

um
2026

Enhancing Resistance Spot Welding Predictive Accuracy Through Automated Calibration and Surrogate Modeling



Dr. TAREK BELGASAM

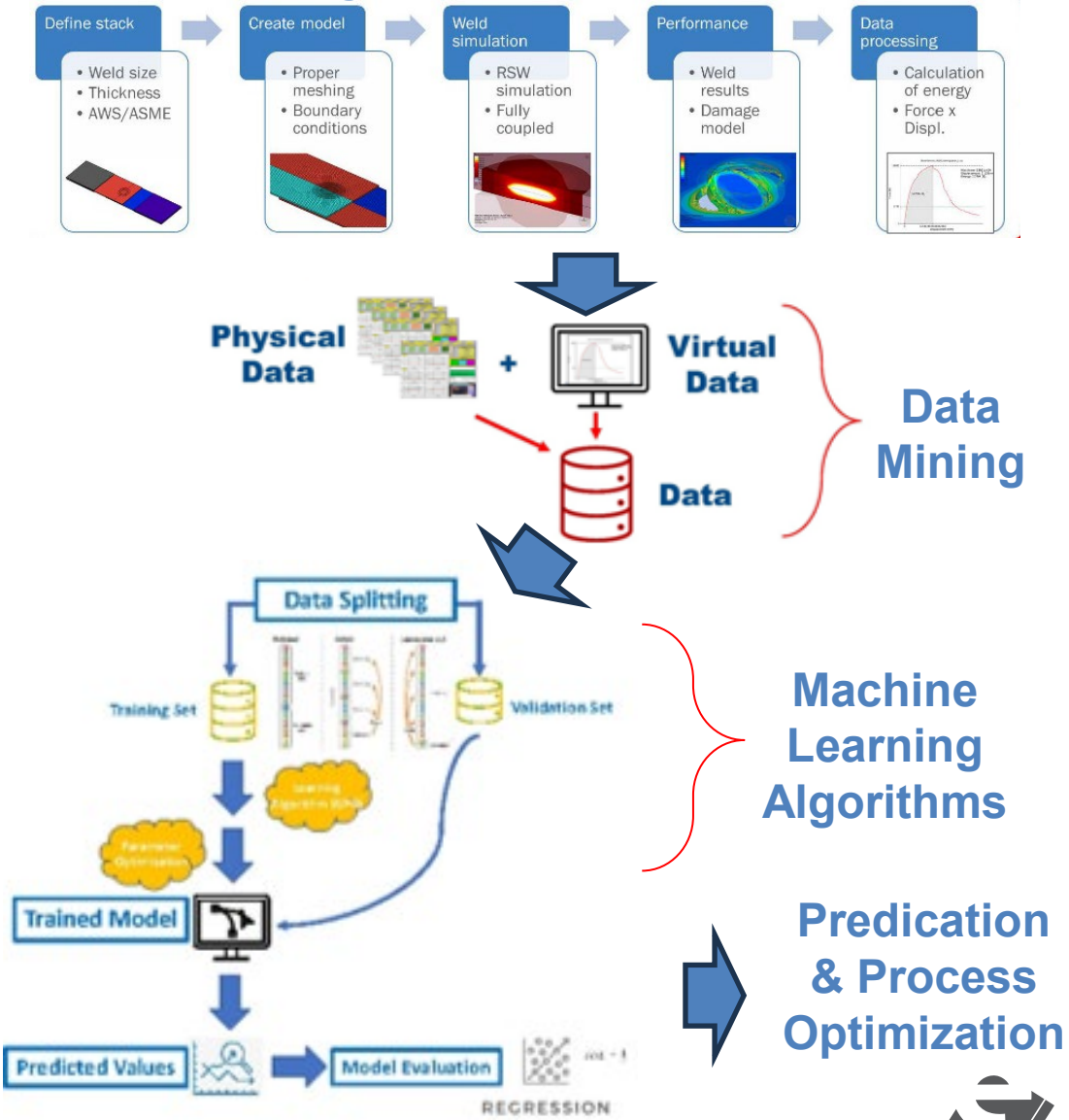
Principal Materials Research Engineer
Honda Development & Manufacturing of America, LLC

HONDA

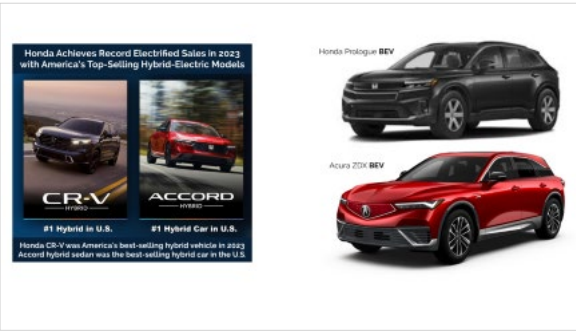
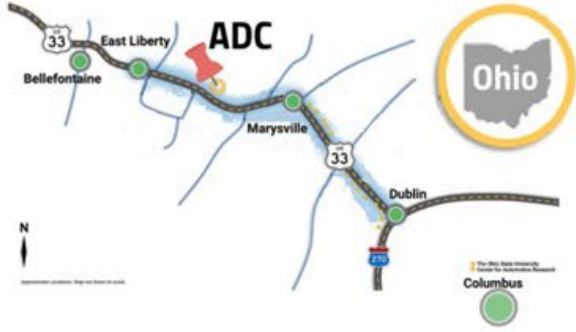
Outline

- Background**
 Industry evolution, high stack ratio welding challenges, and impact on ICE & BEV body construction
- Objective**
 Develop a robust digital approach to improve RSW quality and process reliability
- Methodology & Approach**
 Automated Workflow for RSW Material Card Calibration (MCC), Virtual Welding Quality Assessment (VWQA), and minimal physical trials supported by DoE, RSM, optimization, and robustness assessment.
- Results & Discussions**
 Digital-physical validation, model accuracy, process insights, and VWQA ROI / Benefit.
- Takeaways**

Virtual Welding Tests



HDMA – Automotive Development Center (ADC) Introduction



HDMA Light Truck Products (ICE):



**Honda Achieves Record Electrified Sales in 2023
with America's Top-Selling Hybrid-Electric Models**



#1 Hybrid in U.S.



#1 Hybrid Car in U.S.

Honda CR-V was America's best-selling hybrid vehicle in 2023
Accord hybrid sedan was the best-selling hybrid car in the U.S.

Honda Prologue **BEV**



Acura ZDX **BEV**



HDMA – Automotive Development Center (ADC) Introduction



Acura MDX

HDMA Light Truck Products (ICE):



Honda Pilot



Honda CR-V



Honda Accord



Honda CIVIC



Acura TLX



Honda Passport



Honda Ridgeline



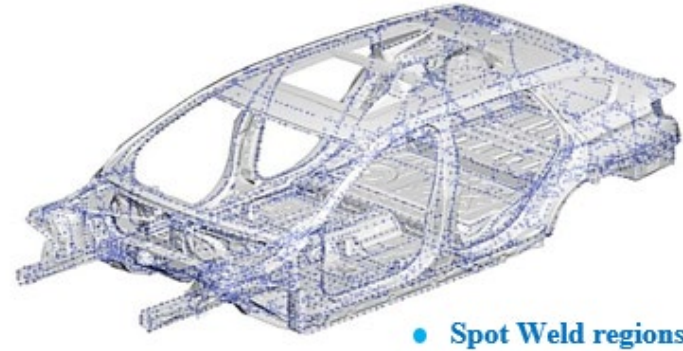
Honda Odyssey

SUMMARY ADC develops both light truck and electrified vehicles for the North American market, demonstrating Honda's commitment to sustainable mobility and innovation.

Background: Industry Context & Motivation

① ICE & BEV BIW Implications

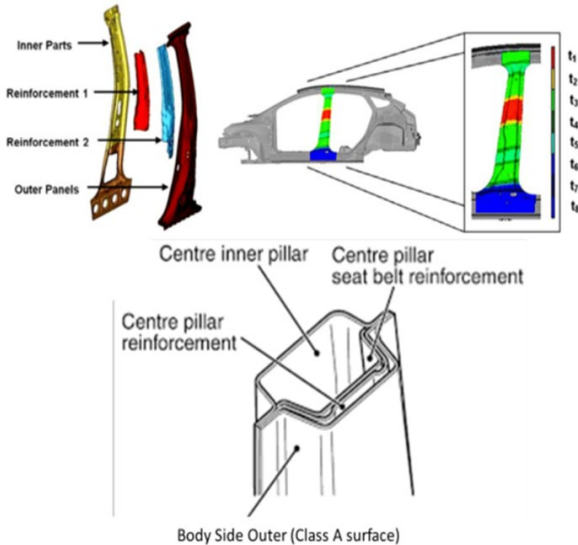
1. BIW designs are shifting toward **stronger, lighter,** and more **complex structures**.
2. ICE programs are expanding **advanced high-strength** and **hot-stamped materials**.
3. BEVs are accelerating demand for **higher stack-ratio joints** and more complex **3T/4T weld applications**.



- White/body structures contain **5000+ spot-welds**.
- New developments have **100+ new spot-weld stacks**.

② High Stack Ratio (HSR) Implications

1. **HSR joints** are emerging as a **critical enabler** for next-generation BIW design.
2. Their complexity **increases welding risk** and structural validation demands.
3. **Digital optimization** and **virtual validation** are becoming essential for efficient development.



<https://engineeringcheatsheet.com/what-type-of-welding-is-used-for-car-frames/>

SUMMARY Increasing BIW complexity—driven by advanced materials, higher stack-ratio joints, and 3T/4T welds—necessitates digital optimization and virtual validation to ensure robust, efficient, and scalable weld performance development.

