Design and Optimization of Welded Products Using Genetic Algorithms, Model Trees and the Finite Element Method

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Abstract. One of the fundamental requirements in the phases of design and manufacture of any welded product is the reduction of residual stresses and strains. These stresses and strains can cause substantial changes in the geometry of the finished products which often require subsequent machining in order to fit to the dimensions specified by the customer, and are usually caused by the contribution of an external heat flux in a small area. All welded joints contain welding seams with more or less regular geometry. This geometry gives the welded product the strength and quality required to support the mechanical demands of the design, and is affected by the parameters controlling the welding process (speed, voltage and current). Some researchers have developed mathematical models for predicting geometry based on the height, width and cord penetration, but is a difficult task as many of the parameters affecting the quality and geometry of the cord are unknown. As the welded product becomes more and more complex, residual stresses and strains are more difficult to obtain and predict as they depend greatly on the sequence followed to manufacture the product. Over several decades, the Finite Element Method (FEM) has been used as a tool for the design and optimization of mechanical components despite requiring validation with experimental data and high computational cost, and for this reason, the models based on FEM are currently not efficient. One of the potential methodologies used for adjusting the Finite Element models (FE models) is Genetic Algorithms (GA). Likewise, Data Mining techniques have the potential to provide more accurate and more efficient models than those obtained by FEM alone. One of the more common Data Mining techniques is Model Trees (MT). This paper shows the combination of FEM, GA and MT for the design and optimization of complex welded products.

Keywords: Genetic Algorithms, Optimization, Finite Element Method, Model Trees, Welding Process.

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1 Introduction

The welding process is a technique widely used in the manufacture of many industrial products. This process requires an external supply of heat flux concentrated in a small area at very high temperature. These high temperatures generate localized residual stresses and strains, which cause harmful defects in manufactured products. Likewise, poor selection of welding process parameters (speed, voltage and current) and a suboptimal manufacturing sequence can further amplify these residual stresses and strains. The design and optimization of any welded product based solely on experimental analysis or trial-and-error results in unacceptable high costs. The advantages of using the Finite Element Method (FEM) to reduce such costs are well known [1]. FEM is classified as a hard computing method and can be used to design and optimize any product or process. This method has also known disadvantages, including the large amount of time and computational cost needed in each simulation especially if the FE model is nonlinear. Generally, FE models of welded product have to take into account the plasticity of materials and must be made in 3D in order to capture the distribution of temperature and residual stresses more accurately. On the other hand, the use of models based on soft computing methods has been proved to be useful to solve complex problems [2, 3]. Soft Computing includes a set of techniques based on handling of imprecise and uncertain information. Artificial Neural Networks (ANN) and Genetic Algorithms (GA) are known branches of soft computing, which can be combined with each other. Some researchers have used ANN models for predicting the geometry of the weld bead based on the parameters of the welding process. In this paper, the prediction of weld bead geometry (width and height) was modeled with models trees (MT), some based on heuristic methods and some based on evolutionary algorithms, because these models had a higher accuracy and effectiveness than ANN in this case. This paper shows the optimized design process based on the combination of Genetic Algorithms (GA), Model Trees (MT) and Finite Element Method (FEM) for industrial products soldered with the Gas metal arc welding process (GMAW process).

2 Proposed Methodology

The proposed methodology for the optimized design process based on the combination of GA, MT and FEM for industrial products welded with GMAW is applied in the following steps (Figure 1).

2.1 Experimental Data

This first stage consists on the manufacture by GMAW of a number of specimens in order to generate data to make the models of the weld cord (with MT). Input Parameters (voltage, current and speed) and Output Parameters (height and width of the cord) are taken into consideration to set up the experiments and in this way to obtain the models of the Weld Geometry. Moreover, during fabrication of the specimens, the temperatures of the cord and welded parts were recorded with a Thermographic camera in order to use the temperature data to validate the FE model.

