A HYBRID DIGITAL-TWIN PLATFORM FOR SEQUENCE DESIGN IN WELDED STRUCTURES

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ABSTRACT
When fabrication deals with multiple welds, an optimal weld sequence design can well manage the undesired damaging effects such as the distortion and residual stress during welding. However, the process of finding an effective weld sequence is a challenging task given a large number of possible combinations, i.e. several thousands of welding scenarios. On the other hand, most of the standards require the development of a control plan for mitigation of those undesired effects. Typically, plans to control the damaging effect are, therefore, mostly intuitive with welding engineers relying on previous experience combined with the results of a limited number of practical tests. Welding simulation tools allow engineers to optimize welding scenarios on a digital twin without the need for multiple physical samples. However, the analysis-time practically limits exploring a large number of possible combinations for a weld sequence design. The use of machine learning (ML) algorithms for simulation and artificial neural network (ANN) can be an alternative for fast exploration of various weld sequence scenarios. As opposed to existing ANN and ML algorithms that require an extensive data set to be up to mimic a behaviour, we developed a hybrid-digital twin platform that wisely picks small data set consist of simulation results to construct a meta-model for fast exploration of welding scenarios. The performance and capability of our platform are shown through an example of a complex welded structure with billions of possible welding scenarios to explore.

1. INTRODUCTION
In the age of fast-growing smart technologies and devices, the art of thinking out of the box to deliver creative solutions for your needs will be the last to replace by technology, perhaps not likely. Welding engineering, similar to many other fields, will ultimately be dominated by smart systems for delivering a welding engineering that has historically relied on the recommendation of standards or any past experience of the welding team, including welders, supervisors and engineers. Becoming innovative beyond the standard and hands-on use of smart tools will be an essential skill for our welding engineers to fit the future of the industry.

On the other hand, the structural complexity is continuously increasing with tightening tolerances on fabrication; as such, our welding engineers routinely face challenges that are not directly addressed by standards nor by previous experience. A good example is when a welding engineer is asked for developing a distortion control plan, which is part of the contractor’s responsibility, by standard regulation. Codes such as CSA W59 or AWS D1.1 has all requirements for distortion control plan, but no solutions are presented on how to achieve them. In general, conventional methods such as back-stepping, use of strong backs, pre-bending, and weld sequencing are all effective methods to reduce the distortion. However, unless they are tailored and specifically engineered for each joint, they are not likely to deliver optimal results. The problem arises when the tolerances for distortion cannot be met after a few trials; the way-out is often to push back on the designer to relax expectations.

The use of modeling and simulation is well established in many areas of engineering; however, welding is among the few fields where simulation is not commonly deployed to develop engineering solutions. Excellent simulation software is now available to capture and couple thermal, microstructure and
stress effects of welds based on 3D transient temperature and thermal stress-strain analysis [1]. Computer simulations are the best tools to help users apply their creativity, expertise and skill to be more productive and innovative beyond the standard. Despite powerful supercomputers, yet welding simulation tools are limited by computational time and, therefore, not mature for practical designs.

We initially [2] developed an industrial-scale framework for the designer-driven exploration of computational weld mechanics (CWM) design space that automates multiple setups and evaluations required to practically explore a design space by the given design of experiment (DOE) matrices. Saving an expert user's time to prepare several analyses and allocating CPUs to be utilized efficiently make this framework cost-effective and time-effective to manage designer-driven optimization and control application of CWM.

This framework enabled us to develop solutions for welding residual stress using Monte-Carlo method [3] and regression analysis [4], as well as, for distortion control using typical welding engineering techniques including optimal tack welding [5], pre-bending [6], and side heating [7]. Additionally, the framework helped us in the process of verification and validation when comparing CWM with experimental data [8].

The framework faced a new challenge when dealing with the weld sequence design. Having “n” welds requires choosing from \(2^n\) possible scenarios or combinations of the welds (n! for permutations and \(2^n\) for change in the direction of welding), e.g., several million for typical weld consisting of 10 weld passes or more. Additionally, the weld sequence design space is a discontinuous space, where theories of interpolation or extrapolation between data are not valid for the exploration of such an ample design space.