Objectives

① Enhance RSW Quality:

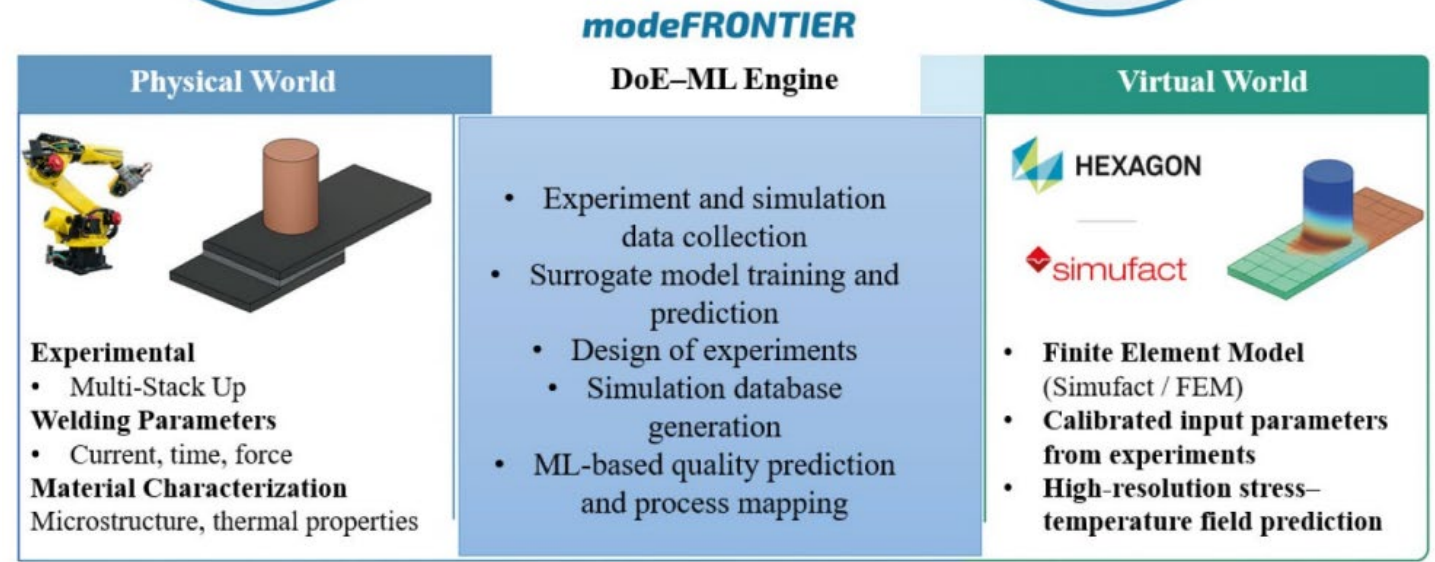
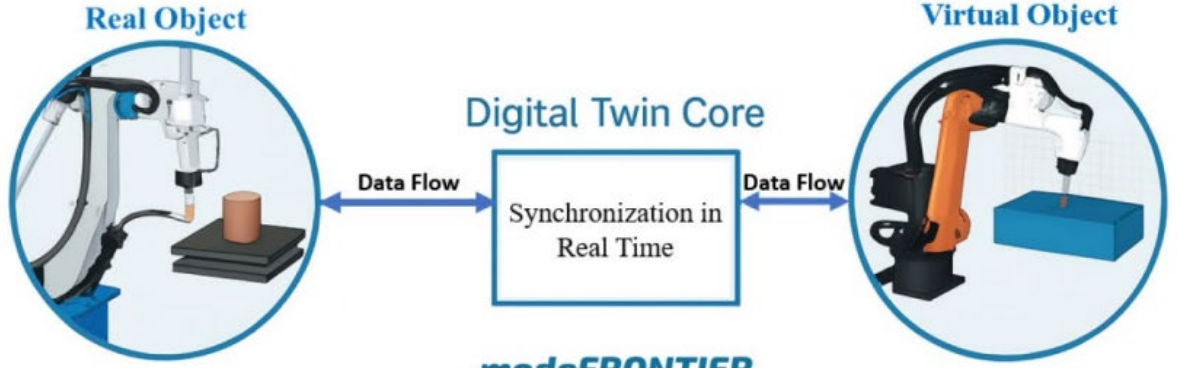
- Optimize RSW via simulations
- Automate for consistent quality
- Streamline efficient welds

② Reduce Resource Usage:

- Cut testing time, materials.
- Optimize workflows efficiently.
- Boost productivity, reduce costs

③ Support Manufacturing:

- Innovate 3T/4T processes
- Improve BEV weld quality
- Expand structural capabilities



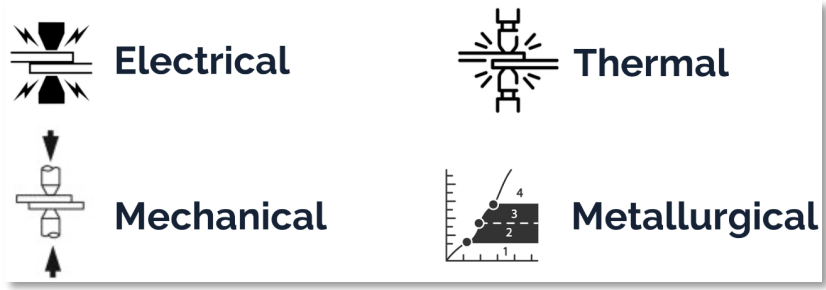
(Aminzadeh & Belgasam et al., 2026, Welding in the World)

SUMMARY The project objective is utilizing advanced simulation, automation, and optimization to improve RSW quality, reduce resource use, and advance joint manufacturing for better BEV welding quality.

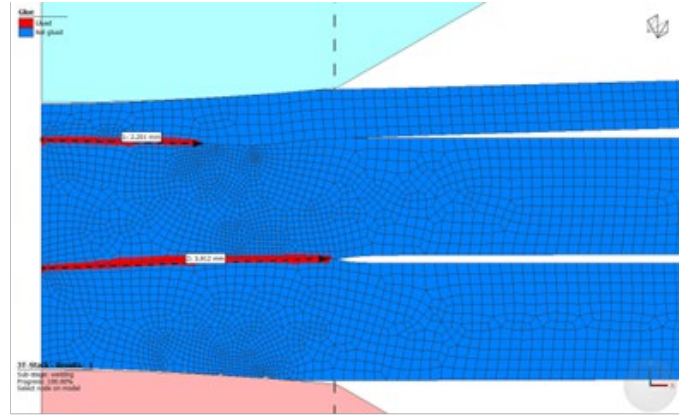
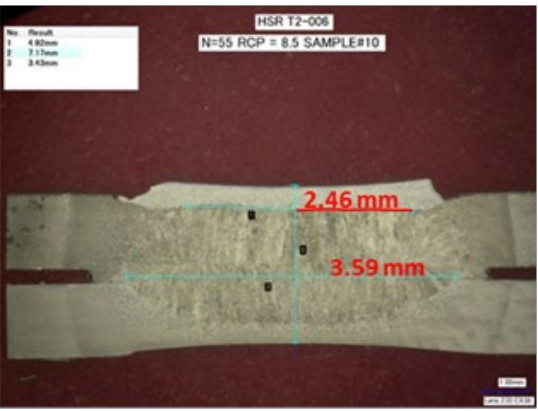
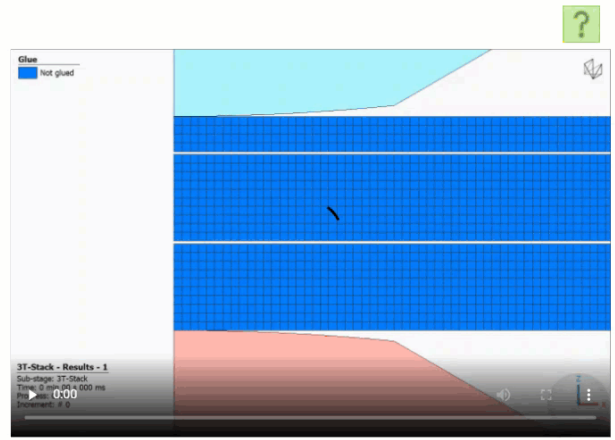
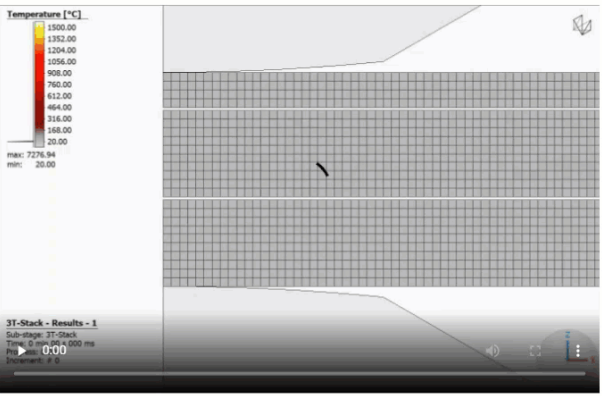
Methodology and Approach: RSW Simulation

Weld Simulation Approaches

- **Simufact (SF)** digital tool simulates the complicated RSW process which involves the interaction of four phenomena:



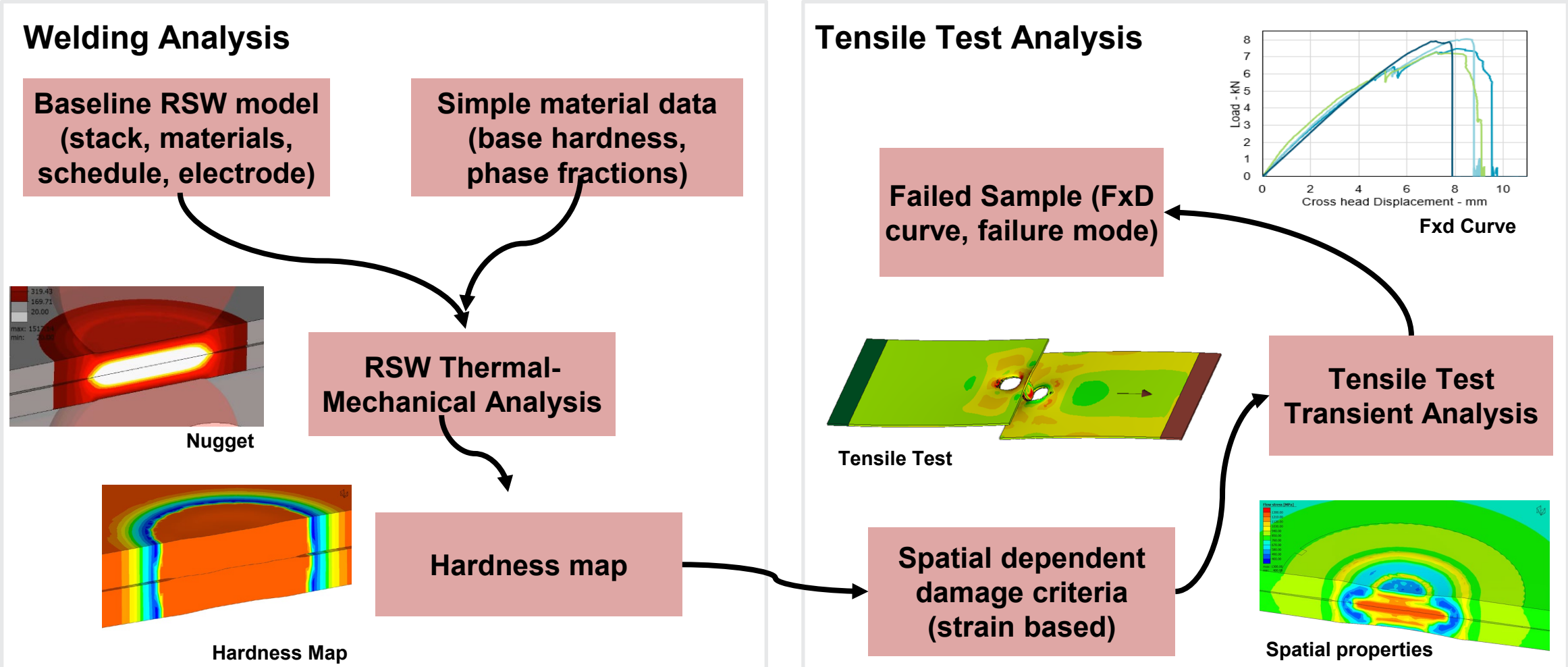
- **Simufact** simulations enable optimization of nugget size and welding parameters, reducing dependence on extensive physical experiments
- **2D Axisymmetric** is used for fast analysis and weld schedule development
- **3D Analysis** is used for tensile test and strength prediction



SUMMARY Simufact (SF) finite element software was used to precisely predict welding distortions and residual stresses by accounting for phase transitions, temperature effects, and mechanical responses

Methodology and Approach: RSW Simulation

Weld Tensile Testing Approach



SUMMARY The coupled thermal-mechanical and tensile-test workflow links nugget formation, hardness mapping, and strain-based damage criteria to predict weld failure response digitally.

