Proceedings of the ASME 2015 Pressure Vessels & Piping Division Conference
PVP2015
July 19-23, 2015, Boston Park Plaza, MA, USA

PVP2015-45556

A METHOD TO DEFINE THE BEST WELD SEQUENCE USING A LIMITED NUMBER OF WELDING SIMULATION ANALYSIS

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ABSTRACT

Weld sequence optimization, which is determining the best (and worst) welding sequence for welding work pieces, is a very common problem in welding design. The solution for such a combinatorial problem is limited by available resources. Although there are fast simulation models that support sequencing design, still it takes long because of many possible combinations, e.g. millions in a welded structure involving 10 passes. It is not feasible to choose the optimal sequence by evaluating all possible combinations, therefore this paper employs surrogate modeling that partially explores the design space and constructs an approximation model from some combinations of solutions of the expensive simulation model to mimic the behavior of the simulation model as closely as possible but at a much lower computational time and cost. This surrogate model, then, could be used to approximate the behavior of the other combinations and to find the best (and worst) sequence in terms of distortion. The technique is developed and tested on a simple panel structure with 4 weld passes, but essentially can be generalized to many weld passes. A comparison between the results of the surrogate model and the full transient FEM analysis all possible combinations shows the accuracy of the algorithm/model.

INTRODUCTION

Weld distortion is caused by localized expansion and contraction of metal as it is heated and cooled during the welding process. This thermal load is non-uniform, occurs with high gradient from the weld to the surrounding materials, and constrained by the adjacent base metal. Distortion comes from the plastic part of strains induced by such a loading condition along with phase changes emanating from the weld pool region.

In multiple welding, weld sequence planning provides an opportunity to manage the plastic strains and stress condition by counter balancing and/or locking effect on one weld from another [1]. Over many years, this has been employed for reducing distortion in panels and bars; however routine industrial practice of welding engineering in weld sequence planning is generally limited to intuition-based designs that are mainly based on the recommendation or similar practices. This approach becomes difficult to be effective in large scale multiple welding involving several welds on a complex geometry [2]. Apparently, a general recommendation is to use a simulation code to predict the distortion of different weld sequence scenarios.

Very good simulation codes are now available to capture and couple thermal, microstructure and stress effects of weld and in welded structure based on 3D transient temperature and thermal stress-strain analysis [3]. However simulation codes are also limited by available resources and using them for problems involving a great number of scenarios might be unfeasible. For example, having n welds leads to choosing from $2^n\, n!$ possible scenarios or combinations of the welds, e.g., 46,080 for n = 6. Even analyzing fraction of this space, it is not feasible to choose the optimal sequence by evaluating all possible combinations yet by simulation codes [2].

There are efforts to develop more affordable approaches to have sufficient and reliable level of understanding of the behavior of structures while welding. One approach is to use fast

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simulation code that captures the most dominant physics of the problem. Although such a code or algorithm loses accuracy, it provides a useful approximation of the behavior. In many design cases, the designers can make a decision based on this rough approximation of the behavior. Good examples of these algorithms are 'Fast Weld' and 'Super-Fast Weld' algorithm that analyzes the weld displacement based on elastic-thermal-strain only [4]. They show a good estimate of a full 3D transient analysis for a truck's axle bridge with 4 welds but are as much as 30 time faster than a normal analysis.

Another approach is to construct an approximate model from the behavior computed by simulation codes and use this approximate model to predict the behavior for all the other cases. Regression models are one such an approximate model that is used in [5] to construct a regression model for the residual stress approximation in a bead-on-plate weld. An analysis with a sample space size of 10,000 is done very quickly using this regression model. Genetic algorithm is also used to find the best sequence in pipe welding [6].

Surrogate models, also called either meta-models or emulators, can be another alternative for the approximate model. They mimic the behavior of the simulation model as closely as possible while being computationally cheaper to evaluate. A surrogate model is employed in [2] to optimize the weld sequence for a tail bearing housing that mounts the engine to the body of the aircraft. There are 6 sub-passes and each sub-pass can be done in two directions. Therefore they must choose the weld sequence from 46,080 possible weld sequences to minimize the distortion. They picked 27 sequences from the combinatory space of 46,080 combinations to analyze with an expensive model and they used those 27 solutions to construct the surrogate model. They solved the remaining 46053 weld sequences with this surrogate model. They show that the solution of the surrogate model was a very accurate by comparing the surrogate solution with the FEM solution.

The main limitation for using models like surrogate models is that the algorithm needs to be tailored to the case and may differ from case to case. The surrogate modeling method that is used in [7] to find the best sequence in a girth pipe welding is different from the one developed in [2] for welding of tail bear housing. The difference, however, is not in the technique of selecting trial weld sequences for space exploration; however the author believes that the method used for this pipe can be reprocessed for other pipes and concludes that the effectiveness of surrogate modeling is that the method remains unchanged in similar class of welded structure.

