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Differential Evolution algorithm applied to FSW model calibration

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Abstract. Friction Stir Welding (FSW) is a solid state welding process that can be modelled using a Computational Fluid Dynamics (CFD) approach. These models use adjustable parameters to control the heat transfer and the heat input to the weld. These parameters are used to calibrate the model and they are generally determined using the conventional trial and error approach. Since this method is not very efficient, we used the Differential Evolution (DE) algorithm to successfully determine these parameters. In order to improve the success rate and to reduce the computational cost of the method, this work studied different characteristics of the DE algorithm, such as the evolution strategy, the objective function, the mutation scaling factor and the crossover rate. The DE algorithm was tested using a friction stir weld performed on a UNS S32205 Duplex Stainless Steel.

1. Introduction

Even though Friction Stir Welding (FSW) is a complex welding process to model, some numerical approaches were developed to provide enough process detail and accuracy while keeping the solution time viable. One approach, which is the one used in this work, is based on a Computational Fluid Dynamics (CFD) model that is useful to obtain the material and heat flow of the weld.

Independent of the numerical model chosen, they all have adjustable parameters that control the heat transfer and the heat input of the process. These parameters are used to calibrate the model based on welding experiments and they are generally determined using a trial and error approach. Since this methodology can be very time consuming and can lead to a suboptimal calibration, an alternative solution is to apply an optimization algorithm to determine these parameters. In this context, this work proposes to apply the Differential Evolution (DE) algorithm to calibrate a FSW CFD model.

DE is an evolutionary strategy algorithm that develops an initial population of solution vectors using operations such as mutation, crossover and selection. It is reported in the literature that the performance of DE is significantly affected by three characteristics: the size of the population (NP), the mutation scaling factor (F) and the crossover rate (CR). The values of these characteristics are also evaluated in this work, since they can directly affect the total time required to calibrate the model.

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In this work, recorded thermal cycles of a friction stir weld performed on a UNS S32205 duplex stainless steel were used as calibration data for the CFD model implemented using the Finite Element (FE) software Comsol® v4.3a.

2. Methodology

2.1. Experimental procedures

Plates of duplex stainless steel UNS S32205 were friction stir welded, both with dimensions of 350 mm × 150 mm × 10.0 mm. The welding was performed using a polycrystalline cubic boron nitride in metallic matrix of W-Re (PCBN-40%W-Re) tool with shoulder diameter of 25.0 mm and pin length of 6.0 mm. The welds were produced using a rotational speed and a weld speed of 200 rpm and 100 $mm.min^{-1}$, respectively. The axial load during weld was controlled and equal to 15 kN.

Thermal cycles were recorded during the welding process using type K thermocouples located at five different distances from the weld centreline: -8.0 mm (T4), -4.0 mm (T5), 0 mm (T1), 4.0 mm (T3) and 8.0 mm (T2). Negative position values represent the retreating side (RS) of the weld, while positive values represent the advancing side (AS) of the weld (figure 1). All the thermocouples were attached 2.0 mm deep from the workpiece top.

2.2. FSW CFD model description

This work implemented a 3-dimensional steady-state CFD model using the Finite Element software Comsol® v4.3a, and it is based on the model proposed by Colegrove et al [1]. In this CFD simulation, the welded material is modelled as an incompressible non-Newtonian fluid with a viscoplastic constitutive behaviour.

In FSW, the tool rotational and translational movement generates heat by friction and/or by plastic deformation of the material. This energy input is modelled as a surface heat flux applied at the tool/workpiece interface for the frictional heat generation and as a volumetric heat source for the heat generated by plastic deformation. The balance between these sources of heat is determined by the contact state variable δ, which lies in the [0, 1] range. This variable defines if the process is generating heat by friction ($\delta=1$) or if it is generating heat by plastic deformation ($\delta=0$). An intermediary condition is also possible ($0<\delta<1$).

During the welding process, the heat generated is distributed in the workpiece by conduction but it is also lost to the backing plate, to the tool and to the environment. Among these three sources of heat loss, the most significant to the process is the heat loss from the workpiece to the backing plate. This thermal boundary condition considerably affects the workpiece thermal cycles influencing not only the peak temperatures but also the cooling rates. For this work, this boundary condition is modelled as a contact gap conductance to represent the imperfect contact between the workpiece and the backing plate and it is represented by the equation $k = a.\exp(bT)$ as proposed by Wang et al [2]. Figure 2 shows all the boundary conditions employed in the model. In this equation, k is the gap conductance, T is the temperature at the interface between the workpiece and the backing plate, and a and b are constants that need to the calibrated. For this model, the constants a, b and δ were determined by the DE algorithm.

