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Author(s)	Goldak, John; Asadi, Mahyar
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# Computational Weld Mechanics and Optimization of Welding Procedures, Welds, and Welded Structures

John GOLDAK\* and Mahyar ASADI\*\*

\* Goldak Technologies inc., Ottawa, K1V 7C2 Canada

\*\* Carleton University, Ottawa, K1S 5B6, Canada

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## 1. Introduction

Progress towards integrating computational optimization with Computational Weld Mechanics (CWM) is presented. Optimization requires evaluating a large number of CWM problems. To be practical, the computing time for the CWM must be short and the time to set up the necessarily large number of CWM projects must be short. The complexity borne by the user in setting up the projects and in post-processing the projects must be minimized. Two examples are shown for parametric design space exploration of an edge welded bar of Aluminum 5052-H32. The combinatorial optimization problem of choosing the sequence of welds that minimizes distortion in a welded structure is briefly discussed. The CWM is coupled to the optimization framework by a Design of Experiment (DOE) matrix.

## 2. Background

In the foreword of [1] Hamming states, "The purpose of computing is insight, not numbers." The authors' believe that insight is very important in CWM. This paper takes the view that the goal of CWM is to optimize the design of weld procedures, welds and welded structures. To achieve that goal CWM must be integrated with computational optimization.

### 2.1 Optimization

Computational optimization of structures developed rapidly in the period from 1980 to 2000 in parallel with CWM but the two have been and largely remain quite separate disciplines. The exception has been the work of Michalaris [2] and the references therein. Van der Platts [3] has a nice introduction to computational optimization. Nocedal and Wright [4] and Bertsekas [5] have more advanced mathematics. Optimization requires a cost or objective function. In this paper the cost function is a function of design variables and this function is to be minimized or maximized. Optimization has three arms; continuous optimization, combinatorial optimization and integer programming. In continuous optimization, the design variables are at least locally continuous functions, e.g., in structures, the cost function is often the weight or stiffness of a structure. In addition to the cost function, equality and inequality constraints are usually imposed. In a stress analysis, the conservation of momentum, i.e., the balance of forces, and the constitutive equations are equality constraints. Examples of inequality constraints

are variables defining the weight, volume, area or length that each must be greater than zero.

The optimization process starts with an initial guess or trial solution. The continuous optimization process then follows a path in the 'mathematical space' defined by the design variables in the cost function. The minimum requirement for continuous optimization is the capability to evaluate the cost function for any feasible set of design variables, i.e., at any point in the feasible design space. If in addition one can evaluate the gradient of the cost function wrt to the design variables if it exists, then the computing time can usually be reduced at the cost of implementing and validating the software needed to evaluate the gradient. If in addition, the second derivative of the cost function can be evaluated if it exists, then computing time could usually be further reduced at the cost of more software development. Using either or both the gradient and second derivative might make the setup more difficult and time consuming for the user.

In combinatorial optimization, one seeks the optimal combination of some set of variables, e.g., choosing the sequence of weld joints or weld passes that minimize distortion is an important and challenging problem in welding. The fundamental mathematical structure in combinatorial optimization is a graph. The solution is the path in this graph that minimizes the objective function. A famous combinatorial optimization problem is the travelling salesman problem [6]. This class of problems is often very challenging. For example, to choose the optimal sequence of 10 welds when each weld can be welded either backward or forward, one must choose from  $10^2 \times 10! = 362,880,000$  sequences. Clearly one could not evaluate all of these sequences using CWM.

In integer programming problems, one chooses from finite set, e.g., choose a pipe size from the sizes in a given catalogue. Space does not permit integer programming to be discussed further in this paper.

### 2.2 Design of Experiment

Design of Experiments (DOE) has a long history in mathematics. Taguchi [7,8,9] is arguably the most notable contributor to DOE in manufacturing and engineering. A fundamental mathematical structure in DOE is the DOE matrix. Each row in this matrix defines one experiment and each column in that row defines the value of the design variable associated with that column. The statistical theory that can be used to design an optimal DOE matrix is mature.

Such a design is based on the available knowledge. Usually the DOE is intended to specify physical or real experiments. However, the DOE matrix can be used to specify numerical experiments.