One class of such a welded structure is panel welding for that the present paper develops a surrogate modeling method and shows that the best sequence can be determined by only 28 simulation analyses out of 384 possible ways of welding a panel structure with 4 welds. The method becomes more attractive for lager number of welds n because the number analyses needed to develop the surrogate model increase linearly with n while th number combinations increases with n!, i.e., n factorial.

FOUR-WELD PANEL

Panel structures are part of many engineering structures and the welding is the sole fabrication method to erect such structures. In this paper, a simplified panel, without the loss of generality, is selected to develop a surrogate model in order to find the best and worst welding sequence pattern for minimal distortion.

Figure 1 illustrates the 4-weld panel structure studied in this paper for developing a surrogate model. The base is a 40x30x2 [cm] structural steel containing 0.13 wt% C on which two stiffeners 40x8x1 [cm] are fillet-welded from both sides. The center line of stiffeners are positioned at 4.5 [cm] from the closest edge and by tack-welded. The base plate is fixed by two clamps in the center of the long edges as shown in Figure 1.

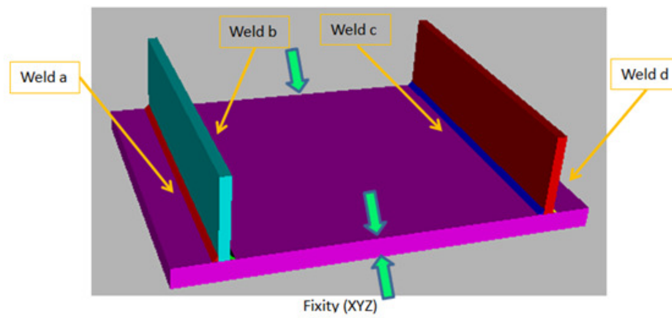

Figure 1: the 4-weld panel structure studied in this paper for developing a surrogate model.

The weld procedure is constant for all 4 passes as written in Table 1.

Table 1: Welding procedure

Parameters	Current [amp]	Voltage [v]	Speed [m/s]
Value	550	33	0.01

SIMULATION OF WELD

A full computational model that includes transient thermal and stress analysis is analyzed by VrWeld software. The mesh type is 8-node brick and finer close to weld paths. The number of volume elements and volume nodes are 1,680 and 2,464 respectively. The details of the model for thermal and stress analysis are described below;

Thermal Simulation

The 3D transient temperature is computed by solving the transient heat equation below with a Lagrangian finite element method.

$$\dot{\boldsymbol{h}} + \boldsymbol{\nabla} \cdot (-\boldsymbol{k}\boldsymbol{\nabla}\mathbf{T}) + \boldsymbol{Q} = \mathbf{0} \cdots\cdots Eq1$$

Where h is the specific enthalpy, the super imposed dot denotes the derivative wrt to time, k is the thermal conductivity, T is the temperature, and Q is the power per unit volume or the power density distribution. The initial temperature was 300 K.

The power density distribution function Q [w/m^3] ‘Double Ellipsoid’ heat source model of Goldak [8] was used and the heat source parameters were a_1 =12 [mm], a_2 = 6 [mm], b = 6 [mm], and c = 6 [mm].

A convection boundary condition generated a boundary flux q [w/m^2] on all external surfaces. This flux is computed from equation below with convection coefficient h_c = 10 [w/m^{2}K] and ambient temperature of $T_{ambient}$ = 300 K (27 ◦C).

$$\boldsymbol{q} = \boldsymbol{h_c}(\boldsymbol{T} - \boldsymbol{T_{ambient}}) \cdots\cdots Eq2$$

The time step length while welding was chosen so that one time step was required to travel one element along the weld path. Filler metal was added as the welding arc moved along the weld path, i.e., the FEM domain changed in each time step during welding. After each weld pass was completed, the time step length was increased exponentially by a factor of 1.2 per time step during the cool down. The computation involved 120 welding time steps plus 47 cool down time steps. The CPU time on 3.3 GHz core was 43 s for full thermal analysis of a project.

Figure 2 illustrates a snapshot of the transient temperature field when the weld is in the middle of the pass b.

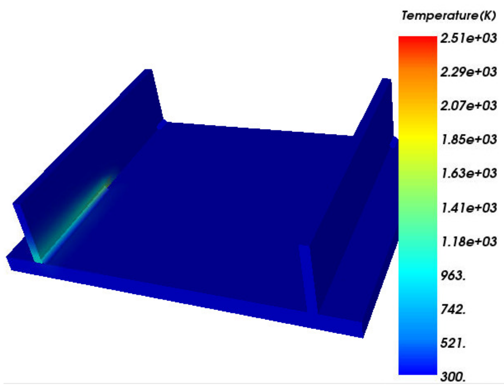

Figure 2: transient temperature when the weld is in the middle of the pass b.