Methodology and Approach: Data Framework

Structured welding data for prediction and optimization

A structured digital workflow links **parameterized welding inputs** with **measured weld quality outputs** to support prediction, validation, and optimization of stack-up welding performance.

1. Parametrized welding schedule

All major steps of the welding schedule are parameterized based on:

1. Foundational welding investigations
2. Process knowledge
3. Welding expert input

These input variables define the virtual design space for evaluating weld behavior across different stack-up conditions.

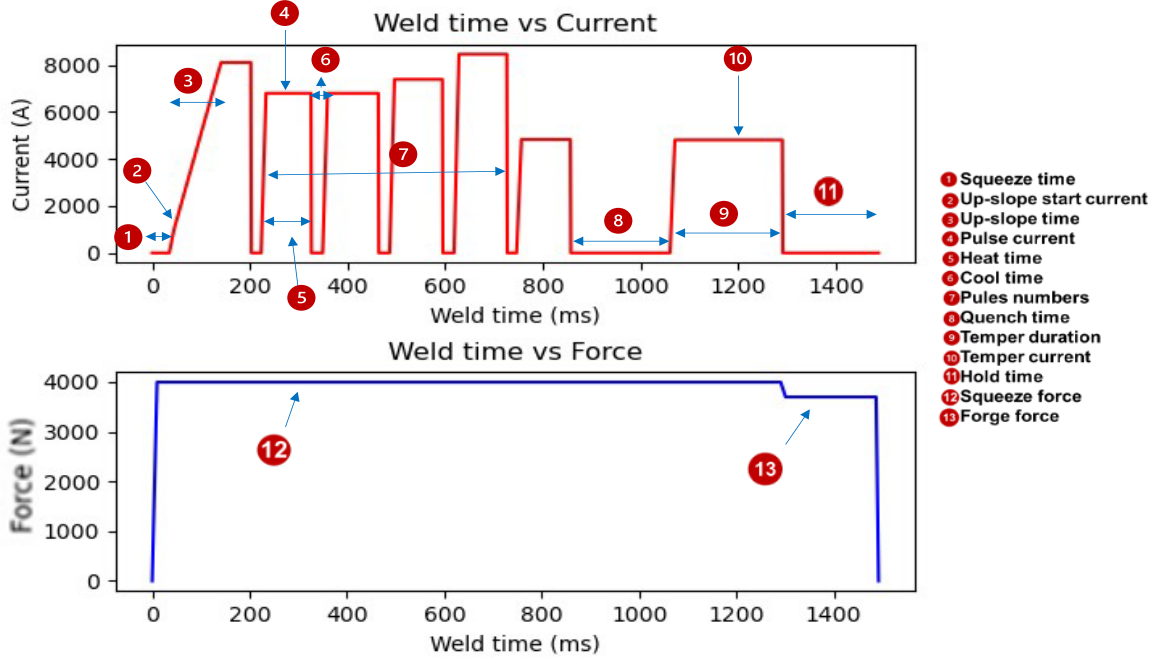
2. Weld Quality Responses

Key weld quality outputs are monitored to assess and optimize performance, with primary focus on:

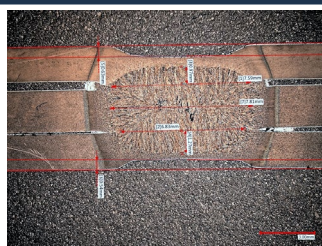
1. Nugget size response
2. Interface behavior
3. 3T and 4T stack-up weld performance

These outputs provide the basis for digital prediction, physical comparison, and schedule optimization.

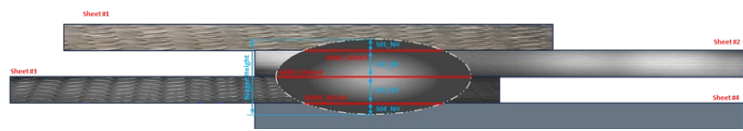
Parametrized Welding Schedule



Physical Measurements



Virtual Measurements



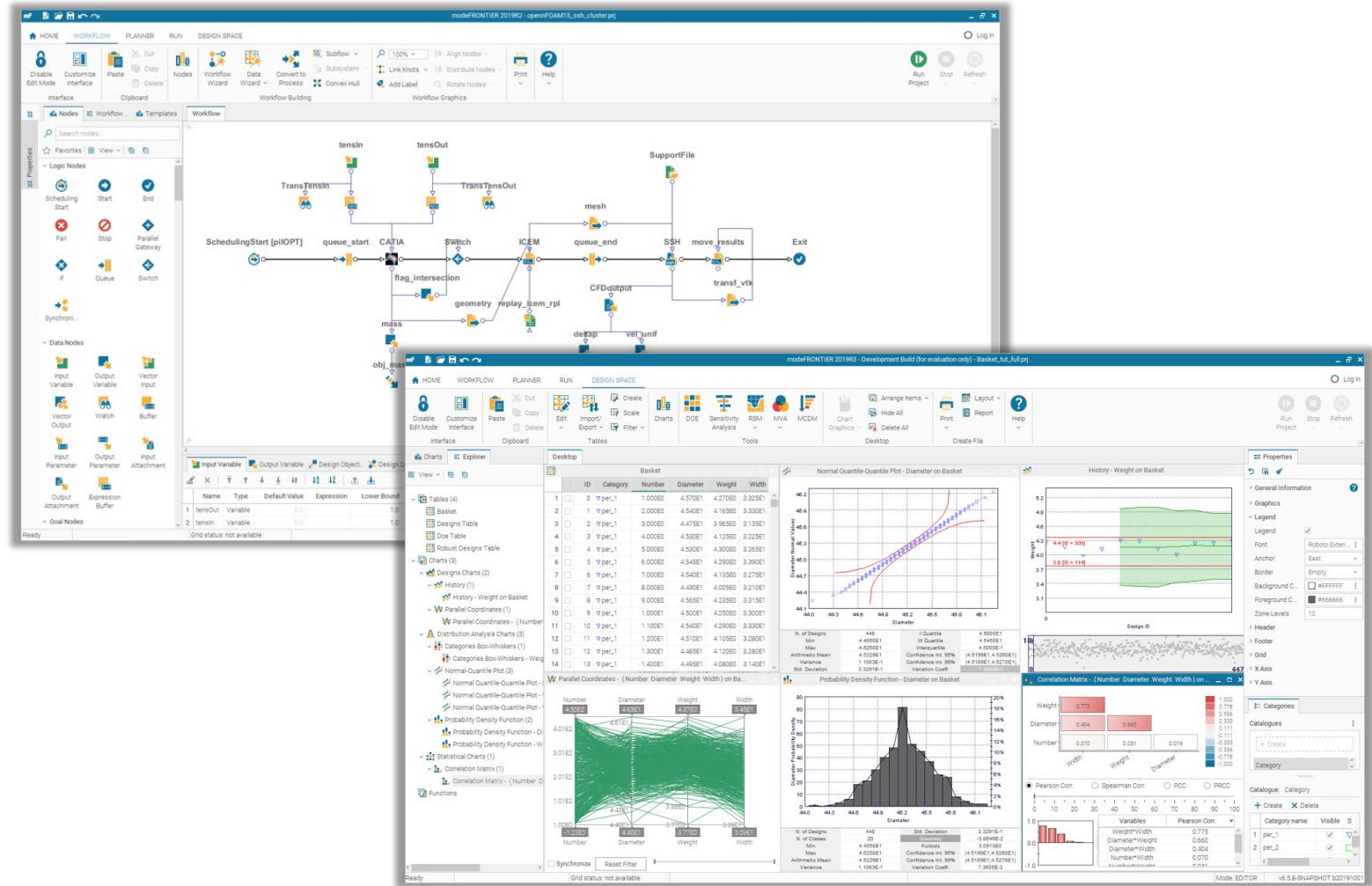
SUMMARY

VWQA converts welding knowledge into a parameterized digital framework that links welding schedules with measurable quality responses, enabling efficient prediction, validation, and optimization of 3T and 4T weld performance.

modeFRONTIER

Is an ESTECO software product:

- *Process Integration*
- *Process Automation*
- *Design Optimization*
- *Data Analytics*
- *Response Surface Modeling*
- *Machine Learning*
- *Robustness & Reliability*



SUMMARY

modeFRONTIER serves as the core platform for automating workflows, integrating simulations, and enabling scalable optimization and analytics.