2.3. Differential Evolution method

DE is a stochastic parameter optimization algorithm that operates using similar steps as employed by traditional evolutionary algorithms such as mutation, crossover and selection. For this work, the DE algorithm was implemented as described in the work of Storn and Price [3] and the objective function used by selection algorithm is expressed by equation 1 as follows:

$$\begin{cases} f(a,b,\delta) = \left[\left(1-\frac{T_{2\,\mathrm{mod}}}{T_{2\,\mathrm{exp}}}\right)^2 + \left(1-\frac{T_{4\,\mathrm{mod}}}{T_{4\,\mathrm{exp}}}\right)^2 + \left(1-\frac{A_{2\,\mathrm{mod}}}{A_{2\,\mathrm{exp}}}\right)^2 + \left(1-\frac{A_{4\,\mathrm{mod}}}{A_{4\,\mathrm{exp}}}\right)^2 \right]^{1/2} \\ \textit{subject to} \quad 1 \le a \le 100 \\ \qquad\qquad\quad 0.001 \le b \le 0.050 \\ \qquad\qquad\quad 0 \le \delta \le 1 \end{cases} \tag{1}$$

The objective function represents the calibration error from the FSW model and the experimental measurements. This equation uses information of the thermal cycles obtained from the model and the experiments to select the values of the parameters a, b and δ that best calibrates the model. This equation uses the peak temperature values of predicted and measured thermocouples T2 and T4, expressed by the terms T_{2mod}, T_{2exp}, T_{4mod} and T_{4exp}, where the subscript *mod* and *exp* represents the peak temperatures obtained by the model and by the experiments, respectively. The terms A_{2mod}, A_{2exp}, A_{4mod} and A_{4exp} in equation (1) represents the integral of temperature over time. The subscripts in these terms have the same meaning as the ones used for the peak temperature.

Only the thermocycles recorded by thermocouples 2 and 4 are used by the DE algorithm because they are located far enough from the FSW tool to avoid any displacement from their original position. The thermocycles recorded by thermocouples 1, 3 and 5 are used to compare the model results with the experimental measurements after calibration.

In this DE algorithm, the crossover method chosen was the binomial method, and two mutation schemes (DE/rand/1 and DE/best/1) were used to evaluate the efficiency and accuracy of the algorithm. This work also studied the effects of the DE parameters (CR, F) for the convergence speed of the optimization algorithm. The values analysed for CR were 0.4 and 0.8, and 0.1 and 0.9 for F. These values were based on the work of Das and Suganthan [4] where the authors opine about good first choices for them. The size of the population NP was set equal to nine for all the runs and the number of generations was limited to fifty generations.

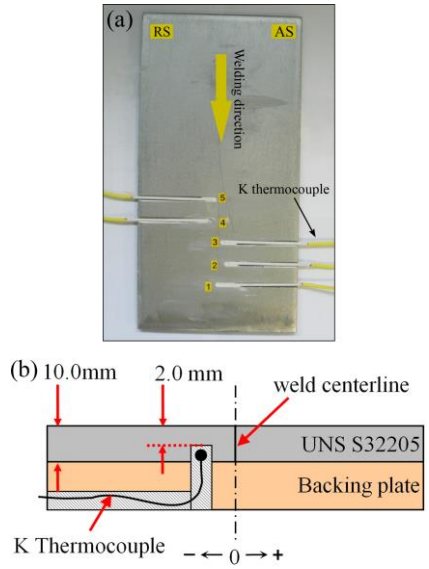

Figure 1. (a) Thermocouples positions for thermal cycle measurement; (b) thermocouples' schematic positions.

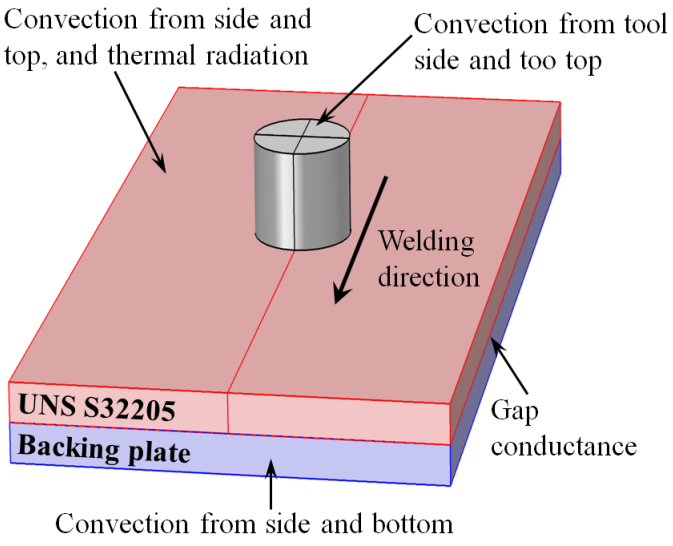

Figure 2. Finite element model geometry and boundary conditions applied to the model.