Stress Simulation

The stress solver solves the conservation of momentum equation given below using the elasticity tensor D as a 6x6 matrix, the body force b and the Green-Lagrange strain ε.

$$\begin{aligned} \nabla \cdot \sigma + b &= 0 \\ \sigma &= D_{el}\varepsilon_{el} \qquad \cdots Eq3 \\ \varepsilon_{el} &= (F_{el}^T F_{el} - \mathbf{I})/2 \end{aligned}$$

This partial differential equation was solved for a visco-thermo-elasto-plastic stress-strain relationship using radial return theory and algorithms [9]. The initial state is assumed to be stress free. The Dirichlet boundary conditions are shown in Figure 1. The system is solved using a time marching scheme with time step lengths used for thermal analysis. The CPU time on 3.3 GHz core was 468 s for full stress analysis of a project followed immediately after thermal analysis.

Figure 3 illustrates the minimal displacement achieved from the best welding sequence (a+, d+, b+, c+) after cool down. By convention, positive sing/direction is from front to back. And negative is opposite.

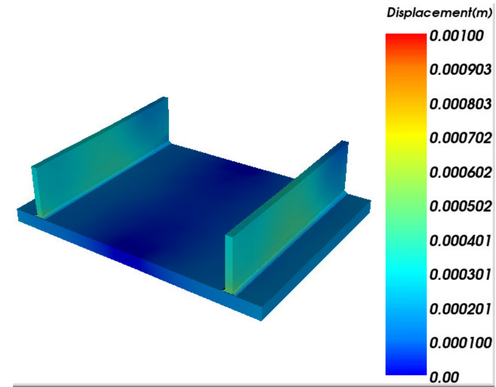

Figure 3: the minimal displacement achieved from the best sequence (a+, d+, b+, c+) after cool down.

Figure 4 illustrates the worse (max) displacement achieved from the worse sequence (c-, d+, a-, b+) after cool down.

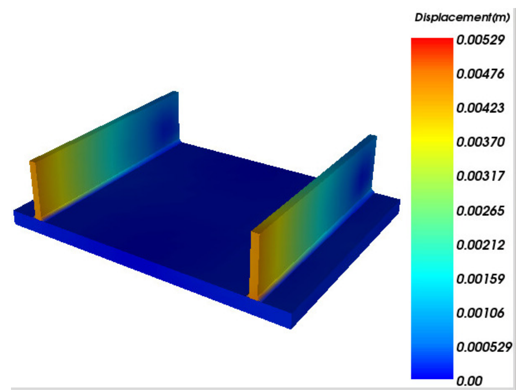

Figure 4: the worse (max) displacement achieved from the worst sequence (c-, d+, a-, b+) after cool down.

Figure 5 illustrates the effective stress distribution from the best welding sequence (a+, d+, b+, c+) after cool down.

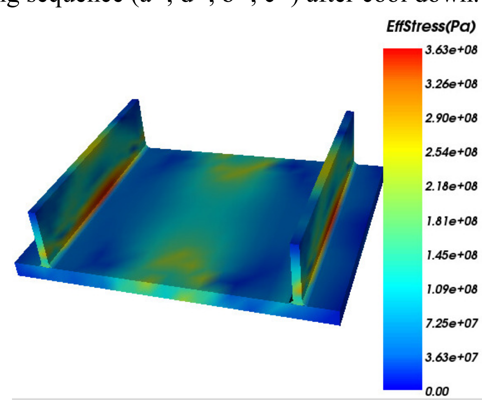

Figure 5: the effective stress distribution from the best sequence (a+, d+, b+, c+) after cool down.

Figure 6 illustrates the effective stress distribution from the worse welding sequence (c-, d+, a-, b+) after cool down.

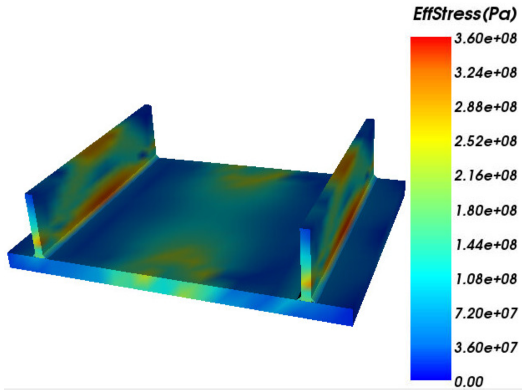

Figure 6: the effective stress distribution from the worst sequence (c-, d+, a-, b+) after cool down.

SURROGATE ALGORITHM FOR PANEL

An optimization algorithm needs a scalar objective function as a measure of decision to select one over the other. Similarly, minimizing distortion using surrogate model needs a scalar definition of plate distortion. This objective function, here, is the maximum deflection along a diagonal line of the panel base (shown in Figure 7). This difference is named δ-deflection, so the objective function is to minimize the value of δ-deflection. Indeed, defining an objective function is for user to decide how to best represent the problem and can be nodal displacement, line displacement, average displacement, deviation from a reference displacement, or similarly for effective stress to mitigate the residual stress.