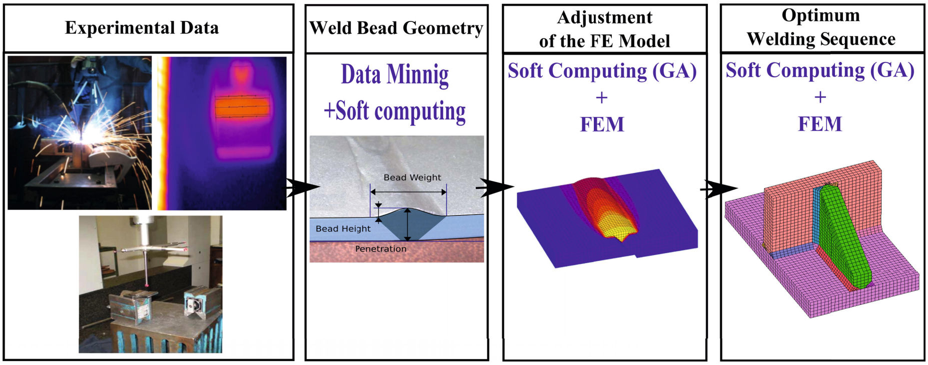

Fig. 1. Proposed methodology for design and optimization of welded products

2.2 Weld Bead Geometry

All welded joints have welding seams with a more or less regular shape. These cords are attached to the parts forming the product manufactured and its geometry is affected by the parameters controlling the welding process (speed, voltage and current) [4]. The geometry of the weld cord gives the welded product the strength and quality required to support mechanical demands of its design.

- **Modeling the Geometry of the Weld Bead**

Research papers discussing the modeling of welding processes are still relatively scarce probably because many of the parameters affecting the quality and geometry of the cord are still unknown. In this sense, some researchers [5] have developed mathematical models for predicting linear cord geometry based on their height, width and cord penetration. Through the widespread use of artificial intelligence, the prediction of the cord geometry has been performed using techniques based on ANN. For instance Srikanthan and Chandel [6] developed one of the first ANN models to predict with sufficiently accurate the bead geometry. More recently better ANN models have been developed to predict and optimize the width of the weld bead using two training algorithms [7].

Other techniques like Regression Trees can be used for numeric prediction. In this methodology, it is going to be used three kinds of regression trees, two built by Heuristic methods and one built by Soft Computing methods in order to determinate which of these machine learning techniques is more suitable to solve the study problem. The three regression trees are:

- Based on a CART algorithm [8, 9] (TC1).
- Based on Quinlan's M5 algorithm [10, 11] for inducing trees of regression models (TC2).
- Based on search over the parameter space of trees using global optimization methods like evolutionary algorithms [12] (TC3).

The first method is based on a CART algorithm, which uses recursive partitioning methods to build the model in a forward stepwise search. This approach is known to be an efficient heuristic where splits are chosen to maximize homogeneity at the next step. Splitting is made in accordance with squared residuals minimization algorithm which implies that expected sum variances for two resulting nodes should be minimized.

The second method improves the idea of a decision-tree induction algorithm using linear regression as a way of making quantitative predictions where a real-valued dependent variable y is modeled as a linear function of several real-valued independent variables $x_1, x_2, ..., x_n$, plus another variable that reflects the noise, ε (Equation 1).

$$y = \varepsilon + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n \tag{1}$$

In the regression tree M5' each leaf contains a linear regression model based on some of the initial attribute values. In that way, it is combined a conventional decision tree with the possibility of linear regression functions at the nodes.

The third kind of tree uses an alternative way to search over the parameter space of trees using global optimization methods, like evolutionary algorithms. In the first two methods the split rule at each internal node is selected to maximize the homogeneity of its child nodes, without consideration of nodes further down the tree, but using a computationally efficient greedy heuristic that often yields reasonably good results. Therefore in some cases it is interesting to use stochastic optimization methods like evolutionary algorithms, like in the case of evtree which implements an evolutionary algorithm for learning globally optimal classification. These algorithms are inspired by natural Darwinian and are used to optimize a fitness function, such as error rate, varying operators that are modifying the tree structure. In this case, accuracy is measured by Bayesian Information Criterion (BIC) (Equation 2) [13].

$$BIC = -2\log\left(L\left(\hat{\vartheta}; y\right)\right) + K\log(n) \tag{2}$$

These trees offer the ability to analyze which of the independent variables possess the strongest degree of influence on the tested data, ability that other techniques like artificial neural networks or support vector machines cannot offer.