Our most straightforward algorithm for weld sequence design was based on joint rigidity, where the methodology can find the best sequence with a minimal number of welding simulations. The quickest joint rigidity method [9] uses “n” simulations to find a sequence for minimal distortion where “n” is the number of weld passes. A better sequence can be selected with the progressive joint rigidity method [10] that needs analysis. This explanatory space is significantly small sub-space of the total combinatorial possibility of welding “n” passes when compares to \(2^n\) possible scenarios. The main limitation of the joint rigidity method was the progressive nature of the methodology that prevents it from parallel computing. Therefore CPU time can increase for a large number of weld passes.

One affordable approach developed to use a fast but low-fidelity model that captures the most dominant physics of the problem. Although such an algorithm loses some accuracy, it provides a useful approximation of relative behavior for judgment between weld sequencing scenarios. In many design cases, a designer can decide based on this rough approximation of the behavior. A low-fidelity model can be merely an analytical solution [11] or empirical correlation [12]. There are many investigations on distortion control based on relatively low-fidelity mathematical formulation [13], such as Design of Experiment (DOE) [14], Analysis of Variance (ANOVA) [15], Response Surface Method [16], or Taguchi Method [17]. The nature of low-fidelity models limits the performance within a case-specific design envelope because these models are good interpolators but poor extrapolators beyond the boundary of a given design envelope.

As an alternative, we presented another methodology to construct a meta-model of distortion based on the surrogate algorithm [18] in combinatorial space. This algorithm is well suited for parallel computing and can find the best sequence by running “\(4^n\)” independent simulations in parallel and within the time frame of a single simulation run. Better fidelity obtained by using Machine Learning (ML) algorithms where the machine can learn about the behavior of a system within multiple level non-linearity [19].

Among practical ML methods for welding sequence optimization, in this paper, we introduced another methodology that constructs a deep learning artificial neural network for data-driven prediction. The resulting optimal sequence significantly reduced the final distortion, and we showed the result on a panel structure with eleven weld passes. A summary of this methodology is presented here. Experimental validation is not part of this paper; however, simple experimental tests were performed in the background for validation of distortion and thermal prediction. We also coupled our ML algorithm with the search algorithm to explore the sequence design space. The resulting optimal sequence seems to significantly reduce the final distortion with a wise selection of cross-over and mutation between sequences to reach the optimal point at a lower computational cost.

2. PANEL STRUCTURE

Panel fabrication is part of many engineering structures, and welding is the sole fabrication method to erect such structures. In this paper, a panel, without the loss of generality, is selected to present our methodology and find the best welding sequence pattern for minimal distortion on the panel plate. Figure 2 illustrates the panel structure with 11 weld passes that connect a 658x360x19 mm panel plate to 11 stiffeners with varied dimensions and thickness from 42 to 50 mm as shown in this figure. There is no symmetry in the configuration of stiffeners, and the stiffeners are tack-welded on both ends before welding starts. An optimal clamping pattern was designed as a separate task where CWM was used to evaluate several clamping scenarios and to iterate toward the optimal clamping shown. The detail for the optimization of the clamping pattern is not in the scope of this paper. The panel material is Aluminum 6061 T6, and temperature dependent material properties were used in the analysis.