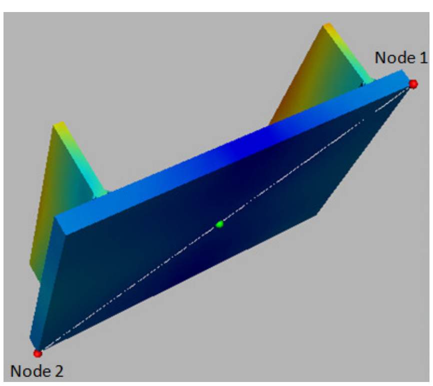

Figure 7: the diagonal line of the panel base.

Surrogate modeling is a mathematical approach that explores a combinatorial design space with relatively few analyses to approximate and find the best sequence.

Let's understand the surrogate modeling by using on this panel where we want to find the best sequence out of 384 possibilities such that the δ-deflection is minimal. We use a computational welding mechanics (CWM) model to solve for deflection.

Imagine you are in a design space with 384 nodes which each one is one sequence configurations and they are independent of each other distributed in the space. You are blind about the response (/state /objective function value) of your system in this design space because there are 384 doors that are blocked your vision. If you have resources enough to open all doors then you will see the full picture of the response state. This is not practical if the number of doors goes to infinity. Now you are asked to play a game, you should explore this space and you can select any door you like but limited to a certain number of tries to open and collect information behind.

One strategy is to randomly select your sample space, but this is not a wise way to do it. You need to use more intelligent method to follow. For example, open one door, learn from it and then decide about the next door that gives you more information. This is exactly the game of surrogate modeling and let's plays this game on our panel structure for weld sequence optimization. Our surrogate model explores the design space with only 28 analyses out of 384 possibilities (opening only 28 doors).

By convention, the sequence (b+, c-, d-, a+) indicates weld b (or # 2) in positive direction (i.e. from front to back) occurs first, then weld c (or # 3) in negative direction (i.e. from back to front), then weld d in negative direction, and finally weld a in positive direction.

The challenge in constructing a surrogate model is to select the minimum number of possible welding sequences to construct a surrogate sample, and meanwhile the surrogate sample should effectively represent the entire population of welding sequences. The panel of this paper has four welding passes, and each pass has two possible welding directions, the possible number of welding sequences is equal to $2^4 \times 4! = 384$. In this paper we used the sampling technique which is proposed in [2] where the runs of surrogate sampling (Table 1) were randomly selected until fully satisfied two constrains which are called R' and R" matrix. R' matrix assures that all weld passes and directions (i.e. a+, a-, b+, b-, c+, c-, d+, d-) occurs at least once in every position. The sampling continues until R' matrix fills with no zero count e.g. Table 3 is R' matrix for this panel. The second constrain, R" matrix, assures every pair occurs at least once in sequence sampling. For example the pair (d-, a+) occurs just once in the entire sample in run number 27, and the pair (c+, a-) occurs twice, in sample run 22 and 28 respectively. Table 3Table 4 is R" matrix for this panel. One can observe that there is no single R' and R" matrix that guides the sampling but an optimal R' and R" should have as close as possible to equal entity count in the matrix rather than biased to one weld pass or sequence unless there is a reason of importance for a weld pass or sequence over others.

CWM is used to calculate the objective function i.e. δ-deflection for sampling runs in Table 2 and all 28 results were finished in about 4 hours of CPU time on a single core with no supervision or intervention required by user. The analysis was limited to use one core of a quad core processor. However, the CPU time could be reduced proportionally to the available number of cores used in parallel e.g. 1 hour for all 28 runs in Table 2 on quad cores.

Table 2: Selected runs of surrogate sampling.

Run #	wp1	wp2	wp3	wp4
1	c+	a+	b+	d+
2	a+	b+	d-	c+
3	a+	c+	b+	d-
4	d-	b+	c+	a+
5	d+	a+	c-	b+
6	b+	a+	d-	c-
7	d-	b+	a+	c-
8	c+	a+	d+	b-
9	a+	c+	d-	b-
10	a+	b-	c-	d+
11	c-	b-	d+	a+
12	d+	c-	b-	a+
13	d-	c-	a+	b-
14	c+	b+	d+	a-
15	a-	b+	c+	d-
16	b+	a-	d-	c+
17	a-	d+	c-	b+
18	d+	b+	c-	a-
19	c-	a-	b+	d-
20	b-	a-	c+	d+
21	d+	c+	b-	a-
22	b-	d-	c+	a-
23	a-	c-	d+	b-
24	c-	a-	b-	d+
25	b-	a-	d-	c-
26	c-	d-	a-	b-
27	d-	a+	b-	c+
28	b+	c+	a-	d+

(wp stands for weld position)

Table 3: R' matrix

	wp1	wp2	wp3	wp4
a+	4	4	2	3
b+	3	6	2	2
c+	3	4	4	2
d+	4	1	4	4
d-	3	2	3	2
c-	4	3	3	1
b-	3	2	4	5
a-	3	5	2	4