Methodology and Approach: Workflow Steps

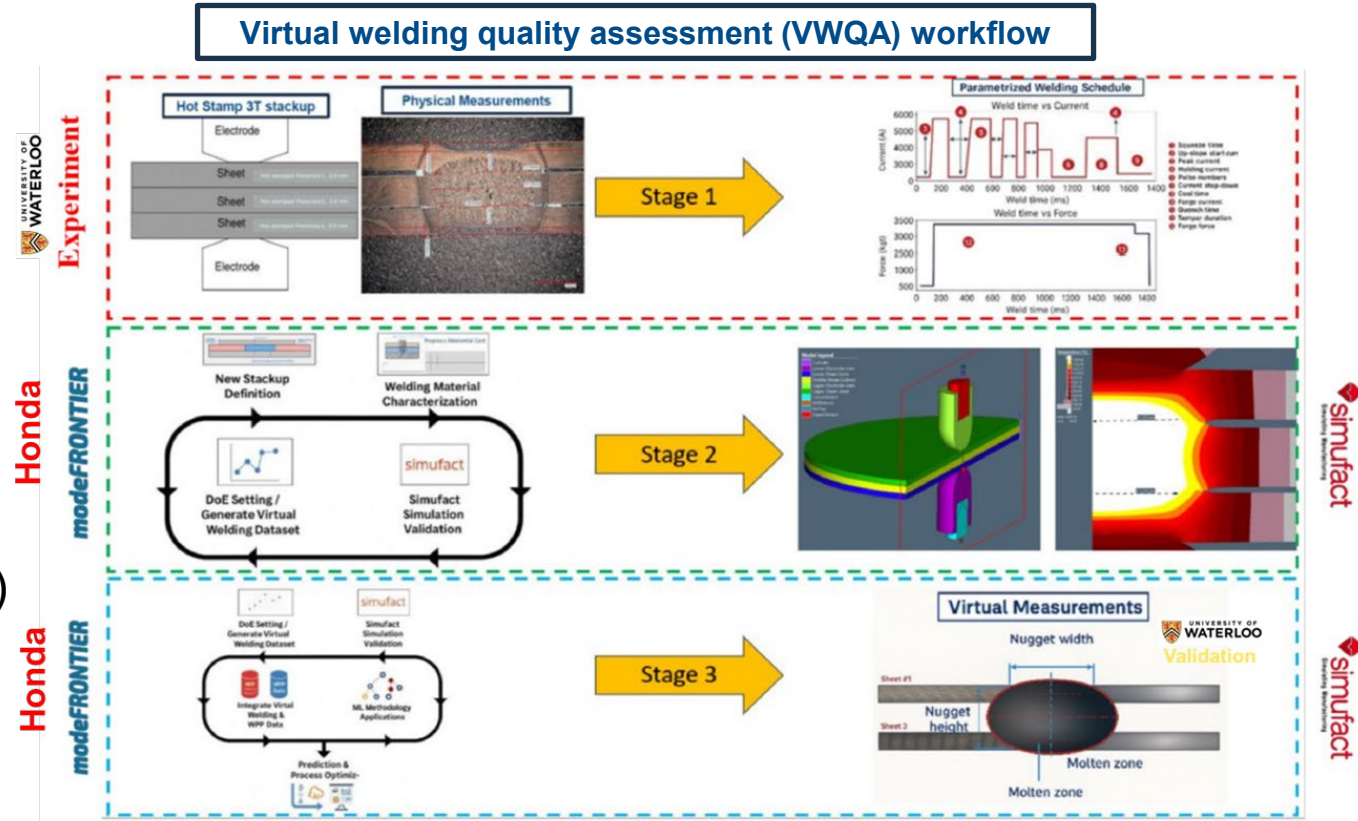
Virtual Welding Quality Assessment (VWQA) Steps:

The VWQA workflow steps for new weld stack-ups involving new material grades, configurations, or welding techniques covers:

Stage 1:
1. Baseline Welding Parameters (UW/Physical)

Stage 2:
1. Setup & Validate Welding Simulation (Honda/Simulation)
2. Implement Design of Experiment (Honda/Simulation)
3. Apply & Train Response Surface (Honda/Virtual)

Stage 3:
1. Identify Virtual Optimization (Honda/Virtual)
2. Validate Virtual Optimization (UW/Physical)

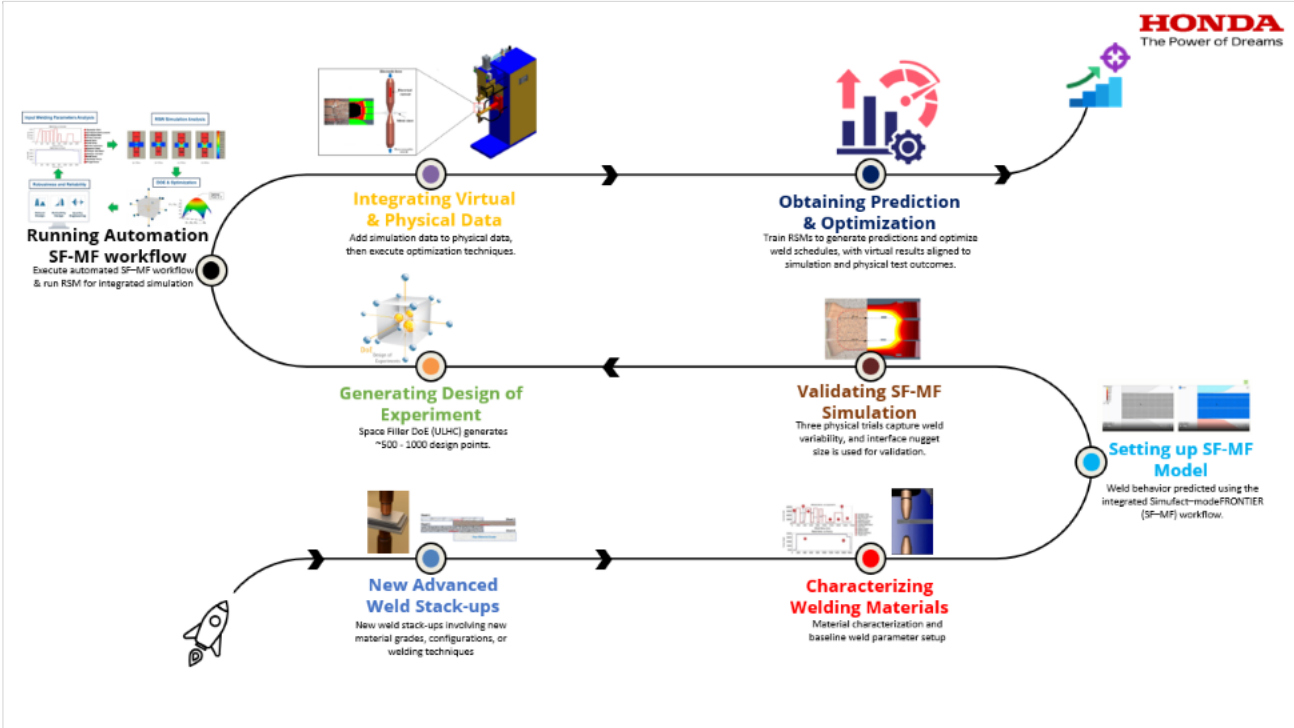


SUMMARY Structured VWQA workflow transitions from physical baseline to simulation, ML-driven exploration, and validated optimization.

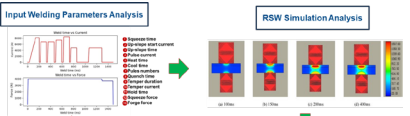
Methodology and Approach: VWQA Roadmap Execution

Roadmap from Stack-Up Definition to Prediction & Optimization:

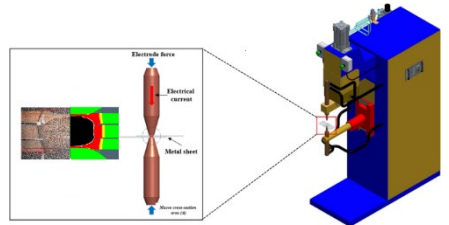
- 1 New Advanced Weld Stack-ups
- 2 Characterizing Welding Materials
- 3 Setting up SF-MF Model
- 4 Validating SF-MF Model
- 5 Generating Design of Experiment
- 6 Running Automation SF-MF workflow
- 7 Integrating Virtual & Physical Data
- 8 Obtaining Prediction and Optimization



SUMMARY End-to-end roadmap connects stack-up definition, modeling, automation, and data integration to deliver predictive and optimization-ready welding solutions.

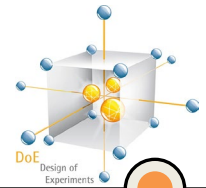


Running Automation SF-MF workflow
Execute automated SF-MF workflow & run RSM for integrated simulation



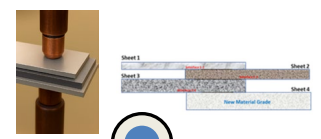
Integrating Virtual & Physical Data

Add simulation data to physical data, then execute optimization techniques.



Generating Design of Experiment

Space Filler DoE (ULHC) generates ~500 - 1000 design points.



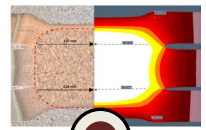
New Advanced Weld Stack-ups

New weld stack-ups involving new material grades, configurations, or welding techniques



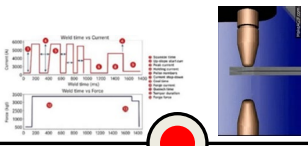
Obtaining Prediction & Optimization

Train RSMs to generate predictions and optimize weld schedules, with virtual results aligned to simulation and physical test outcomes.



Validating SF-MF Simulation

Three physical trials capture weld variability, and interface nugget size is used for validation.



Characterizing Welding Materials

Material characterization and baseline weld parameter setup



Setting up SF-MF Model

Weld behavior predicted using the integrated Simufact-modeFRONTIER (SF-MF) workflow.



Methodology and Approach: ML-Driven Optimization Framework

Optimization through MCC, DoE, ASF, and RSM

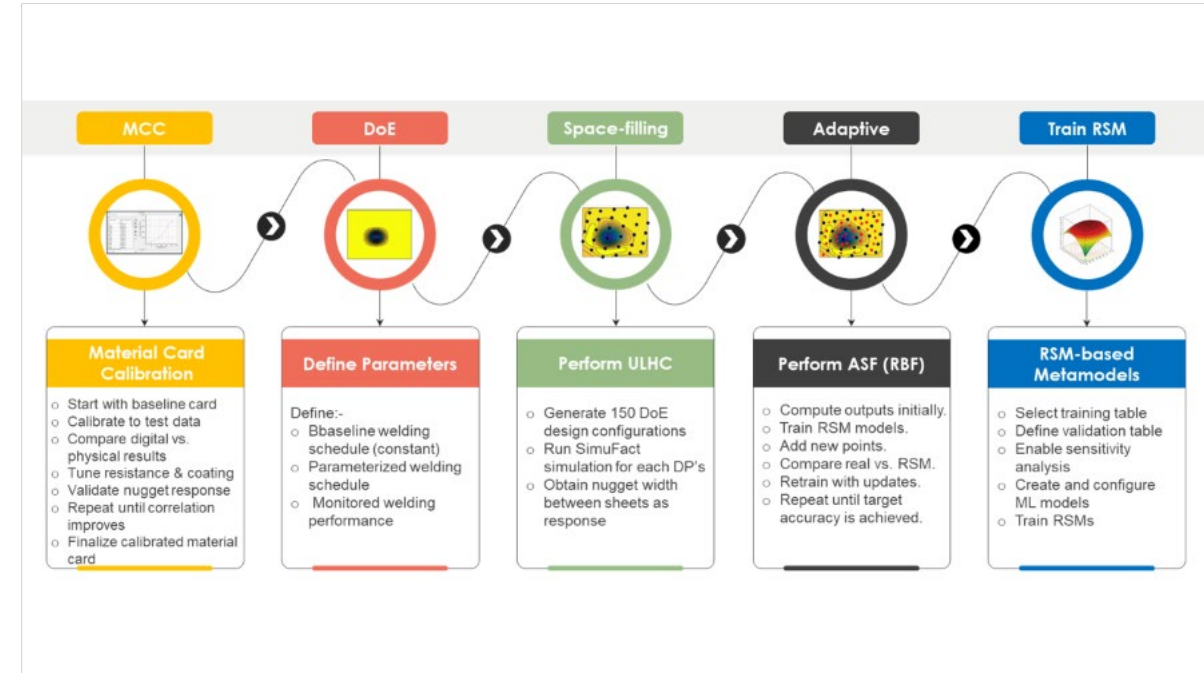
- ### 1. Material Card Calibration (MCC)