By convention, Figure 1 shows the name designation for each weld pass, and changing capital letters to little letters means changing in the direction, as well, as the objective function that was characterizing the distortion using Eq. 1. Our task was to determine the welding sequence out of (A/a, B/b, C/c, D/d, E/e, F/f, G/g, H/h, I/i, J/j, K/k) welds. The objective is to find the best sequence that gives the lowest distortion. We chose to characterize this distortion by Eq.1 where
“j” represents all FEA nodes in the panel par, and dx, dy, dz are deformation in the coordinate system. The first term captures the root mean square average of deflection on the plate and the second term is to capture the most substantial deflection on the plate. Therefore minimizing Eq.1 can co-minimize the average deflection and the most substantial deflection.

\[
\left( \frac{1}{j} \sum_{j} \sqrt{dx^2 + dy^2 + dz^2} \right)(\max \begin{bmatrix} dx \\ dy \\ dz \end{bmatrix} - \min \begin{bmatrix} dx \\ dy \\ dz \end{bmatrix}) \quad \text{Eq. 1}
\]

3. MATERIAL PROPERTIES
Below are the properties that are taken from [20], [21] for this welding analysis:
- Temperature-dependent Thermal Conductivity
- Temperature-dependent Thermal Expansion
- Temperature-dependent Heat Capacity
- Temperature-dependent Modulus of Elasticity
- Temperature-dependent Yield Stress
- Temperature-dependent Density
- Poisson's ratio

Details of these properties are shown in Table 1.

4. COMPUTATIONAL SETUP & ANALYSIS OF WELD
A full 3D model of the panel was created using Abaqus Welding Interface (AWI) and in-house subroutines. The AWI uses the fusion line defined by the user and assigns a melting temperature. We used the Dirichlet temperature; however, AWI also offers a flux-based model based on Goldak’s Double Ellipsoid [1]. The user controlled the weld sequence through an in-house subroutine. This allowed for the automation of each weld pass in sequence. The welding time is automatically calculated from the pass length and the torch speed. Weld passes were deposited in five chunks to save CPU time while capturing the effect of welding direction. A series of cool down steps were added after the welding was finished. Figure 2 and Figure 3 show snapshots of welding thermal results.

In this analysis, the initial temperature was 21 °C. A convection boundary condition generated a boundary flux on all external surfaces. The temperature-dependent convection coefficients \((w/m^2°C)\) is computed from Eq.2 [22] where \(T\) is the temperature in °C.

\[
h_c = 7.2 - \frac{355000}{(T+273)^2} + 0.001(T + 273) \quad \text{Eq.2}
\]

![Figure 1: Panel structure of interest for distortion control.](image)

![Figure 1: FEA nodes used for the objective function Eq.1 (top), tag and direction convention for weld passes in the panel (bottom).](image)

<table>
<thead>
<tr>
<th>Table 1: Material properties for 6061 T6 aluminum alloy.</th>
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<tbody>
<tr>
<td>Temperature (°C)</td>
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<tr>
<td>Yield strength (MPa)</td>
</tr>
<tr>
<td>Young’s modulus (GPa)</td>
</tr>
<tr>
<td>Thermal exp. (μ m/m K)</td>
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<tr>
<td>Density (kg/m³)</td>
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<tr>
<td>Thermal cond. (W/m K)</td>
</tr>
<tr>
<td>Heat capacity (J/kg K)</td>
</tr>
<tr>
<td>Poisson ratio (-)</td>
</tr>
</tbody>
</table>
Figure 2: A snapshot of welding thermal analysis for the start of a pass.

Figure 3: A snapshot of thermal analysis at the end of the pass.

The stress analysis was quasi-static because inertial or dynamic forces are sufficiently small that they can be neglected. Therefore, at each instant of time, the domain is in static equilibrium. However, the temperature is time dependent and therefore the thermal strain due to thermal expansion is time-dependent. The initial state was assumed to be stress-free. The boundary conditions were identical to the clamping defined and shown in Figure 1. The system is solved using a time marching scheme with time step lengths used for thermal analysis. The stress analysis followed immediately after the thermal analysis. Figure 4 shows the plate displacement after a given sequence.

Figure 4: Plate displacement after completing a sequence.

5. MACHINE-LEARNING AND DIGITAL-TWINS
The state-of-the-art in weld modeling and simulation is the development of a computational replica of the structure called a digital twin of the component to be welded. A machine-learning algorithm (ML) can then be used to train the digital twin, over time, from real observation and data assimilation (IoT). The result is a customized digital twin that accurately replicates a practice for distortion control and suggest options for continued welding.