Table 4: R" matrix entities.

	a+	b+	c+	d+	d-	c-	b-	a-
a+	0	2	2	1	1	2	3	0
b+	2	0	3	2	3	1	0	1
c+	3	2	0	1	2	0	1	2
d+	2	1	1	0	0	2	2	1
d-	1	2	1	0	0	3	1	1
c-	1	2	0	2	1	0	2	3
b-	1	0	1	2	1	1	0	3
a-	0	2	1	2	2	1	2	0

Second, we construct a surrogate algorithm which is used to approximate the objective function (δ-deflection) for all possible welding sequences, or trial runs. Note that the use of surrogate algorithm to approximate trial runs does not consume either time or computational power. The third step is to define x number of approximated trial runs which have minimum values of δ-deflection. Eventually, these approximated trial runs are solved by finite element analysis to calculate their exact values of δ-deflection, so the best welding sequence which has the minimum objective function is defined.

Having CWM results for sequences in Table 2, provides information enough to approximate δ-deflection for sequences other than sampling table hereby called trial runs. The proposed surrogate approximation scheme is presented in Table 5.

Two type of occurrences, R' and R'', exist in Table 5; the first type of occurrence (R') indicates that the position of weld pass in trial runs and sampling runs is matching, the second type of occurrence (R'') indicates that the sequence remains matching however the position can be arbitrary among the sampling runs.

For example, if a trial run has (b-) pass in the first welding position such as (b-, a-, c+, d-), then the sample run which may be used in approximation should have (b-) pass in the first welding position. For example, the sample run which can be used to approximate the first pass, R'_1(b-), of the trial run (b-, a-, c+, d-), can be sample run number 20, 22, or 25 in Table 2. Similarly, the approximation of the second pass R'_2(b-, a-) can be taken from run number 25. The second type of occurrence, R'', does not concern the positions of welding passes. For example, R''_2 (b-, a-) can be the run number 21.

Some conventions;

The subscript number (R'_2) indicates the number of welding passes that are considered to surrogate.

Reducing the subscript number indicates that the algorithm starts to truncate the number of welding passes.

If the sign ($\pm$) is mentioned beside a welding pass ($\pm wp$), the direction of the pass does not matter in the selection of sample run.

The priority of picking from sample runs is reducing from top to bottom in Table 5.

The first priority is given to the first type of occurrence with matching weld direction e.g. $R'_2(wp_1, wp_2)$. Then, the priority is the first type of occurrence regardless of direction e.g. $R'_2(wp_1, \pm wp_2)$. If the surrogate sample does not have any run to satisfy the first type of occurrence, then the priority shifts down to the second type of occurrence (R'') with the same welding passes and directions $R''_2(wp_1, wp_2)$ and then after to $R''_2(\pm wp_1, \pm wp_2)$. Yet there is no selection, the next priority continues with truncation. The existence of the last row in Table 5 is guaranteed by R' matrix.

Table 5: Proposed surrogate approximation scheme.

wp1	*wp2*	*wp3*	*wp4*	*CLD*
$R'_1(wp_1)$	$R'_2(wp_1, wp_2)$	$R'_3(wp_1, wp_2, wp_3)$	$R'_4(wp_1, wp_2, wp_3, wp_4)$	$R'_4(wp_1, wp_2, wp_3, wp_4)$
	$R'_2(wp_1, \pm wp_2)$	$R'_3(wp_1, wp_2, \pm wp_3)$	$R'_4(wp_1, \pm wp_2, wp_3, wp_4)$	$R'_4(wp_1, \pm wp_2, wp_3, wp_4)$
	$R'_2(\pm wp_1, \pm wp_2)$	$R'_3(wp_1, \pm wp_2, \pm wp_3)$	$R'_4(wp_1, \pm wp_2, \pm wp_3, wp_4)$	$R'_4(wp_1, \pm wp_2, \pm wp_3, wp_4)$
	$R''_2(wp_1, wp_2)$	$R'_3(\pm wp_1, \pm wp_2, \pm wp_3)$	$R'_4(\pm wp_1, \pm wp_2, \pm wp_3, wp_4)$	$R'_4(\pm wp_1, \pm wp_2, \pm wp_3, wp_4)$
	$R''_2(\pm wp_1, \pm wp_2)$	$R''_3(wp_1, wp_2, wp_3)$	$R'_4(\pm wp_1, \pm wp_2, \pm wp_3, \pm wp_4)$	$R'_4(\pm wp_1, \pm wp_2, \pm wp_3, \pm wp_4)$
	$R'_1(wp_2)$	$R''_3(wp_1, wp_2, \pm wp_3)$	$R''_3(wp_2, wp_3, wp_4)$	$R'_2(wp_3, wp_4)$
		$R''_3(wp_1, \pm wp_2, \pm wp_3)$	$R''_3(\pm wp_2, wp_3, wp_4)$	$R'_2(\pm wp_3, wp_4)$
		$R'_2(wp_2, \pm wp_3)$	$R''_3(\pm wp_2, \pm wp_3, wp_4)$	$R'_2(\pm wp_3, \pm wp_4)$
		$R'_2(\pm wp_2, \pm wp_3)$	$R''_3(\pm wp_2, \pm wp_3, \pm wp_4)$	$R''_2(\pm wp_3, wp_4)$
		$R''_2(wp_2, \pm wp_3)$	$R'_2(\pm wp_3, wp_4)$	$R''_2(\pm wp_3, \pm wp_4)$
		$R'_1(wp_3)$	$R'_2(\pm wp_3, \pm wp_4)$	$R'_1(wp_4)$
			$R''_2(\pm wp_3, wp_4)$	
			$R''_2(\pm wp_3, \pm wp_4)$	
			$R'_1(wp_4)$	