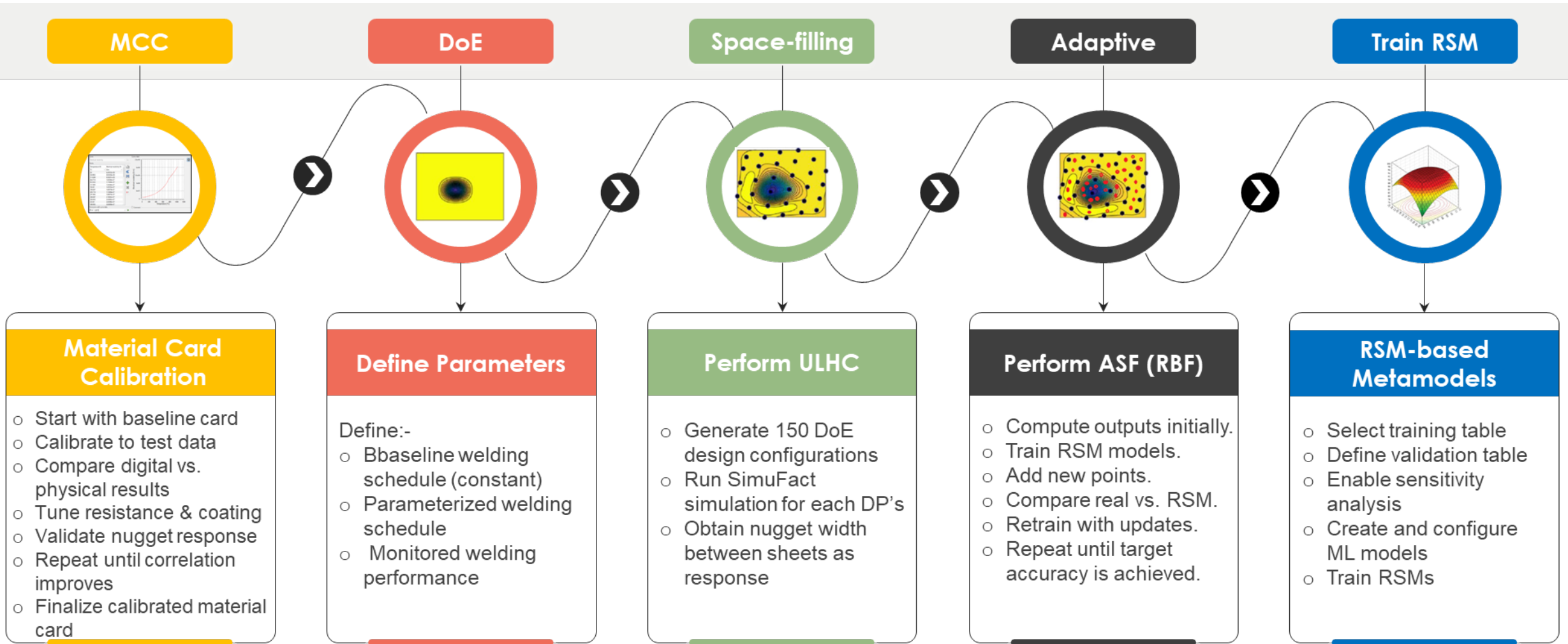
Calibrate material cards using **test data by tuning resistance and coating** to ensure accurate **nugget prediction and digital-physical alignment**.
- ### 2. Space filler algorithm(DoE)

Stochastic DoE generated uniform random numbers using **Uniform Latin Hypercube (ULHC) algorithm**. (**Generate ~100 - 1000 Design Points**)
- ### 3. Adaptive Space Filler (ASF)

ULHC DoE points expanded using **Machine Learning Adaptive Space Filler (ASF)** for iterative design space exploration and response surface refinement. (**Add ~ 50 - 500 Design Points**)
- ### 4. Train RSMs

RSM-based metamodels developed using the ASF DoE database, optimized, and validated by comparing virtual predictions with actual design outcomes (**Generate 5000 virtual Design Points**)

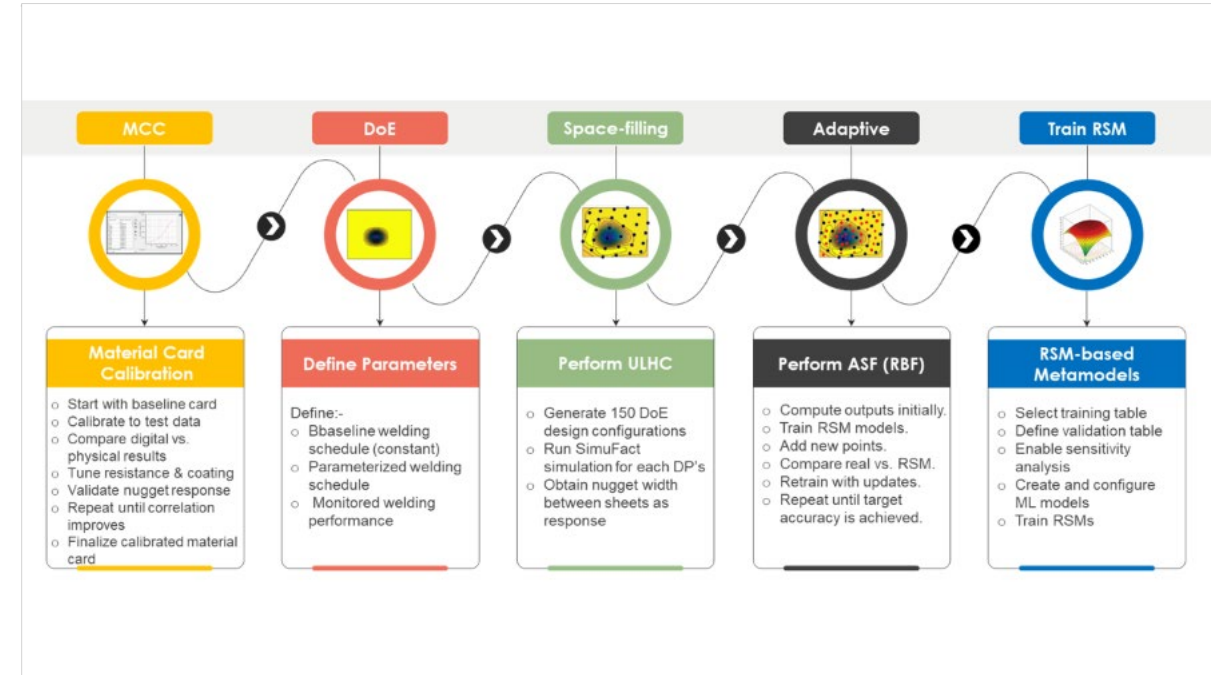




Methodology and Approach: ML-Driven Optimization Framework

Optimization through MCC, DoE, ASF, and RSM

- 1. Material Card Calibration (MCC)**
 Calibrate material cards using **test data by tuning resistance and coating** to ensure accurate **nugget prediction and digital-physical alignment**.
- 2. Space filler algorithm(DoE)**
 Stochastic DoE generated uniform random numbers using **Uniform Latin Hypercube (ULHC) algorithm**. (**Generate ~100 - 1000 Design Points**)
- 3. Adaptive Space Filler (ASF)**
 ULHC DoE points expanded using **Machine Learning Adaptive Space Filler (ASF)** for iterative design space exploration and response surface refinement. (**Add ~ 50 - 500 Design Points**)
- 4. Train RSMs**
RSM-based metamodels developed using the ASF DoE database, optimized, and validated by comparing virtual predictions with actual design outcomes (**Generate 5000 virtual Design Points**)



SUMMARY MCC establishes a calibrated foundation, enabling **DoE** exploration, **ASF**-driven learning, and **RSM** modeling for robust welding optimization.

Results & Discussions: MCC Calibration Performance

Automated Workflow for RSW Material Card Calibration (MCC)

Enabling robust digital–physical correlation

① **Data Variability:**

Physical and simulation data exhibit inherent variability, requiring structured calibration

② **Experimental Alignment:**

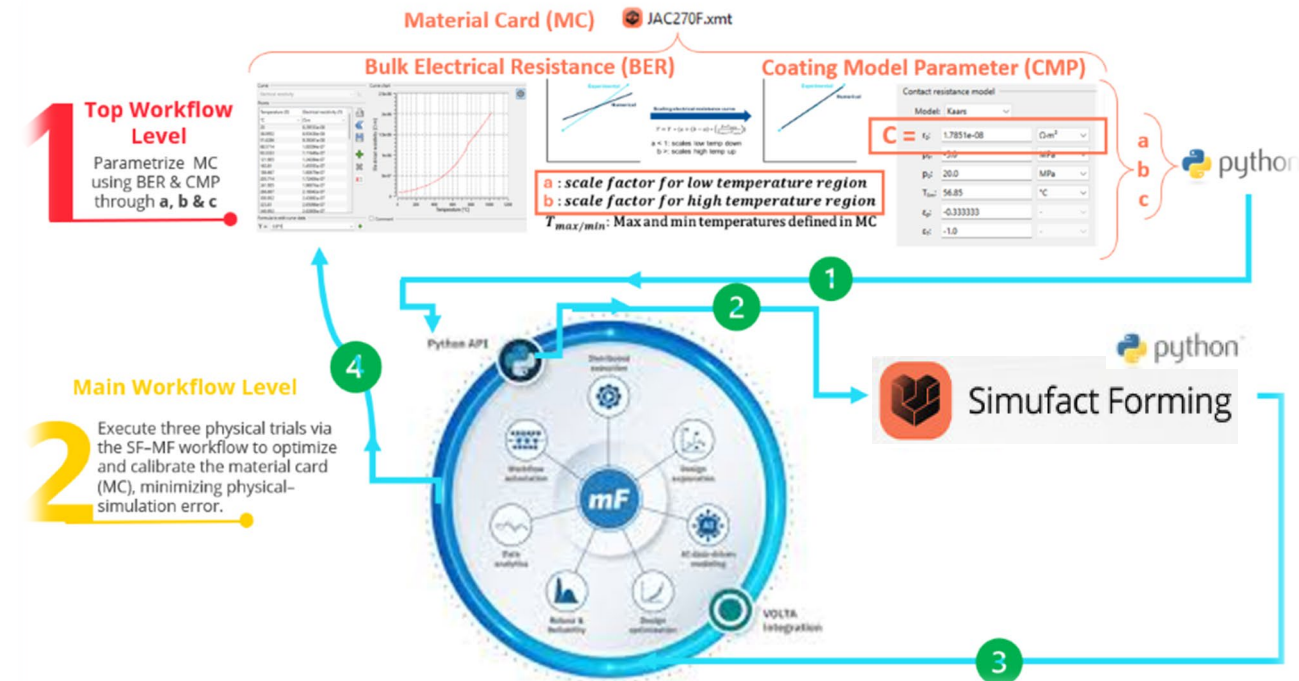
Material cards are calibrated to experimental conditions before predictive use