These various optimization types are all mature disciplines with many textbooks, journals and conferences. Only rarely do these papers deal with optimization of welds, welding procedures or welded structures.

### 2.3 Optimization, Welding and CWM

Arc welding technology began slightly more than 100 years ago. It was largely developed by experiment, i.e., largely trial and error tests guided by people's intuition and insight. Although much of electrical engineering was based on Maxwell's equations, the magneto-hydro-dynamics of the arc and the CFD of the weld pool were too complex to be solved and to a large extent remain open problems today. Distortion and residual stress involves involve plastic deformation. It was not until 1970 that Ueda [5] did the first FEM computation of residual stress in welds. From 1980 to 2000 CWM research evolved rapidly. From 2000 to the present, CWM is being adopted rapidly by industry.

In the authors' judgment, CWM is currently not well integrated with optimization software. The important book [7], edited by Michalaris, describes the state of the art of techniques to minimize distortion and residual stress in welded structure. The fact that none of the examples in this book were solved by integrating formal computational optimization and CWM suggests that there is work to be done.

Since 2007, the authors have worked to integrate computational optimization and CWM. In this paper, a brief overview of several examples is provided to try to present an overview of what has been accomplished. Section 2.4 discusses the notion of a parametric design space. Section 3 discusses minimizing camber in an edge welded bar by prebending, i.e., prescribing displacements, and by applying side heaters. Section 4, discusses direct optimization with least square polynomials to optimize prebending. Section 5, briefly summarizes work on computing the optimum sequence of weld passes to minimize distortion. Section 6 provides a closely statement.

### 2.4 Parametric Design Space

A continuous problem with a quite large range of possible variation in the design parameters could be discretized by a certain step size for each design parameter for a full or reduced set of discretized points in a DOE matrix to give a well-covered map from the design parameters to a response surface, i.e., parametric design.

The parametric design space for the authors' computer model for CWM has about 300 parameters. Most optimization and control applications of CWM are defined on a small sub-space of this parametric space, often with dimension less than 10, i.e., fewer than 10 design parameters would be varied. The CWM parameters can be categorized as below.

- **Weld Process**, e.g., process type, weld power, travel speed, double ellipsoid shape, and so on.

- **Weld Joint**, e.g., weld path, weld start/end time, start/end position, delay times, and so on.
- **Weld Sequencing**, e.g., number of sub-passes/weld path, different sequencing patterns, sequential/simultaneous patterns, inter-pass temperature, and so on.
- **Fixtures & Boundary Conditions**, e.g., Dirichlet / Neumann BCs, clamping position, apply/release time, convection coefficient, contact parameters, and so on.
- **Chemical Composition**, e.g., carbon, alloying components, uncertainty range, and so on of base metal and filler metal.
- **Material Properties**, e.g., temperature dependent specific heat, thermal conductivity, initial grain size, initial hardness, Young modulus, Poisson's ratio, yield stress, hardening modulus, and so on.
- **Thermal, Microstructure, and Stress Simulation Parameters**, e.g., solver type, heat source model used, number of NR iterations, convergence criteria, and so on.
- **Meshing and Parts**, e.g., mesh type, level and type of refinement, coarse-fine perturbation, rigid body movement, contacts, and so on.
- **Initial State**, e.g., data flow from other projects, re-start time step, result mapping, and so on.

These parameters can vary in time or space during welding and cool-down after welding. Increasing the number of design parameters enlarges the parametric design space. A parametric design with 5 to 10 parameters is a quite large space to explore. Considering that a CWM model can have roughly 300 parameters, unless a small subset of parameters is selected, exploring a parametric design would not be feasible. For example, to compute Taguchi's sensitivities [8,9,10] for 15 design parameters with 3 levels, L36 requires 36 analyses to screen the parameters. Selecting 8 parameters with 3 levels for a full factorial analysis requires  $3^8 = 6,561$  analyses to compute a local approximation to the response surface. A fractional factorial analysis still requires a large number of analyses. To compute a response surface requires many more design points. Using an automated framework and depending on the problem's characteristics, exploring a parametric design with less than 10 parameters could be feasible.