RESULTS, COMPARISON, AND DISCUSSION

In order to check the accuracy of the constructed surrogate modeling, a collection of 30 trial-runs is randomly chosen out of total 384 possibilities but not from those have been used for sampling. The minimum number of sample-runs to construct this surrogate modeling is $4n$, where n is the number of welding passes. This is because the number of R"-matrix fields which need to be filled are equal to $4n(n-1)$. Thus, we need $4n(n-1)$ deferent pairs to fill the fields of R"-matrix. Since each run has three different pairs $(n-1)$, we need at least $4n$ runs in the surrogate sample to fill R". However, the runs of surrogate sample needs to be carefully selected in such way that each sample-run contains three distinct pairs. For example, both (a+, b-, c-, d+) and (b+, c-, d+, a+) are not recommended to be selected together because they provide a duplicated pair (c-, d+). Thus, the best choice needs to select a new sample-run that compensates missing pairs.

We noticed that the position of welding passes in the sequence has dominant effect on the objective function (δ-deflection). Therefore, the first priority of the surrogate algorithm is to pick, out of surrogate sample, a welding sequence whose weld passes position and direction is conforming to a trial run. For example, the algorithm picks the run number 27 whose welding sequence is (d-, a+, b-, c+) to approximate the trial run that has (d-, a+, b+, c+) welding sequence. Both runs have the same weld position for all passes and the same directions except the direction of the third weld pass. Figure 8 compares the surrogate approximation with and actual computation for (d-, a+, b+, c+). The top table in this figure shows which sample-run was used to approximate wp#.

wp1	*wp2*	*wp3*	*wp4*	*After CLD*
Sample run_4	Sample run_27	Sample run_27	Sample run_27	Sample run_27

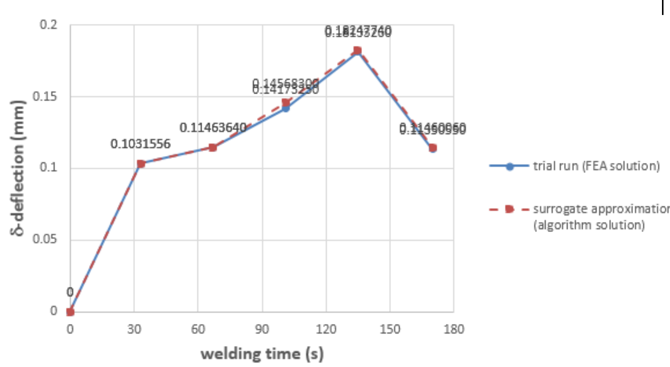

Figure 8 : Comparison of surrogate approximation and FEA solution of the trial run (d- , a+, b+, c+).

The priority of selection algorithm is to pick a sequence which has the closest welding position. For example, the algorithm picks the sample run number 2 (a+, b+, d-, c+) to approximate the welding sequence (a+, b-, d+, c+) and a comparison is made in Figure 9 between surrogate approximation against the actual computation.

If no sequence satisfies this condition, the algorithm will pick a welding sequence that has the closest welding position regardless of direction. For example, the algorithm picks the sample run number 28 (b+, c+, a-, d+) to approximate the welding sequence (b-, c+, a+, d-) as shown in Figure 10.

wp1	*wp2*	*wp3*	*wp4*	*After CLD*
Sample run_3	Sample run_10	Sample run_2	Sample run_2	Sample run_2

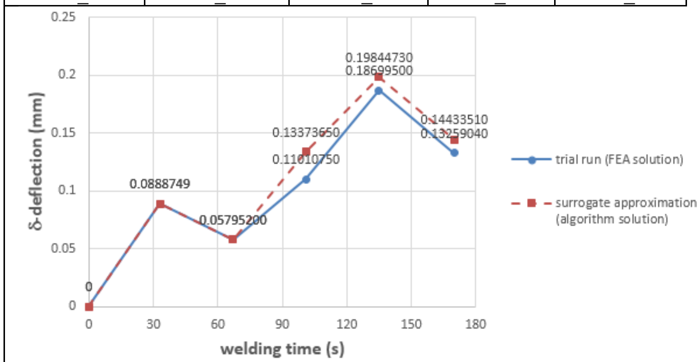

Figure 9 : Comparison of the surrogate approximation and FEA solution of the trial run (a+, b- , d+, c+).