③ **Key Parameter Tuning:**

Calibration focuses on electrical resistance and coating behavior due to their strong influence on nugget formation

④ **Correlation Readiness:**

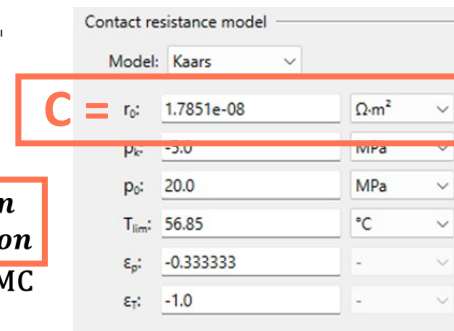
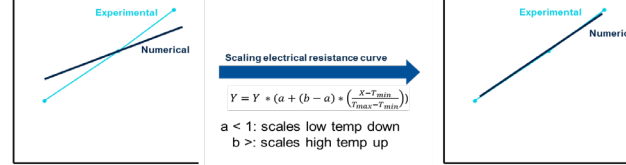
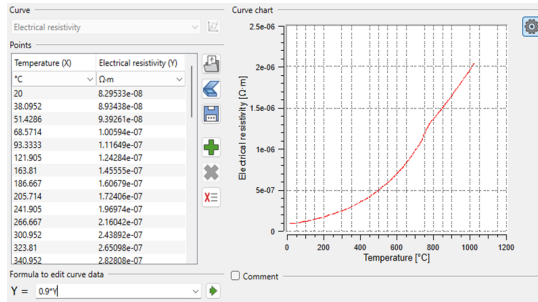
Automated calibration improves correlation and enables reliable digital–physical alignment



Material Card (MC)  JAC270F.xmt

Bulk Electrical Resistance (BER)

Coating Model Parameter (CMP)

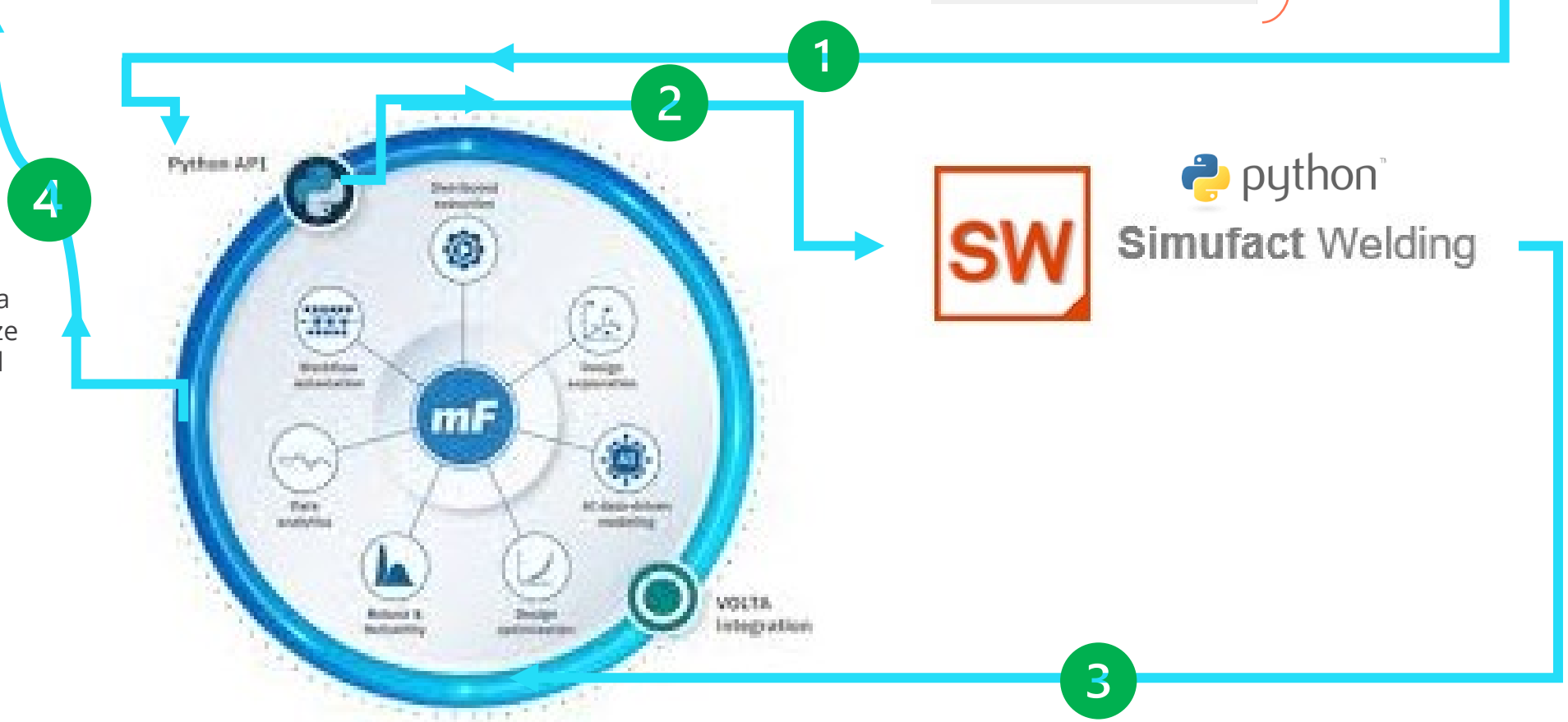


a : scale factor for low temperature region
b : scale factor for high temperature region
 $T_{max/min}$: Max and min temperatures defined in MC

a
b
c }  python™

1 Top Workflow Level
 Parametrize MC using BER & CMP through **a, b & c**

2 Main Workflow Level
 Execute three physical trials via the SF-MF workflow to optimize and calibrate the material card (MC), minimizing physical-simulation error.



Results & Discussions: MCC Impact Assessment

Driving efficiency and accuracy in weld prediction

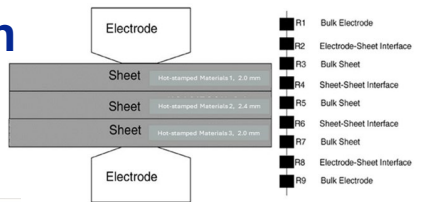
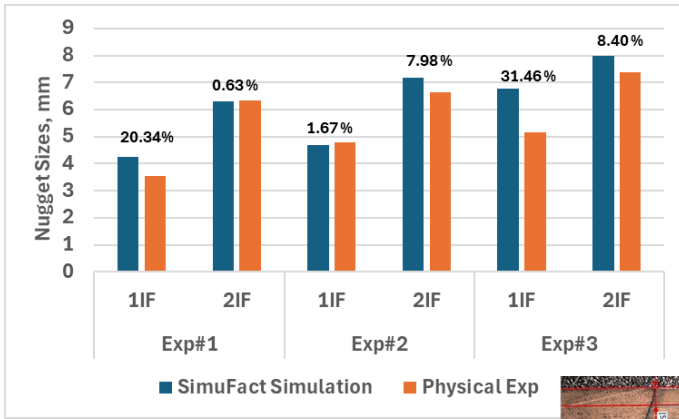
Before MCC

- Run more than 300 simulation to calibrate material card manually
- Best lowest error compared to 3 physical trails for IF1-2:

Exp#1: 20.34%, Exp#2: 1.67% & Exp#3: 31.46%

- Run all 60 physical trails with the optimal MC and average error for :

Ave, Error of IF1-2 = 40%
Ave Error of IF2-3 = 8%



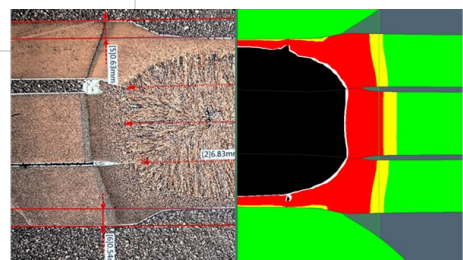
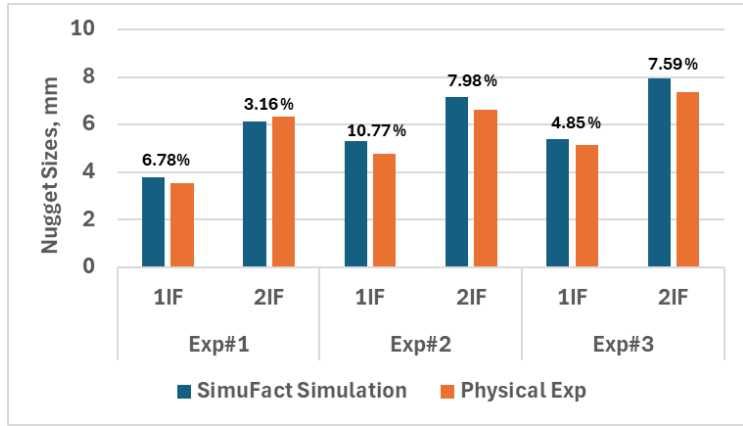
After MCC

- Run less than > 50 simulation to calibrate material card via MCC
- Best lowest error compared to 3 physical trails for IF1-2:

Exp#1: 6.78%, Exp#2: 10.77% & Exp#3: 4.85%

- Run all 60 physical trails with the optimal MC and average error for :

Ave, Error of IF1-2 = 19%
Ave Error of IF2-3 = 9.3%

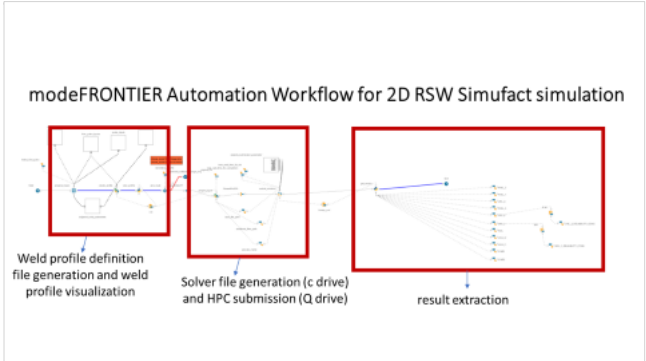


SUMMARY MCC reduced calibration effort by >80% while cutting prediction error by ~50%—delivering faster, more accurate digital–physical weld alignment.