2.3 Adjustment of the FE Model

One of the first FE models in which the welding process was simulated was in 1995 [14]. The model was formulated in 3D and considered the plasticity of the material and generated the residual stresses and strains in the manufactured product. More recently and based on validation by deformation and strain gauges, a 3D FE model was created to calculate the temperatures, deformations and residual stresses in welded joints [15]. Other researchers [16] used the FEM to model a welding process, validating the model by angular deformations and temperatures measured with thermocouples. The FE model presented in this paper, was a model formulated in 3D, which considered the plasticity of the materials and was simulated as transient nonlinear thermo-mechanical problem.

- **Validating the Proposed FE Model**

In this case the FE model was validated with the temperature values that were collected by a Thermographic camera. The Weld Flux in the FE model was modeled according to the theory of double ellipsoidal shaped [17]. The FE model had 11 different parameters to adjust to allow for validation, so GA was used as the adjustment technique [18]. This adjustment process was conducted as follows: Firstly, a range for the 11 parameters was established. Subsequently, a number of individuals (i.e. FE models) from the initial generation or generation 0 were randomly generated. Once all the individuals were simulated, the objective function J_T was applied (Equation 4). This objective function was defined as the average difference between the temperature obtained from the key nodes of the FE model and the temperature obtained from the thermal camera at each instant of time. The best individuals were those with the lowest value in the objective function and became the first generation or generation 0.

$$J_T = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{TFE_i} - Y_{TTH_i}\right| \tag{3}$$

The next generation (first generation and subsequent generations) were generated using crossing and mutation. The new generation was made up as follows:

- 25% comprised the best individuals from the previous generation (parents of the new generation).
- 60% comprised individuals obtained by crossovers from selected parents.
- The remaining 15% was obtained by random mutation, through a random number used to modify the chromosomes within the pre-determinated ranges.

The aim was to find new solutions in areas not previously explored.

2.4 Optimum Welding Sequence

Since the majority of the mechanical component is complex to manufacturing, the final stresses, and temperature are more difficult to obtain and predict, and depend mainly by the manufacturing path used. Some researchers ([19, 20, 21]) have used experimental data and GA to optimize the welding sequence of complex welded products. This combination requires a significant amount of actual specimens to be welded with different sequences and welding parameters, so that the final cost is very high. In this paper, the combination of the FEM with GA was used to optimize the welding sequence in order that the welded products present the lowest state of stress and deformation possible.

3 Results

- **Results of Weld Bead Geometry**

In the case studied in this work, classic trees, lineal regression trees and evolutionary algorithms trees to predict width and height properties in weld beads are used. In order to improve the quality of the predicted models, the data is normalized between 0 and 1. Once the data is normalized, and using the 33 instances available from the experiments, 23 are chosen randomly to train the model and 10 to test it. The trees are built using different splitting index but with a minimum number of 4 observations that must exist in a node in order for a split to be attempted. The complexity parameter must be 0.01 where any split that does not decrease the overall lack of fit by this factor is not attempted. And the maximum depth of any node of the final tree must be less than 5.

Using CART methodology, where every class value is represented by the average value of instances that reach the leaf, it is got in the test process a MAE = 21.56% and a RMSE = 32.97% for width weld beads, and a MAE = 33.08% and a RMSE = 45.73% for height weld beads (Figure 2).