At this time, our parametric design analyses for CWM usually solves tens or hundreds of design points to explore or map the associated design space specified by a parametric design DOE matrix to find optimal designs. In a parametric design, algorithms that use DOE matrices for more efficient searching are preferred. Such DOE matrices take advantage of the fact that multiple trial solutions can be obtained simultaneously in contrast to sequential algorithms that do search based on solving one-problem at a time. In a framework for exploring a parametric design space using DOE matrices, the number of processors and cores allocated to the problem affects the number of rows in the DOE matrix. To use the available processors and cores efficiently, the total number of projects, (rows) in a DOE matrix should be divisible by the number of cores or

processors that are to be utilized.

### 3. Minimizing Distortion in an Edge Welded Bar

An edge weld on a 152 x 1220 x 12.5 mm Aluminum bar shown in Fig. 1 was employed for validation in [11]. In this paper this edge-welded-bar test is used as an example of minimizing the distortion in the bar due to an edge weld. The objective function is the maximum displacement on the bottom surface of the bar after cool-down. The mesh employed has 6600 8-node brick elements and 9680 nodes.

The material was aluminum 5052-H32 alloy with chemical composition Al 96.7, Mg 2.5, Cr 0.25, Cu max 0.1, Fe max 0.4, Mn max 0.1, Si max 0.25, Zn max 0.1 Wt %. The temperature dependent material properties of Al 5052-H32 were given in [12] and this data was employed in the analysis of this test. The gas metal-arc-welding process was employed to weld the specimen and the welding parameters were current 260 amperes, voltage 23 volts, travel speed 7.34 mm/s, filler metal Al-4043 with 1.6 mm wire diameter, wire feed speed 170 mm/s and the shielding gas was Argon. The specimen was allowed to cool to ambient temperature after welding was completed.

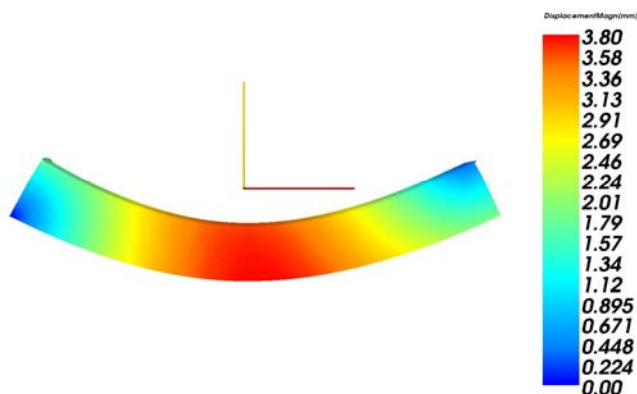


Figure 1 Camber in an edge-welded beam with no mitigation of distortion.

#### 3.1 Nodal Pre-bending Technique

In this technique, the bar is pre-bent during welding by prescribing the y-displacement of FEM nodes on the bottom surface of the bar. Point pre-bending prescribes nodes on the end edges of the bottom surface to zero vertical displacement and prescribes nodes on a line in the bottom surface normal to the welding direction prescribed to five different values. In addition, the delay time after the weld was completed was designated a design variable. Nine values of delay times were chosen. All pairs of 5 prescribed displacements and 9 values of delay times ranging from 0 to one hour were chosen. This generated a DOE matrix with two columns for the two design variables and 45 rows for the 45 experiments.

In Fig. 3, the vertical axis is the value of the objective function, i.e., the maximum y-displacement. The horizontal axes are the maximum prescribed displacement and the

delay or waiting time after welding to release the prescribed displacement. The intersection of the horizontal zero plane and the tilted surface is the curve of design parameters that generate zero maximum y-displacement.

Without pre-bending, the camber in the beam was 3.8 mm after cool-down. The camber after cool-down for the 45 experiments is shown as dots in Fig. 2. Each curve shows a fitted curve for one prescribed y-displacement. Curves from bottom to top correspond to 7.6, 6.67, 5.7, and 4.75 mm of prescribed y-displacement.

The pairs of values of prescribed displacement and delay that generate zero camber is shown in Fig. 3 which is intersection between a 3D plot of Fig 2 and a flat plane showing zero final displacement.