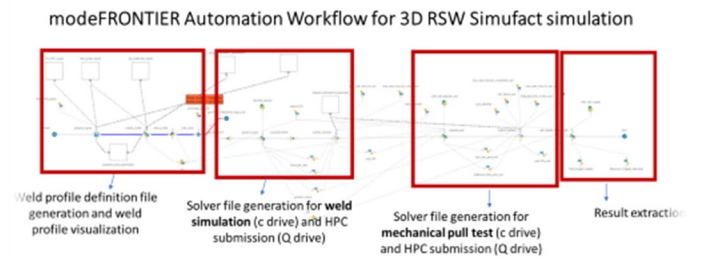
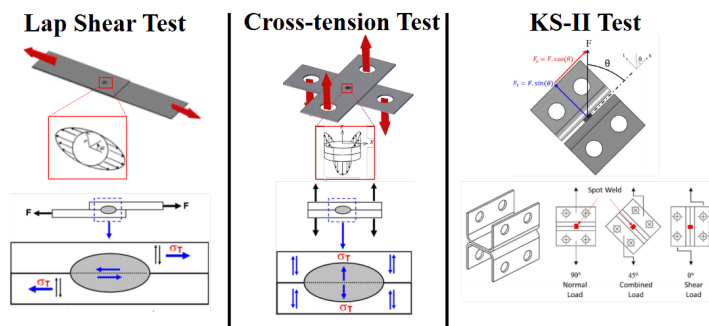
Results & Discussions: Automated 2D/3D RSW Workflow Deployment

SimuFact–modeFRONTIER integration enabled scalable automation, optimization, and validation readiness

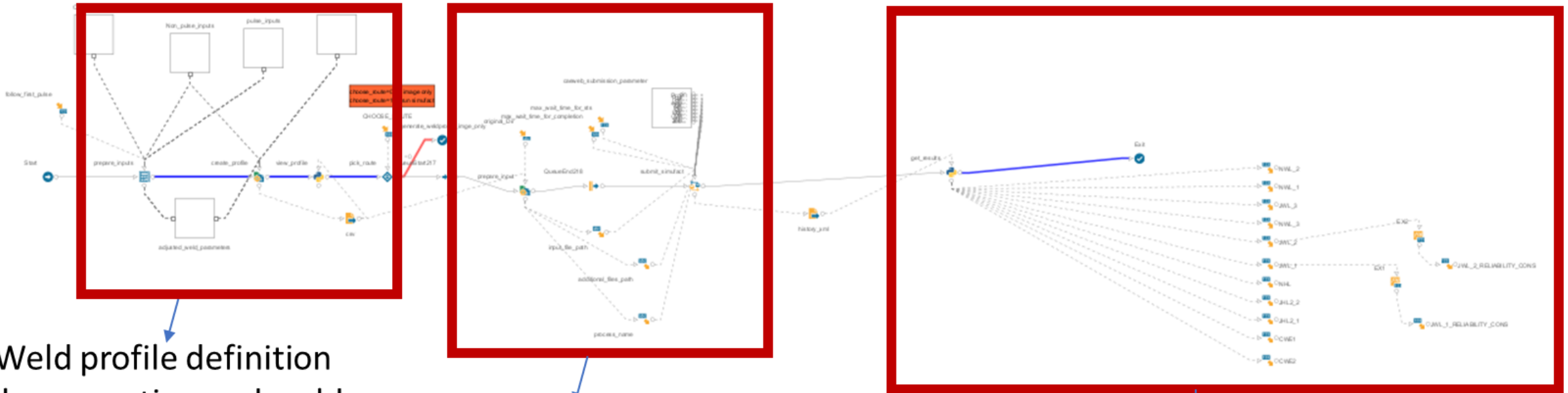
- Developed automated **2D RSW workflows** integrating SimuFact and modeFRONTIER for **parameterized simulation and optimization**.
- Developed an automated end-to-end **3D RSW workflow** integrating welding process simulation with **mechanical validation (e.g., lap shear, cross tension, or KS-II)**.
- Enabled end-to-end automation: weld schedule definition → solver setup → HPC execution → result extraction.
- Standardized workflows for scalable DoE and optimization across multiple stack-ups.
- Validated automated pipelines with physical trials to ensure reliable digital–physical correlation.



Mechanical and Materials Tests



modeFRONTIER Automation Workflow for 2D RSW Simufact simulation



Weld profile definition
file generation and weld
profile visualization

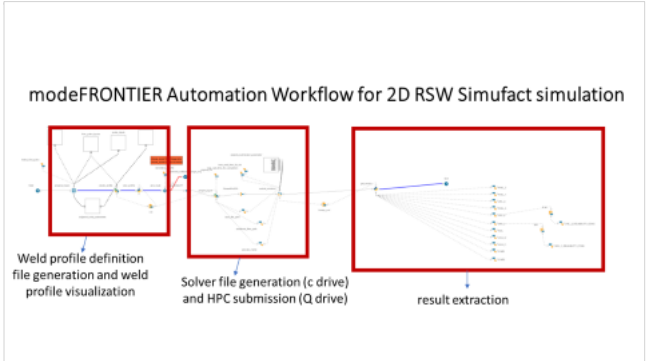
Solver file generation (c drive)
and HPC submission (Q drive)

result extraction

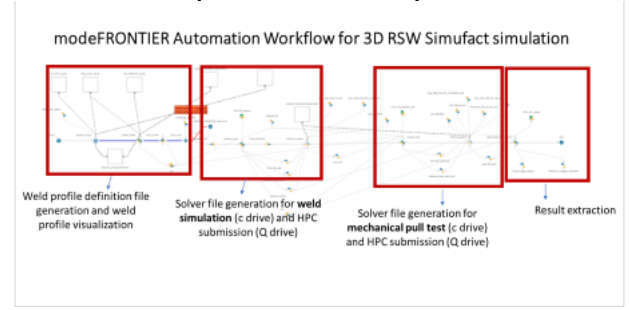
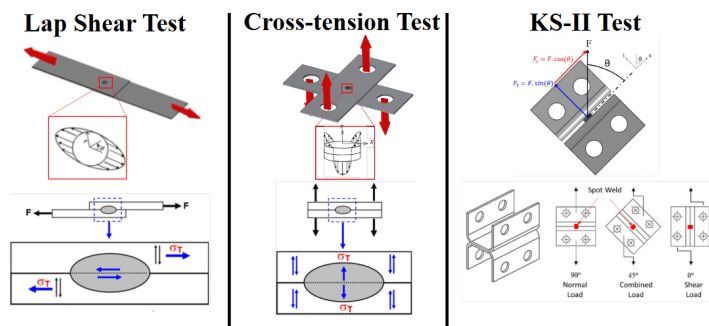
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Mechanical and Materials Tests



modeFRONTIER Automation Workflow for 3D RSW Simufact simulation



Weld profile definition file generation and weld profile visualization

Solver file generation for **weld simulation** (c drive) and HPC submission (Q drive)

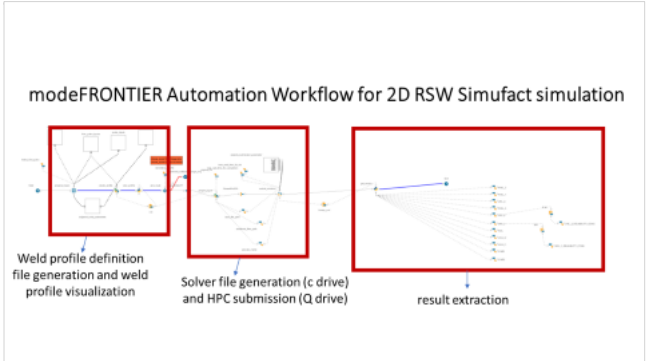
Solver file generation for **mechanical pull test** (c drive) and HPC submission (Q drive)

Result extraction

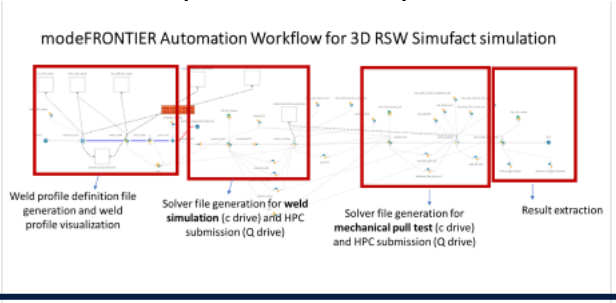
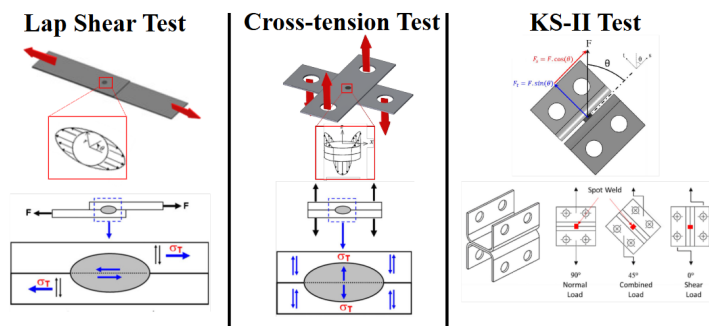
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Mechanical and Materials Tests