High-performance computing (HPC) enables engineers to perform data-driven engineering where a computer can act without being explicitly programmed. However, the current data-driven algorithm like machine learning takes a large initial data set to construct a model. In most engineering applications, there is no initial large data set to draw on. Therefore, big data mining tools cannot be a good solution for many engineering applications.

As a solution, we developed a methodology to construct a digital twin from limited data as opposed to big data. Our digital twin uses a small set of data (by far less than a typical set of data mining) from computational simulations as its initial training set to form a minimal fidelity model. Then, wisely extend a useful training set to train ML toward higher fidelity properly.

6. ARTIFICIAL NEURAL NETWORK (ANN) CONSTRUCTION
The first step was the definition of a weld deposition pattern for the Artificial Neural Network (ANN). Three points on the weld pass defined each weld, i.e. start, middle and end. The ANN feature vector used the spatial distance of these characteristic points to two reference points (see Figure 5). Each sequence and direction generates a unique array of 66 elements.

Figure 5: The spatial distance of the weld characteristic points to two reference points in the structure.

The selection of reference points can significantly improve the rate of training; for example, we observed better training by choosing the location of fixtures as our references. We also tried different schemes for the definition of a weld deposition pattern for our ANN, such as binary and ASCII definition. Our weld
definition scheme needs a smaller training set because it contains a crucial physical feature that affects the final distortion.

Generally, theory-guided machine learning (TGML) [23] improves the problem of using limited training data. We implemented TGML through an informed selection of the initial training dataset as well as the physics-guided feature vector. An informed initial training dataset was selected based on the distortion resemblance that can adequately represent the entire population of welding sequences. The main criteria of resemblance were the occurrence of each weld in every position and occurrence of each sequence pair in the pattern [19].

Further, a physics-based feature selection approach was used to include two physical aspects of a sequential welding process, including weld orientation and weld vicinity information. Weld orientation added 6 elements to the ANN’s feature vectors consists of the angle of welding deposition to a fixed axis. Weld vicinity added 10 elements to the ANN’s feature vectors consists of the center-to-center distance of weld passes in the sequence. We used a Dense Neural Network (DNN) and the prediction of DNN was the normal distortion (Y-displacement) for all FEA nodes on the base plate from the simulation mesh.

Development and training of DNN took advantage of the high-level API, Keras, running on top of Tensorflow library. The training dataset consists of 61 selective samples with the high likelihood of resemblance [19], and test-set includes 20 samples. Although the DNN requires the application of all 61 samples during training, the order of these samples in the input matrix is randomized to avoid bias. Feature space (x) is standardized (x') using the built-in function form Scikit Learn. Model training uses Rectified linear unit (ReLU) [24] activation function and an L2-regularized Adam optimizer [25]. A linear activation function was used for the output layer. The neural network trained by limited training data is prone to the noises, hence overfitting. Dropout method [26] is used to address this overfitting issue. The loss function was set to root-mean-square-error (RMSE).

In addition to RMSE, correlation coefficient (r-value) and the slope of the regression line evaluate the developed model’s predictability for each data point in the test set. Finally, model hyperparameters are selected using a Bayesian optimization [27] tool from SciKit Optimize library. These hyperparameters comprise; the number of hidden layers, number of neurons in a hidden layer, dropout rate, and regularization coefficient.

7. SEARCH ALGORITHM

As mentioned earlier, we chose to characterize the overall distortion by Eq.1. In a practical situation (like our main structure with 11 weld passes), the space of possible sequences is very large, and therefore it is not possible to fully explore all possibilities to select the best one. Using search algorithms such as genetic algorithm (GA) is necessary to be linked with the DNN model for active exploration toward the best sequence.