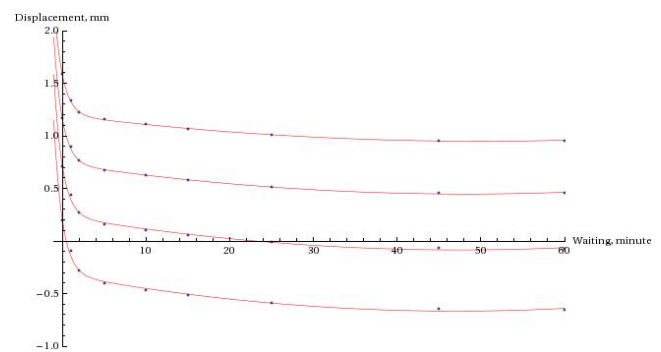


Figure 2 Points on each curve show the objective function for a nodal prescribed displacement.

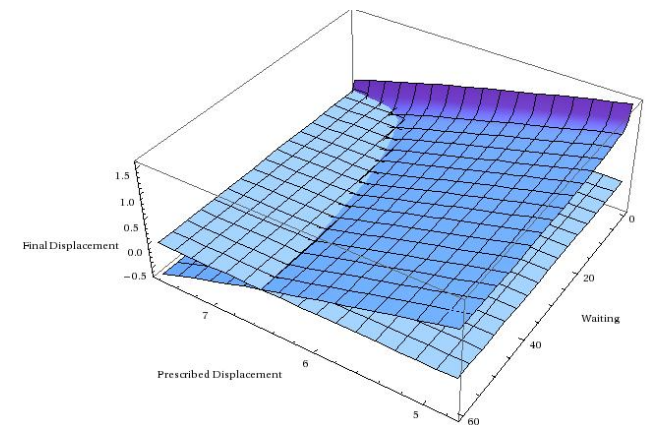


Figure 3 The pairs of values of the nodal prescribed displacement and delay that generate zero camber

#### 3.2 Parabolic Pre-bending Technique

In this technique, the bar is pre-bent during welding by prescribing the vertical y-displacement of all nodes on the bottom surface of the bar to a parabola of specified amplitude. The maximum value of the parabola was prescribed to five different values. Again, the delay time after the weld was completed was designated a design variable. Nine values of delay times were chosen. All pairs of 5 prescribed displacements and 9 values of delay times ranging from 0 to one hour. This generated a DOE matrix with two columns for the two design variables and 45 rows for the 45 experiments. One experiment was

dropped to make the number of experiments divisible by four so that the 44 experiments could run in 11 groups of 4 on a quad core processor.

The camber after cool-down for the 44 experiments is shown in Fig. 4 for curves corresponding to 9.5, 8.55, 7.86, and 6.67 mm of parabolic prescribed displacement from bottom to top. The curve showing the pairs of values of prescribed displacement and delay that generate zero camber is shown in Fig. 5.

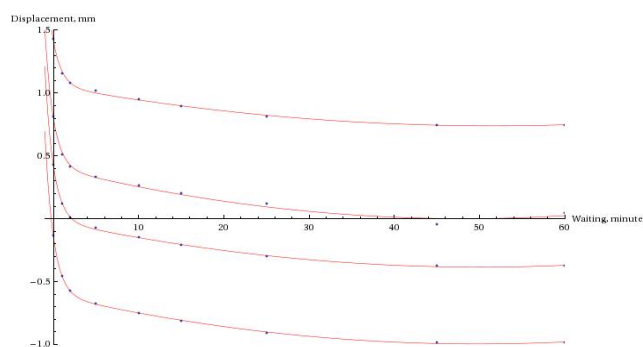


Figure 4 Points on each curve show the objective function for a parabolic prescribed displacement.

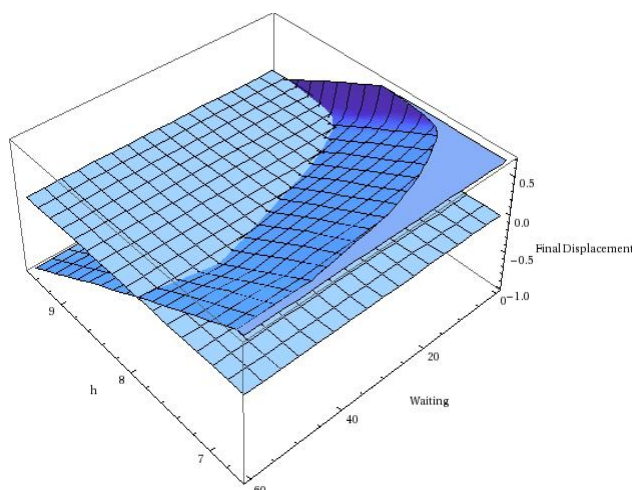


Figure 5 The pairs of values of the parabolic prescribed displacement and delay that generate zero camber.