wp1	*wp2*	*wp3*	*wp4*	*After CLD*
Sample run_20	Sample run_28	Sample run_28	Sample run_28	Sample run_28

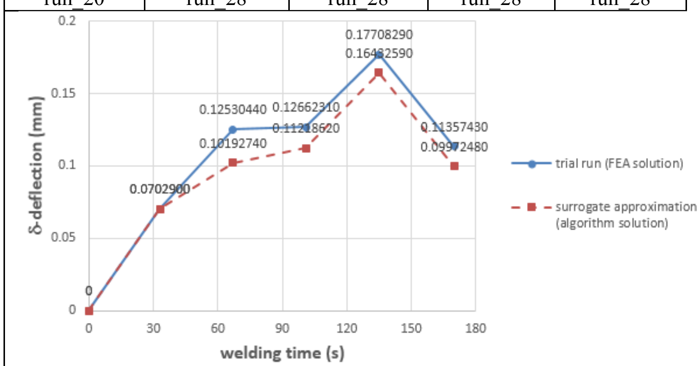

Figure 10 : Comparison of the surrogate approximation and FEA solution of the trial run (b-, c+, a+, d-).

Since the surrogate sample composes of limited number of runs, it is not possible to find a welding sequence which has identical welding position for every trial runs. Therefore, the surrogate algorithm is designed to truncate the number of weld passes and look for closest sequence regardless of where is happening in sequence. The algorithm may approximate a trial run by using different sample runs for each welding position as shown in Figure 11.

In some cases similar to Figure 12, the approximation path actual calculation that indicates that the surrogate algorithm picks a sequence that has the same positions of welding passes but with different directions to approximate a trial sequence.

It has been observed that the last two welding passes have the dominant effect in approximation of cooling down. Thus, the algorithm is constructed to match the positions and directions of last two welding passes as close as possible. A comparison is shown in Figure 13.

Wp1	*wp2*	*wp3*	*wp4*	*After CLD*
Sample run_6	Sample run_28	Sample run_15	Sample run_26	Sample run_11

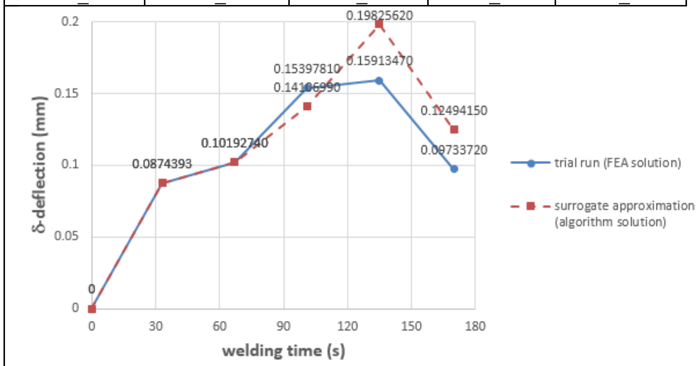

Figure 11 : Comparison of the surrogate approximation and FEA solution of the trial run (b+, c+, d+, a+).

Wp1	*wp2*	*wp3*	*wp4*	*After CLD*
Sample run_11	Sample run_19	Sample run_8	Sample run_8	Sample run_8

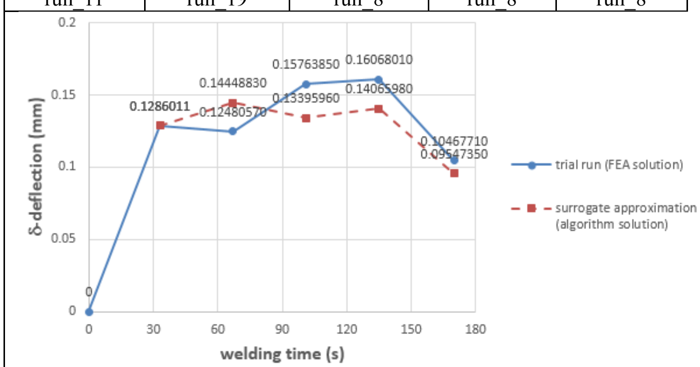

Figure 12 : Comparison of the surrogate approximation and FEA solution of the trial run (c-, a+, d+, b+).

The best welding sequence, which has the minimum δ-deflection (a+, d+, b+, c+), and the worst one, which has the maximum δ-deflection (c-, d+, a-, b+), can be detected approximating total space (/possibilities) using surrogate modeling. However, the surrogate modeling yet approximates the deflection and therefore there is a possibility to miss the actual best among those are close to the best sequences. The recommended practice is to use surrogate algorithm to find a collection of 2n-best (n is number of weld passes) depending on available source and use actual model to pick the best out of the n-best of surrogate approximation. Figure 14 and Figure 15 show the best and worst sequence.

