contact gap conductance heat transfer coefficient have been used. The ANN was able to find the contact gap conductance heat transfer successfully in both cases, however the error was significantly lower for the constant value. The key to successful implementation is the ANN topology (e.g. generalized feedforward), and the development of effective methods of abstracting the thermal data.

1. Introduction

Determining the input parameters and in particular the thermal boundary conditions in a numerical model of a welding process is often difficult. The boundary condition is not only difficult to measure experimentally, but is dependent on the type and temperature of the backing bar as well as the clamping used. If we consider thermal models of Friction Stir Welding (FSW) as an example, three different approaches have been used to describe the heat loss to the backing bar. The first method assumes that there is no heat loss at the bottom of the workpiece [1], giving an adiabatic boundary condition. This gives a significant over-estimation of the temperature. Alternatively, the heat loss can be represented by a convective heat transfer coefficient by excluding the backing bar in the model. Khandkar et al. [2] showed that this method was able to predict the peak temperature, however getting a good match with the cooling region was difficult. A more comprehensive method involves including the backing bar in the model and using a contact gap conductance heat transfer coefficient k (W m^{-2} K^{-1}), to represent the imperfect contact with the workpiece [1–3]. In this case, the contact gap conductance heat transfer k is implemented in the model with the flowing equation:

$$Q = k(T_W - T_B) \quad (1)$$

where Q is the heat flux from workpiece to the backing bar, T_W is the temperature at the workpiece and T_B is the temperature at the backing bar. This method has been claimed [2] to give a better prediction of the temperature profile than the convective heat transfer coefficient method. An even better prediction can be obtained with a variable contact gap conductance heat transfer coefficient. Variable values have been used by Simar et al. [1] who used a value which varied with the normal pressure. Colegrove et al. [3] applied a higher constant contact gap conductance heat transfer coefficient to the welded area under the tool and Shi et al. [4] used a temperature dependent contact gap conductance heat transfer coefficient. Recent work by Wang et al. [5] showed that a temperature dependent value based on an exponential function provided a good fit with experimental data for FSW. These methods were used because in FSW there is better contact under the tool due to the high temperatures and pressures – hence the reason for increasing the contact gap conductance with temperature. Regardless of the method used, there is the issue of obtaining representative values of the boundary condition, which is usually done by trial and error. The problem can be classified as an Inverse Heat Conduction Problem (IHCP) [6], which involves calculating the boundary conditions from measured outputs such as the temperature history.

One way of finding the boundary conditions in a more efficient manner is with an artificial neural network (ANN). An ANN is a numerical modelling technique that simulates the structure and functions of biological neural network [7]. It consists of an interconnected group of artificial neurons and processes information

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using a connectionist approach to computation. In most cases it is an adaptive system that changes its structure based on external information that flows through the network during the learning stage, which is used to investigate complex relationships between inputs and outputs or to find patterns in data.

ANN models can be linked with process models to find unknown boundary coefficients. In an analysis of the heat transfer that occurs between solid particles and a fluid, Sablani [8] and Sreekanth et al. [6] have demonstrated how an ANN can be used to solve an IHCP. Three steps were used to find the solution [8]:

- Use an analytic or numerical thermal model to generate a series of temperature–time histories from a series of training input parameters.
- Train the ANN using the outputs from the thermal model as inputs. Likewise the inputs to the thermal model are used as the outputs to the ANN.
- Once the ANN has been trained, a series of test input thermal profiles can be used to determine whether the ANN is able to accurately predict the outputs, i.e. the boundary conditions.

This method has been highly effective in determining the fluid to particle heat transfer coefficient. One important step in the analysis is to find a way of inputting the thermal history. The authors did this by identifying the slope and intercept of the thermal profile. Another important outcome of this work is the importance of the ANN topology to the success of the ANN model. Three important topologies are:

- The multilayer perceptrons network (MLP) [9]. This is a layered feed-forward network typically trained with static back-propagation. It can be used for most problems, but it requires a large amount of data for training.
- The generalized feed-forward network [9]. This is a variant of the MLP network which allows information to jump over one or more layers. It can solve problems more efficiently than an MLP network with less training data, however it needs more time for training.
- The modular feed-forward network [10]. This has the most sophisticated structure, and the information is processed through several parallel MLPs, which are then recombined. This network requires the least training data.

