Physics-Based Digital Twins of Welding Fabrication in Real-Time

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1 Summary

Physics-based digital twins offer a critical core-competency that enables the smarting through limited data. The current data-driven digital twins that use machine learning take a significant initial data set to mature for making decisions. In most manufacturing processes, there is no such data set to draw on. The majority of SMEs need cyber-manufacturing systems that work with limited data and physics-based digital twins. However, physics-based digital twins that are entirely built on deploying simulation tools such as finite element analysis (FEA) cannot be responsive enough for real-world applications. A solution is to use machine learning (ML) algorithms that emulate the time-consuming FEA-solver behaviour at a much shorter time. We build a hybrid physics-based digital-twin that takes advantage of data-driven digital twins for quick response while gaining fidelity through adaptive learning with FEA simulation tools. We use our hybrid digital-twin to explore various weld sequences in real-time to form a platform for smart welding fabrication. This tool enables engineers to analyze and compare different patterns to assess fabrication scenarios without computational time delay..

2 Background

The basis of smart factories is the cyber-physical system (CPS) platform [1] consists of three parts;

a) Intelligent physical assets that include physical manufacturing machines with embedded AI capabilities as digitals muscles.
b) Cyber twin systems that are the digital representation of physical assets. This digital twin is designed to act as the brain of the system for making wise decisions.
c) Communication platform for data and information exchange between the cyber twin (the brain) and physical assets (digital muscles).

The focuse of this talk is on the cyber twin part of the CPS and uses the digital twin (DT) in cyber-manufacturing – a CPS sub category. Authors propose two approaches for smarting a digital twin (DT) in the content of cyber-manufacturing. We can construct a data-driven DT or knowledge-driven DT in smart factories [2].

The data-driven smart factories navigate the tsunami of data from embedded manufacturing sensors, use data-mining tools for converting data to information, and then use the upcoming real-time information for dynamic wise decision-making. The foundation of this category includes big data mining algorithms, digital thread and machine-learning (ML).

In the other approach, which is the knowledge-driven smart factories, the cognition of the manufacturing brain is based on the manufacturing process's physics rather than pure data manipulation. This category's foundation includes theory-guided digital twins that include physics of the process, theory-trained ML, and simulation tools in the learning cycle.

3 Digital Twins of Welding

We explain the methodology on a real panel structure shown in Figure 1 as an example without restraining other structures' application. This panel fabrication is part of many engineering structures, and welding is the sole fabrication method to erect such structures. Weld engineers use many techniques to control the welding distortion during the erection of panels including the best welding sequence pattern for minimal distortion. For example, having "n" welds requires choosing from $2^n n!$ possible welding scenarios. This welded structure with 11 welds provides over 80 Bn weld sequence scenarios which is a large design space to explore.

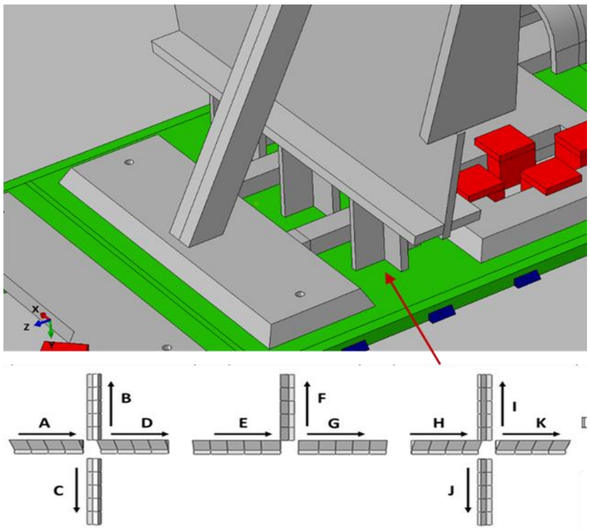

Figure 1 Panel structure including the convention used in this paper.

4 Responsive Cyber-Twin

We use a Dense Neural Network (DNN) meta-model in building our cyber-twin where the cyber-twin receives a weld sequence string and quickly returns the distortion of the panel.
Although simulation tools such as FEA predict the distortion with high fidelity, we cannot use them in our cyber-twin because of the CPU time beyond a DT requirement. On the other hand, DL models are responsive enough for a DT requirement, but they need a large dataset to gain a certain level of fidelity.
As a solution, we build a hybrid DT that takes advantage of DL modeling for quick response while gaining fidelity through adaptive learning with a simulation tool as an oracle for labeling data [3]. We have challenged our DT with a large number of welding sequences that are not in the training set. We have compares our DT's prediction against the exact solution from the FEA model. Table 4 summarizes the statistical report of the performance.

Table 4 Statistical report of our DT's performance.

	R^2	RMSE
Training	0.90	0.29
Validation	0.88	0.55

5 Conclusions

We build a digital twin that can quickly explore weld sequence scenarios for finding the best design with the lowest distortion in welded structures. Our digital twin consists of a quick learner that is data-driven to be responsive, and it uses an active learning algorithm to wisely navigate the data selection toward a higher training rate and gain fidelity using critical data points rather than an aggregated data set. Our oracle is a finite element representation of the structure that labels queries from the active learning algorithm. The learner uses a physics-guided machine learning approach to become more informed and reducing data dependency.

6 References

[1] B. Bagheri, "Big future for cyber-physical manufacturing systems," University of Cincinnati, Cincinati OH, 2015.
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[3] B. Settles, R. J. Brachman, W. W. Cohen and T. G. Dietterich, Active Learning, Morgan & Claypool, 2012.