CONCLUSION

A combinatorial optimization technique is used to develop a surrogate model to optimize the welding sequence of the four-weld panel. The technique is not limited to this panel and can be used for more welds in other panel structures.

The objective is deflection along the diagonal line of the panel base to be the objective function however any other objective function can be defined.

The minimum number of sample-runs required to construct the surrogate sample is equal to $4n$, where n is the number of welding passes. This is comparable with total number of possibilities which is $2^n \, x \, n!$. This difference is noticeable when the n increases.

The surrogate algorithm is tailored to this specific problem in such way that the first priority of approximation is given to the identical occurrence, the first type of occurrence R', the the second type of occurrence R'', wherein the position of weld passes is not concerned.

All possible welding sequences can be approximated by the surrogate algorithm very fast and at low cost since it consists of basic operations to select the best and worst.

It is recommended to select the 2n-best (n is the number of weld pass) from surrogate results and use the expensive model to actually calculate for the best sequence out of these approximated 2n-bests.

The best welding sequence for this specific problem is (a+, d+, b+, c+), and the worst welding sequence is (c- , d+, a- , b+).

ACKNOWLEDGMENTS

Ghazi Alsoruji; I gratefully acknowledge the financial support from King Abdulaziz University for my graduate study; also would like to thank Dr. Mahyar Asadi who introduced the topic of computational welding mechanics to me.

Mahyar Asadi appreciates Dr John Goldak for his tremendous support as well as Goldak Technologies Inc for license and knowledge assist for VrWeld simulation software.

Wp1	*wp2*	*wp3*	*wp4*	*After CLD*
Sample run_6	Sample run_28	Sample run_15	Sample run_26	Sample run_14

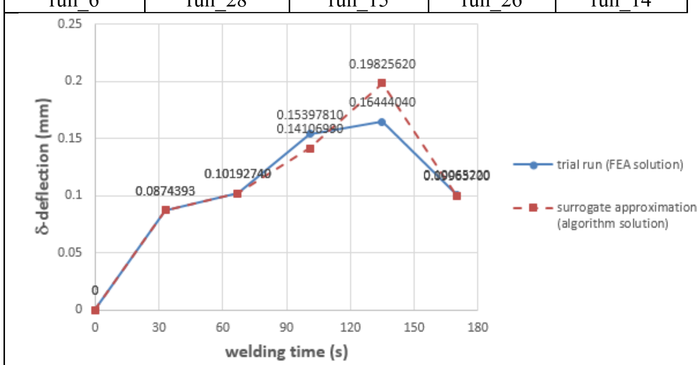

Figure 13 : Comparison of the surrogate approximation and FEA solution of the trial run (b+, c+, d+, a-).

wp1	*wp2*	*wp3*	*wp4*	*After CLD*
Sample run_2	Sample run_17	Sample run_8	Sample run_4	Sample run_27

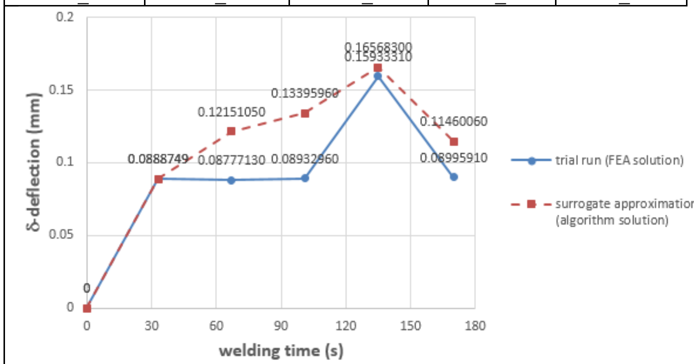

Figure 14 : Comparison of the surrogate approximation and FEA solution of the best welding sequence (a+, d+, b+, c+).

wp1	*wp2*	*wp3*	*wp4*	*After CLD*
Sample run_11	Sample run_26	Sample run_26	Sample run_26	Sample run_26

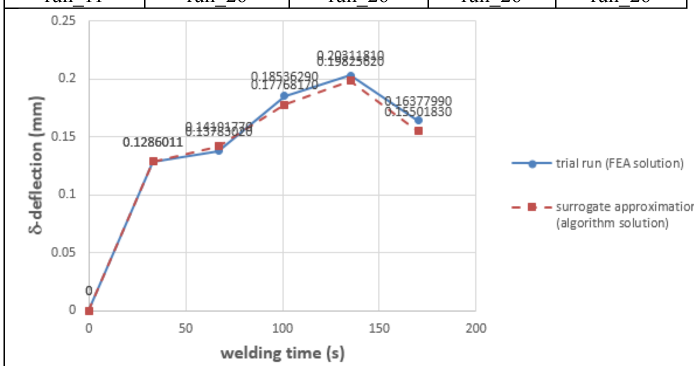

Figure 15 : Comparison of the surrogate approximation and FEA solution of the worst welding sequence (c-, d+, a-, b+).

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