The back propagation algorithm is the most common way of adjusting the weights in the neural network. There are however two gradient decent methods which are used to adjust the local weights. These are the momentum method and the Levenberg–Marquardt (LM) algorithm, which has the advantage of being higher order.

Some authors have applied similar concepts to welding processes. Weiss et al. [11] developed a similar hybrid modelling approach and applied it to hybrid laser welding. The model automates the determination of the fitting parameters for the thermal model using an ANN. However, rather than using thermal profiles as inputs, the author used the dimensions of the fusion zone. Alternatively, genetic algorithms can be used to find the adjustable parameters in models of FSW [12] and arc welding [13].

The aim of this work is to find the input parameters and in particular the heat loss to the backing bar for a simple welding process using a hybrid finite element (FE)/ANN model.

2. Method

2.1. Thermal model

A simple FE thermal model is developed in COMSOL multiphysics, and the geometry is shown in Fig. 1. This model only calculated the heat flow during the welding process to simply the case for analysis. The model is steady state and only half the geometry is modelled because of the symmetry along the welding axis. Gaussian power distributions have been used by many researchers [14–18] to represent the heat input from a welding arc. It can also be used to represent the power input from a laser process [19]. The Gaussian heat flux q applied to a semi-circle, as shown in Fig. 1, is given by:

$$q(r) = Q_{weld} \cdot \frac{\exp\left(\frac{-r^2}{r_s^2}\right)}{\left(1 - \exp\left(\frac{-r_h^2}{r_s^2}\right)\right) \cdot \pi \cdot r_s^2} \tag{2}$$

where Q_{weld} is the total power input to the weld; r_h is radius of a semi-circle. In this study r_h is set to 15 mm; r is distance from the centre of the spot; r_s is a constant which describes the distribution of the power. All the models in this study use a value of 5 mm.

The welding speed is set to 400 mm/min and is fixed for all the trials in this study. Note the welding speed is not included in the ANN model because it is a known parameter in any welding experiment. The properties of the workpiece and backing bar are shown in Table 1. Please note that in this simple model constant values are used and latent heat effects are ignored. A convective heat transfer coefficient of 10 W m^{-2} K^{-1} by Shi et al. [4] was used on the top surface of the workpiece and a value of 1000 W m^{-2}K^{-1} from Colegrove et al. [23] was used on the underside of the backing bar. The adjustable parameters in the model are the total power input, Q_{weld} and the contact gap conductance heat transfer coefficient, k. The contact gap conductance heat transfer coefficient describes the imperfect heat transfer between the workpiece and the backing bar due to asperity contact. Two different models are used in this work. One model uses a constant value of k and the other uses a temperature dependent value [4]. Although Shi et al. [4] does not provide a function for k, the values approximate an exponential of the form:

$$k = a \cdot \exp(b \cdot T) \tag{3}$$

where T is the temperature in unit of K, a and b are constants whose values are approximately 22.16 W m^{-2} K^{-1} and 0.0107 K^{-1} respectively for the data in this paper.

2.2. ANN model

The ANN methodology is the same as for the Inverse Heat Conduction Problem described in Sablani [8] previously. Two stages of applying an ANN model are described in Fig. 2(a). The input parameters to the ANN are the thermal profiles from the thermal model which are obtained at distances of 10, 15 and 20 mm from the weld centreline, mid-thickness. The outputs are the weld power input and the contact gap conductance heat transfer coefficient.

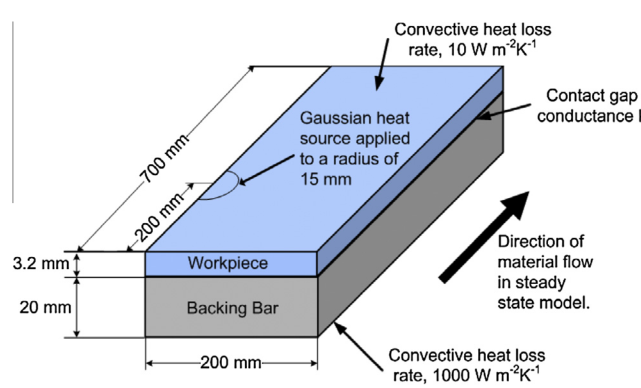

Fig. 1. Geometry used for the FE model.