3. Results and discussion

Table 1 shows the results of the algorithm runs with the final values obtained for the objective function and the optimization parameters (a, b and δ). Runs 1-4 were tested with a randomly initialized population to evaluate the convergence speed for different mutation strategies and values of CR and F. Runs 5-7 were tested with a badly conditioned initial population. Figure 3 shows the evolution of the mean value for the objective function over each generation.

Table 1. Final values obtained for the optimization parameters in each DE algorithm run.

Run #	Mutation	CR	F	$f(a, b, \delta)$ $[10^{-2}]$	A	b $[10^{-2}]$	δ
1	DE/rand/1	0.1	0.4	14.50 ± 0.05	31.64 ± 17.37	0.80 ± 0.17	0.71 ± 0.03
2	DE/rand/1	0.9	0.4	13.97 ± 0.00	26.98 ± 0.04	0.74 ± 0.00	0.71 ± 0.00
3	DE/rand/1	0.9	0.8	14.09 ± 0.01	79.22 ± 5.15	0.50 ± 0.02	0.72 ± 0.01
4	DE/best/1	0.9	0.4	14.00 ± 0.00	37.27 ± 0.02	0.67 ± 0.00	0.72 ± 0.00
5	DE/best/1	0.1	0.4	33.73 ± 5.63	86.72 ± 33.85	2.25 ± 1.06	0.54 ± 0.06
6	DE/best/1	0.9	0.4	14.11 ± 0.05	65.01 ± 15.30	0.55 ± 0.04	0.72 ± 0.01
7	DE/best/1	0.9	0.8	34.01 ± 3.79	42.06 ± 8.54	2.42 ± 0.93	0.52 ± 0.04

Runs 1-4 and run 6 reached convergence for a mean objective function equal to around 0.14, with run 4 being the fastest to achieve convergence (15 generations to stop the algorithm) while run 1 was the slowest one (maximum number of generations reached). The slow convergence of run 1 can be attributed to the low value of CR, which is not appropriate for a FSW model where the functions parameters are not separable. Runs 1-4 show a tendency that a value of F equal to 0.4 performs better than 0.8, which can also be noted by the convergence of runs 5-7. Without further runs, no conclusion regarding the mutation strategy can be made, but the DE/best/1 method seems to perform a little better than DE/rand/1. Even though runs 5 and 7 converged with a small number of generations, their results cannot be used since the confidence interval for the objective function and the optimization parameters a and b are too large in comparison with the other runs. So, for an optimization procedure to be considered successful, the confidence interval must be small.

For this model, the final values obtained from run 2 are the ones that better calibrate the model. So, the FSW model can be successfully calibrated using the DE algorithm, eliminating the need for a trial and error approach.

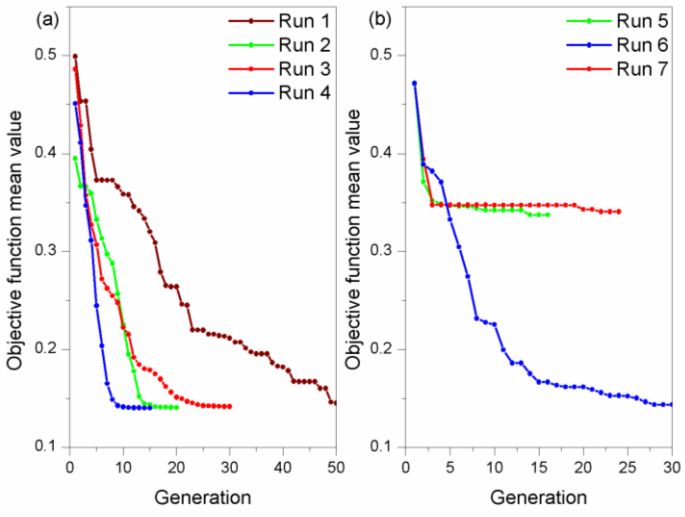

Figure 3. Objective function mean value evolution: (a) runs 1-4; (b) runs 5-7.

4. Conclusions

A DE algorithm can be successfully used to calibrate a FSW model using experimental data from recorded thermal cycles. This study found that a value of 0.9 for CR and 0.4 for F gives a faster convergence for the algorithm, but no final conclusions can be made regarding the mutation strategy. Still, a larger number of numerical experiments need to be made to better optimize the DE algorithm parameters.

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6. References

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