#### 4 Side Heater Technique

In a continuous response surface of a given system, if the initial pattern cannot find the optimum, there are direct-search algorithms [13, 14, 15] to learn from current observation and find a possible path toward an optimum. The algorithm repeats the learning to follow the path until it reaches the minimum or some imposed limits.

Okerblom [16] discussed different techniques for mitigation of distortion from welding. One of the techniques is to apply a transient thermal tension by side heaters [17]. This technique introduces a significant tension around the weld. The side heater's power, heated area, the distance from the weld either longitudinal or transversal are the design parameters chosen for this technique. Song et al [18] solved a similar problem

The side heater source is characterized by a double ellipsoid model [12] moving parallel to the weld path. The power is computed from  $\eta VI$ ; side heater efficiency, current and voltage. Power is varied by changing  $\eta$  from 0.2 to 0.7 using fixed  $I$  and  $V$  equal to 260 amp and 23 V. Four semi-axes lengths of the parameters of the double ellipsoid geometry are assumed equal and therefore form a sphere. In effect, the area formed by the intersection of this sphere and the surface of the bar is the area that absorbs the power and therefore is one of the side heating parameters. We characterized this parameter, area, by a single value that is the radius of the sphere,  $R$ . This parameter ranges from 10 to 70 mm. The quasi-transient position of the side heater wrt the weld, can be moved ahead/behind the arc or shifted closer or farther from the weld path. We put the origin of the coordinate system on the bar's centerline and exactly below the weld tip as shown in Fig. 6. The relative position of the side heater therefore can move in the  $X$  or  $Y$  direction. Finally, the optimized side heater design parameters are;  $\eta = 0.6$ ,  $R = 6$  cm,  $(X, Y) = (0.012, -0.025)$  mm, denote power, area's radius, longitudinal and transverse shift respectively.

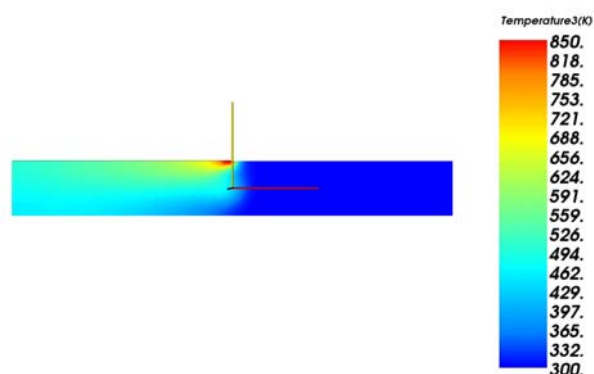


Figure 6 Origin of the coordinate system. X is red and Y is yellow.

Side heating could add plastic strain to the bar if the power density is too high. To avoid forming such plastic strain, power is constrained to be in the gray area in Fig. 7. This plot is drawn based on the plastic strain computed by FEM analyses when the side heater is applied with no weld. The gray area shows no-plastic-strain zone. Our analyses show that if the maximum temperature in the side heater stays below 480 K, plastic strain does not form.