A GA algorithm starts by generating an initial population (i.e., an initial set of sequences). This initial population is sorted based on the surrogate model’s estimation of distortion. The initial population then is used to produce children (new set of sequences) for the next generation (iteration) of search. “Crossover” between two parents (initial sequences) and “Mutation” of a parent are the common GA tools to generate children (new sequences). However, for the welding sequence, GA’s functions shall satisfy some constraints to generate a correct sequence. For example, a weld pass cannot be repeated in a sequence including in a different direction.

A modified GA algorithm was developed for weld’s “Crossover” and “Mutation” functions. This GA algorithm was integrated with our surrogate model to explore the design space of welding sequences.

For a crossover, a proper sequence (parent_a) was found in the population by using the N-way tournament selection method for the lowest distortion. Another right sequence (parent_b) was found for parent_a using an auxiliary function, “Match Finder” to assure compatibility of parents for the welding constraints. Finally, crossing parent_a and parent_b over random weld passes, generated two new sequences (children). Figure 6 shows a schematic example of the algorithm implemented for crossover.

For a mutation, a good parent was selected from the population by using the same tournament selection method. Two random positions were picked along the sequence, and the corresponding welds were switched. The algorithm was set to change the direction with 50% likelihood. Figure 7 shows a schematic example of the algorithm implemented for mutation.

![Figure 6: Crossover schematic for the evolution of weld sequences in GA.](image)

![Figure 7: Mutation schematic for the evolution of weld sequences in GA.](image)
8. PANEL DISTORTION CONTROL

Table 5 partially shows the training set that was generated for 11 weld passes where all weld passes, and directions occur at least once in every position as well as every pair occurs at least once somewhere in sequence [19]. Our optimal training set had 61 weld sequences that were used for training with the high likelihood of weld resemblance.

**Table 5**: Partial presentation of an optimal training set for 11 weld passes.

```
DHBaCkjiFEG bjkgHCedEi JalkFcCdGhEB
fJICGDdBhK ejKaFbgdDei AcgFdhEHBK ...
hFklaGJDCEb EKHDAleJfge kFjiGEdaHEb
CEbkJdaHh fhGEjBdaKC HeKfBgfadfC
```

An ML-based digital-twin of the structure was through a series of independent ML models where each represents the deposited weld, except for the first weld that has an identical FEA solution. A DNN defines the history of weld sequence deposition and makes a prediction when informed with physical components of the feature vector explained earlier. The DNN hyper-parameters (here, “dropout”, Number of hidden layers”, “number of neurons in every hidden layer”, and “learning rate”) were automatically optimized by a Bayesian Optimization tool (SciKit Optimize). Figure 8 to Figure 19 compare ML prediction and FEA prediction of distortion on the panel after depositing each weld pass for a weld sequence (fGHaJDcEKbi) outside of the training set. ML prediction performs better in terms of accuracy for initial depositions than the later ones when compared with FEA; however, the CPU time for ML prediction was instantaneous on a modest processor such as in iPad vs. FEA with several hours of CPU time on an HPC server.

**Figure 8**: Comparing ML prediction (left) with FEA prediction (right) after depositing 1st weld in sequence fGHaJDcEKbi

**Figure 9**: Comparing ML prediction (left) with FEA prediction (right) after depositing 2nd weld in sequence fGHaJDcEKbi

**Figure 10**: Comparing ML prediction (left) with FEA prediction (right) after depositing 3rd weld in sequence fGHaJDcEKbi

**Figure 11**: Comparing ML prediction (left) with FEA prediction (right) after depositing 4th weld in sequence fGHaJDcEKbi

**Figure 12**: Comparing ML prediction (left) with FEA prediction (right) after depositing 5th weld in sequence fGHaJDcEKbi
Figure 13: Comparing ML prediction (left) with FEA prediction (right) after depositing 6th weld in sequence fGHaJDcEKbi

Figure 14: Comparing ML prediction (left) with FEA prediction (right) after depositing 7th weld in sequence fGHaJDcEKbi

Figure 15: Comparing ML prediction (left) with FEA prediction (right) after depositing 8th weld in sequence fGHaJDcEKbi