To improve these poor results, it is used the second kind of trees, where a linear regression model predicts the class value of instances that reach the leaf, it is got in the test process a MAE = 11.66% and a RMSE = 13.51% for width weld beads, and a MAE = 8.43% and a RMSE = 17.43% for height weld beads (Figure 3). In this study case, the obtained model to predict width weld beads contains the 10 linear models that belong at the 10 leaves, labeled LM1 through LM10. Where, for example, the Equation 3 defines the lineal regression that all the cases in leaf LM1.

$$Width = 0.405 \cdot Current - 0.4087 \cdot Speed + 0.3881 \cdot Voltage + 0.3112 \tag{4}$$

And in order to see what is the different between using classic methods, like case 1 and 2, and methods based on evolutionary algorithms, like case 3, it is used the third kind of trees that provides evolutionary methods for learning globally optimal regression trees. It is got in the test process a MAE = 13.85% and a RMSE = 17.94% for width weld beads, and a MAE = 10.25% and a RMSE = 19.04% for height weld beads (Figure 4).

To compare these three models the following parameters are used: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) [22]. In Table 1, it is showed that the use of evolutionary algorithms, when the tree is built, improves a lot the accuracy of the model, but improve more if instead of fix the value of the instances in each leaf with an average value, it is used a lineal regression model in each one.

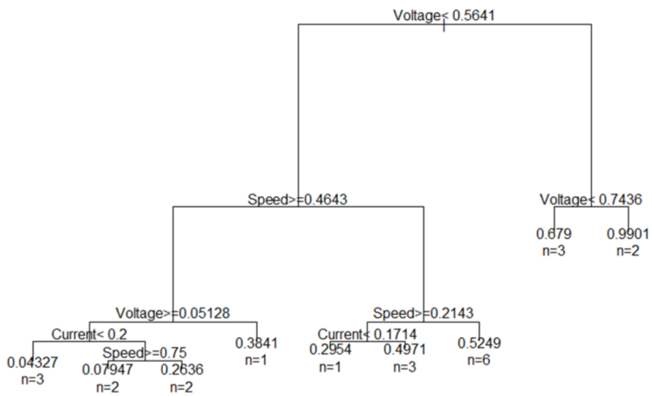

Fig. 2. Tree obtained in the case 1, where every class value is represented by the average value of instances that reach the leaf using CART methodology. In this case tree to predict width beads.

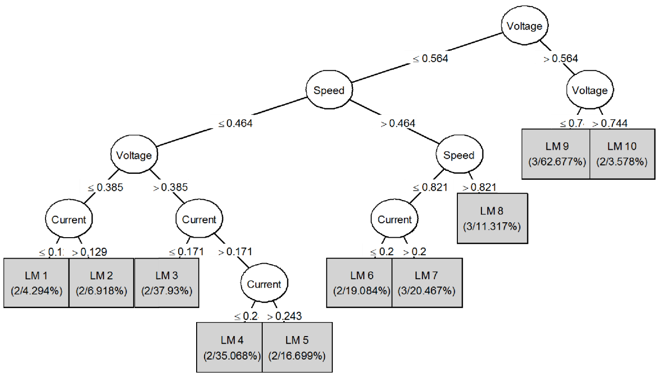

Fig. 3. Tree obtained in the case 2, where a linear regression model predicts the class value of instances that reach the leaf using Quinlan's M5 algorithm. In this case tree to predict width beads.

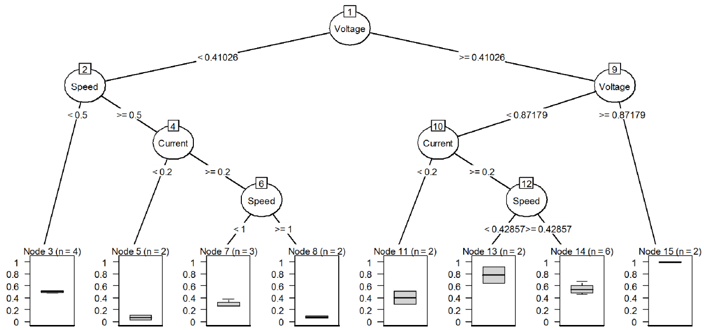

Fig. 4. Tree obtained in the case 3, where every class value is represented by the average value of instances that reach the leaf using evolutionary algorithms in the splitting. Constructed by evtree algorithm. In this case tree to predict width beads.