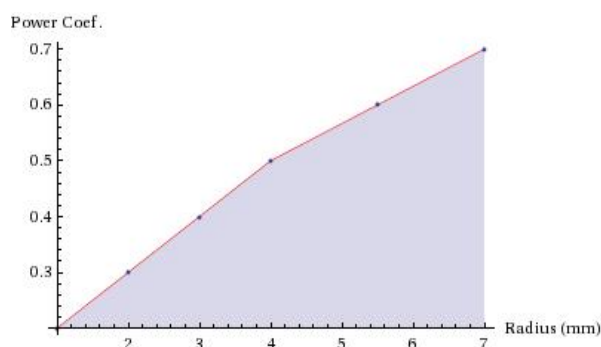
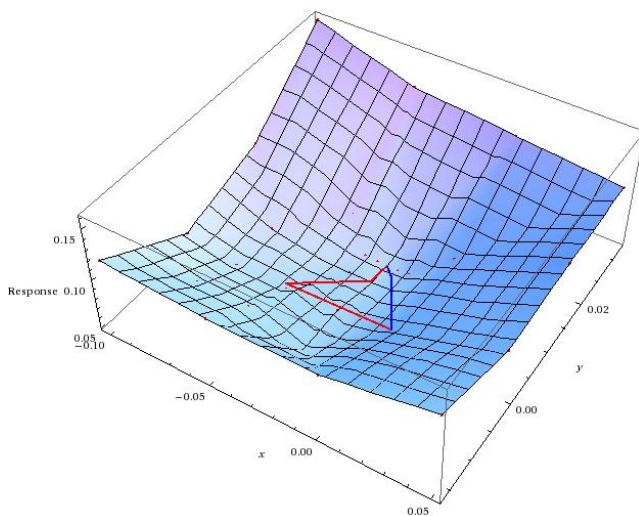


Figure 7 Constraint showing the feasible region for the side heater's power and area.



A regular direct-search moves to a new trial optimum chosen from the result of the last DOE matrix and forms a new DOE-matrix for the next iteration. Coupling a least-square approximation in a regular direct-search algorithm followed the path to the minimum more efficiently in the neighborhood of a smooth basin. However the least-square approximation is not expected to work as well when the response surface is not a smooth basin, e.g., if the response surface is very wavy or rough. This is very similar to the expected behavior of a Newton-Raphson algorithm. The regular and least-square direct-search algorithm are illustrated graphically in Fig. 8 to show the path followed by each algorithm to the minimum.



**Figure 1** The regular and least-square direct-search are shown in red (the longer path) and blue (the shorter path) respectively.

## 5. Optimal Sequence of Weld Passes

Space does not permit a detailed discussion of optimizing the sequence of weld passes. Voutchkov et al [19] present a novel algorithm for optimizing a sequence of 6 weld sub-passes in which each weld pass can be welded in either direction. There are 46,080 possible sequences in the graph. They construct a graph with 27 sequences such that every weld pass is welded in both directions at least once, i.e., each edge of the graph is an ordered pair of weld sub-passes. Therefore every edge of the complete graph is traversed at least once in each direction. They solve these 27 sequences as full CWM problems using FEM. From these 27 solutions they obtain an estimate of the displacement caused by each edge. They construct a simple surrogate model that can evaluate each sequence with 6 multiplies and 6 adds. With this surrogate model they can evaluate an estimate of the displacement caused by each of the 46,080 sequences. They pick the optimal sequence predicted by the surrogate model and evaluate it with a full CWM solution.

Asadi and Goldak [20] used this approach to optimize the sequence of welding 6 sub-passes in a 2 pass girth weld in a pipe. Currently the surrogate equation must be devised for each new type of problem. Thus it is not a general

method. Nevertheless when the surrogate model works, it can be a very efficient model for solving for an optimal weld sequence.

## 5. Summary

The authors have applied these methods to large industrial problems, e.g., in a complex machine with tens of parts and tens of welds including a 4 m long 8 pass weld joining two 50 mm thick plates. In this weld, each weld pass was partitioned into 3 weld passes for a total of 24 weld sub-passes. The optimal sequence was computed from a set of 32 sequences. The mesh for this project had 68371 8-node brick elements, 90879 nodes and 272,637 DOFs. Each sequence was solved with 1360 time steps and required 4 days CPU time on one core of processor. The 32 projects were solved 16 days by running 8 projects in parallel on a dual processor with 8 cores.

Several examples of integrating computational optimization with CWM have been described. It was argued that the following points were important: simple, quick generation of variations of the CWM problem in order to explore an design space and generate a response surface; a fast solver, direct optimization with parallel processing effectively reduces total elapsed time and avoids the time, cost and complexity of developing software to compute first or second derivatives. Some parameters are more difficult to vary, e.g., varying the mesh topology or the topology of the geometry and changing boundary condition types. However, for many types of parameters, the authors have found that it is easy to set up parametric problems for CWM.

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