Figure 16: Comparing ML prediction (left) with FEA prediction (right) after depositing 9th weld in sequence fGHaJDcEKbi

Figure 17: Comparing ML prediction (left) with FEA prediction (right) after depositing 10th weld in sequence fGHaJDcEKbi

Figure 18: Comparing ML prediction (left) with FEA prediction (right) after depositing 11th weld in sequence fGHaJDcEKbi

Figure 19: Comparing ML prediction (left) with FEA prediction (right) after cool down of sequence fGHaJDcEKbi

The digital-twin of the panel structure was coupled with the GA search algorithm for improving the distortion. GA was performed on 100 new weld sequences in population. Table 6 shows the top 10 sequences after 50 generations of evolution with the lowest distortion (i.e., Eq. 2). We selected the top 5 for FEA verification and as the best candidate of the lowest distortion. Weld sequence “GebjffsDhhk” was selected out of these candidates as the best sequence with the low distortion shown in Figure 20.

If one decides to continue for a better distortion, it is recommended to select “n” lowest fidelity scores from the GA search to add FEA to the training set and reconstruct the surrogate model. We implemented an iteration of training to
show it. Figure 21 shows the weld sequence \textit{“idefJHgabcK”} can generate lower diction than other candidates can.

Iteration of re-training the surrogate model can be repeated until the whole design space is covered, and for a large design space, the limitation is the availability of computational resources and the project’s schedule to achieve a good distortion.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Sequence</th>
<th>Objective</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>GlebDjchfak</td>
<td>0.999</td>
<td>0.597</td>
</tr>
<tr>
<td>2</td>
<td>jcbhDeGeatk</td>
<td>0.939</td>
<td>0.556</td>
</tr>
<tr>
<td>3</td>
<td>GbjeGfiaDhk</td>
<td>0.991</td>
<td>0.522</td>
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<tr>
<td>4</td>
<td>jcbhDeGfak</td>
<td>1.061</td>
<td>0.550</td>
</tr>
<tr>
<td>5</td>
<td>IcbeGDjghK</td>
<td>0.947</td>
<td>0.478</td>
</tr>
<tr>
<td>6</td>
<td>IEBaejDGrK</td>
<td>1.118</td>
<td>0.513</td>
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<tr>
<td>7</td>
<td>bcdjGifatK</td>
<td>1.310</td>
<td>0.595</td>
</tr>
<tr>
<td>8</td>
<td>IEBacjDjhK</td>
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<td>0.521</td>
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<tr>
<td>9</td>
<td>IebDDeGjaK</td>
<td>1.161</td>
<td>0.514</td>
</tr>
<tr>
<td>10</td>
<td>aBejiGcfDhk</td>
<td>1.273</td>
<td>0.540</td>
</tr>
</tbody>
</table>

**Table 6** The top 10 sequences after 50 generations of evolution with the lowest distortion.

**Figure 20:** The best selection of distortion from the weld sequence “GebjeGfiaDhk” with no iteration of training.

**Figure 21:** An improved selection of distortion resulted from the weld sequence “idefJHgabcK” after one iteration of re-training.

9. **CONCLUSION**

Constructing a digital twin of manufacturing processes such as those involving welding is now practical. A responsive digital twin is a hybrid digital twin that combines simulation tools with machine learning algorithms for data-driven prediction using limited data for manufacturing and fabrication applications. This hybrid approach is different from typical big data analysis. It becomes more attractive when our engineers deal with complex processes or structures with CPU time as the bottleneck of engineering decisions. Active learning methodology, together with theory-guided machine learning, are useful tools for the wise exploration of a training set for gaining fidelity with a minimal number of data. The hybrid digital twin uses FEA simulation for training ML networks, so using a validated FEA is critical for an appropriate presentation of the reality in this hybrid approach. Nevertheless, the skill of our engineers is paramount for using these tools for developing an innovative solution to our manufacturing challenges.

**REFERENCES**