Table 1. Results obtained in the three models analyzed in the study

	Width weld beads			Height weld beads		
	TC1	TC2	TC3	TC1	TC2	TC3
MAE (%)	21.56	11.66	13.85	33.08	8.43	10.25
RMSE (%)	32.97	13.51	17.94	45.73	17.43	19.04

- **Results of Finite Element Model for the Weld Bead**

In Figure 5 is shown the temperature field obtained by a Thermographic camera and by the FE model in 6 seconds. The FE model shown in these images corresponds to the best individuals obtained from the 3rd generation. In this case, the objective function J_T not vary significantly with respect to the objective function from the 2nd generation and for this reason, the 11 parameters which define the FE model were fixed and used for optimizing the welding sequences to construct then the complex welded product.

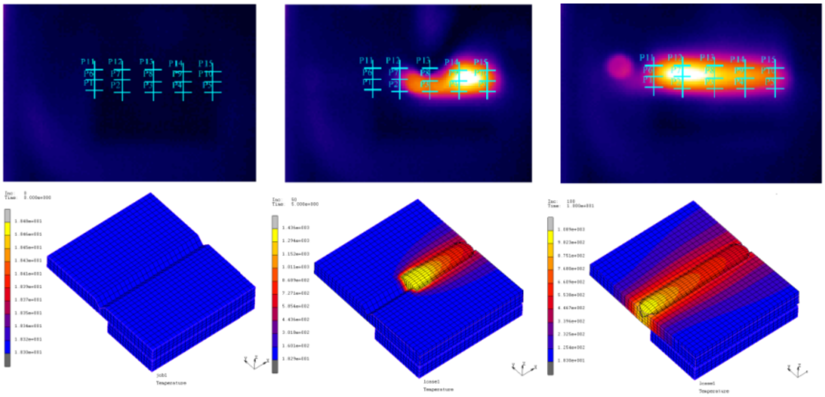

Fig. 5. Comparison between the temperature distribution obtained with thermographic camera and with the FE model for a single weld bead

- **Optimizing the Welding Sequence**

In the left side of Figure 6 is shown two different welding sequences, which involve different points of start and end of the weld, as well as different configuration parameters (speed, current and voltage). The numbers represent the different start points of each of the cords that form the welded product. Each of these welding sequences has been optimized by GA in order that the temperature distribution was as uniform as possible while the deformation was between established ranges. The right side of Figure 6 shows the temperature field induced in the welded product with these two different sequences.

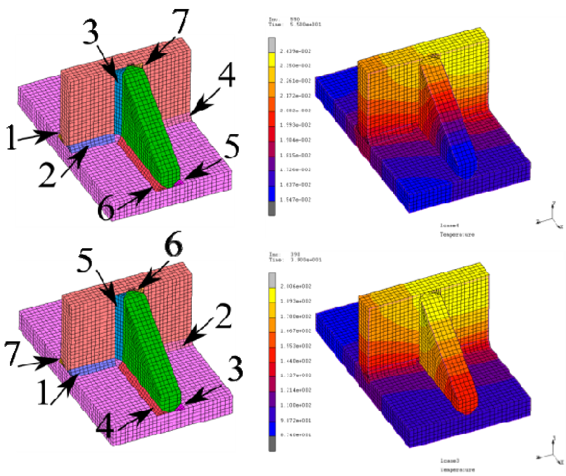

Fig. 6. Different welding sequences used to produce the same complex welded product

4 Conclusions

This paper demonstrates an efficient methodology that may be used to optimize the design of welded joints. An initial FE model is validated against experimental results with the assistance of genetic algorithms. The validated FE model may then be used to optimize more complex welding processes. By combining FEM, GA and MT techniques, it has been shown that it is possible to optimize complex welding processes and to, potentially, automate this process.

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