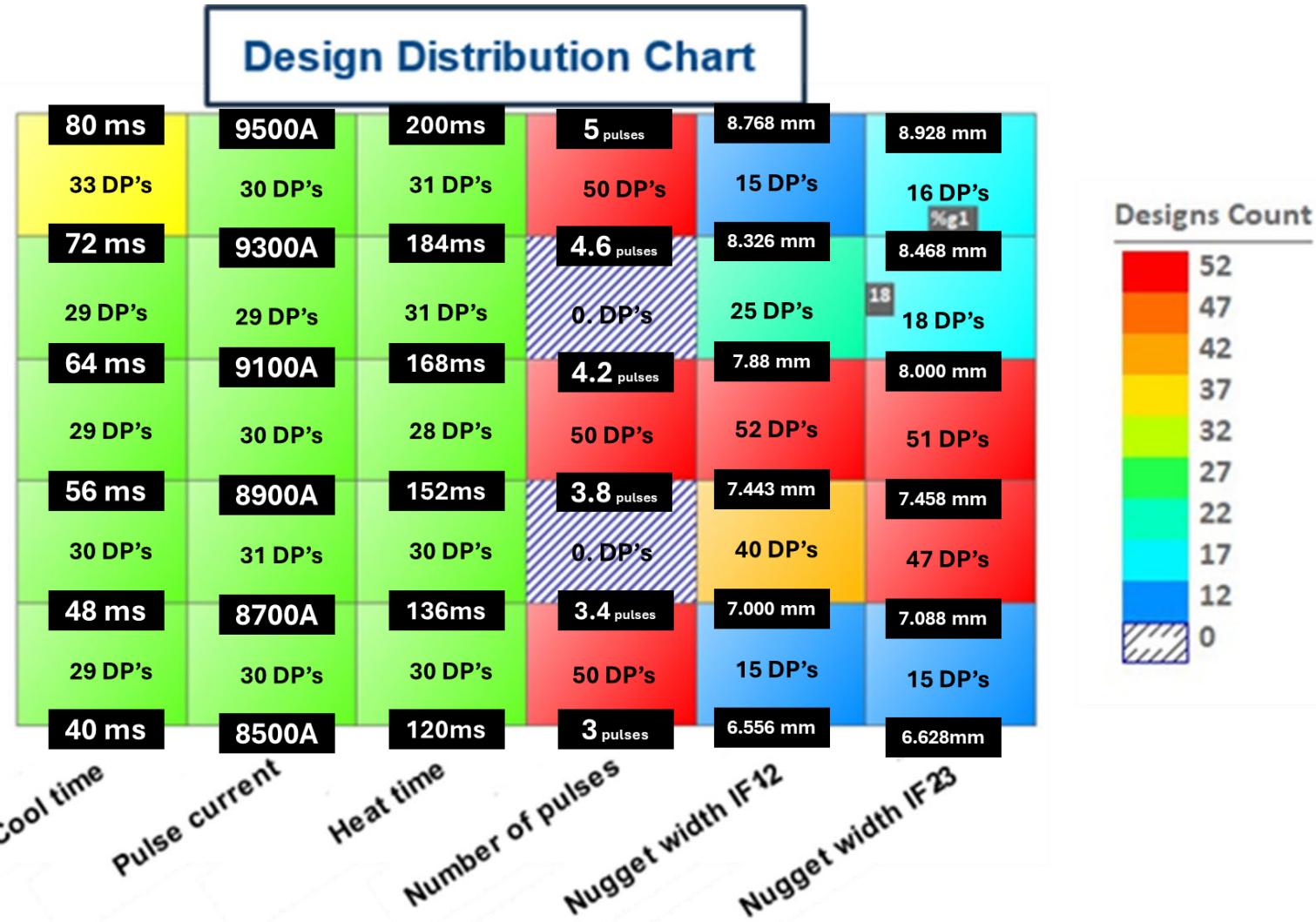


SUMMARY Automated 2D/3D SimuFact–modeFRONTIER workflows enabled scalable DoE, streamlined HPC execution, and strengthened digital–physical correlation across weld stack-ups.

Results & Discussions: Design Space and Parameter Influence

Design distribution and correlation identified key weld drivers

- **ULHC** generated a well-distributed initial design space, and **ASF** refined it through targeted adaptive sampling.
- The combined **ULHC-ASF** approach provided strong design space coverage for robust modeling and optimization.
- **Heat time, pulse current, and pulse number** were identified as the primary weld-quality drivers and cool time showed relatively limited influence.



SUMMARY

ULHC and ASF created a high-quality design space that supported reliable driver identification, robust modeling, and efficient weld optimization.

Results & Discussions: Identify Most Influential Variables

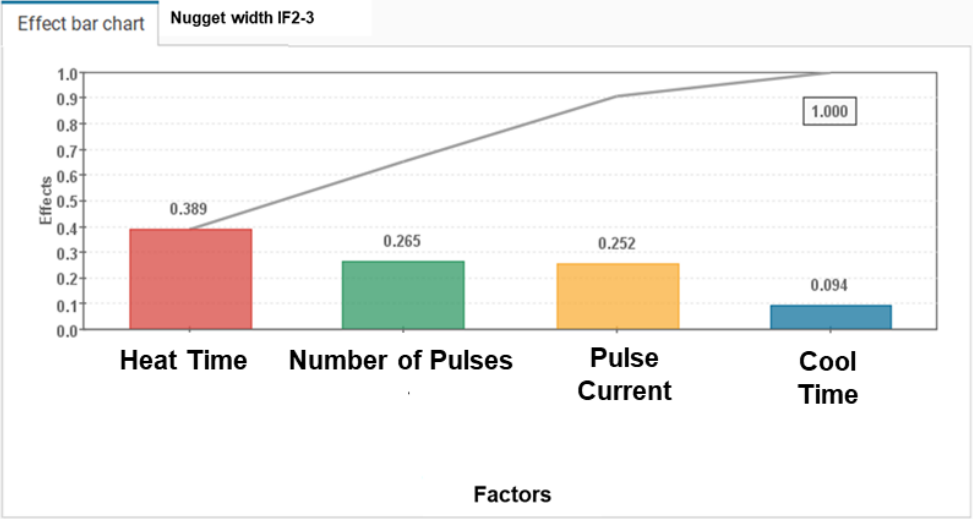
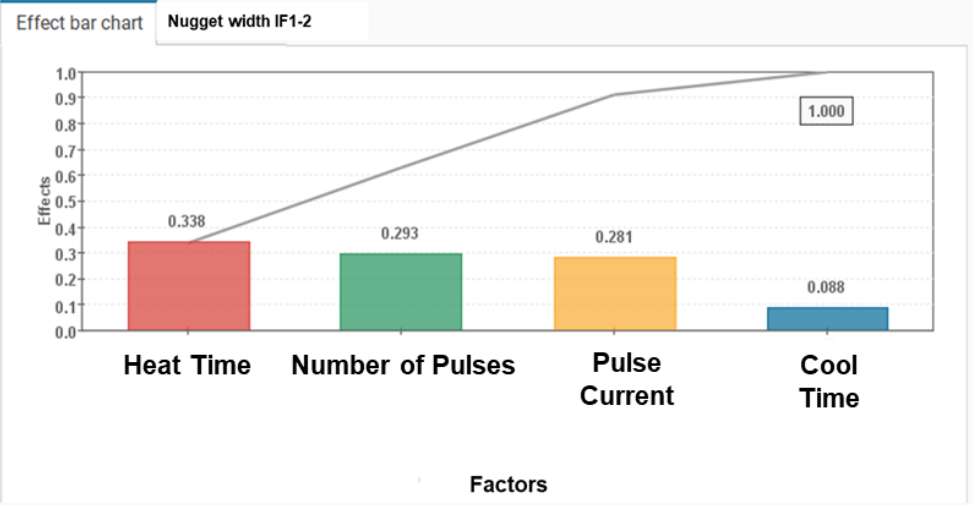
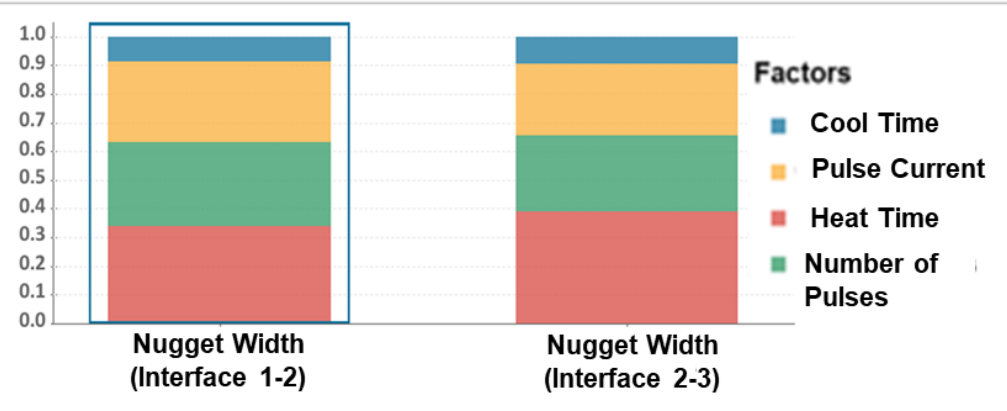
Distributed Random Forest-based Sensitivity Analysis

- DRF algorithm detects which welding schedule parameters contribute most to the nugget width and which contribute the least.
- Heat time, number of pulses and pulse current are most effective factors in nugget width between sheets

Performance Indices

| | Mean absolute error | Mean relative error | Mean normalized error | R-squared |
|-------|---------------------|---------------------|-----------------------|-----------|
| JWL_1 | 0.000 | 0.016 | 0.055 | 0.919 |
| JWL_2 | 0.000 | 0.017 | 0.055 | 0.912 |

Overall Effect



SUMMARY The DRF-based Sensitivity Analysis revealed that heat time, number of pulses, and pulse current are the most critical factors impacting nugget width between sheet interfaces (InterFace1-2 and InterFace2-3).

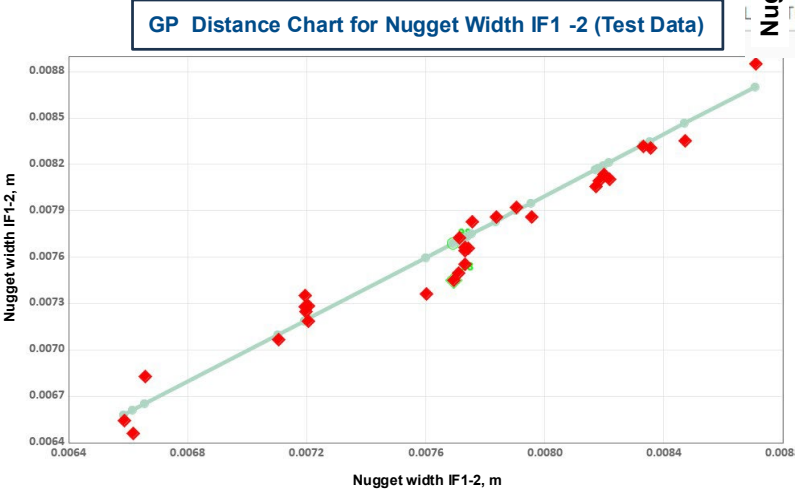
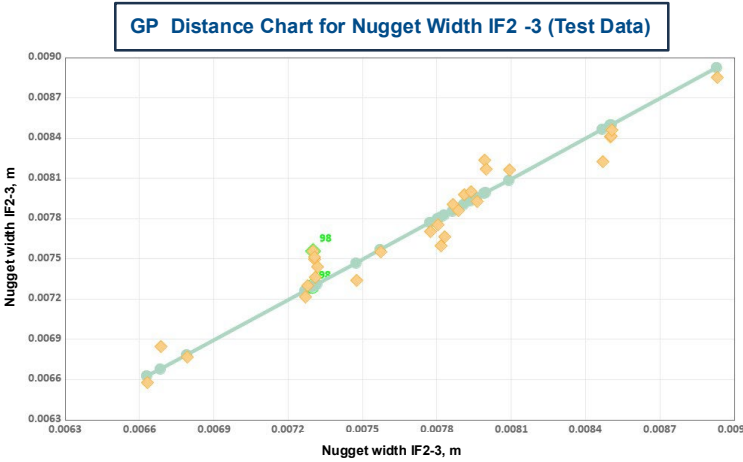
Results & Discussions: RSM Model Performance

Metamodel comparison identified the most accurate model

- **Multiple RSM-based metamodels** were trained and evaluated using the 150-point design space.
- **The Gaussian Process (GP) model** delivered the strongest overall predictive accuracy for nugget width responses.
- Distance charts showed strong agreement between **SF-MF model** results and ML model predictions on test data.
- **The trained RSM** provided a reliable foundation for fast prediction and subsequent optimization.

RSM comparison chart

| Model | Training Progress | Mean Abs. Error | Mean Rel. Error | Mean Norm. Error | R-squared |
|---------------------------------|--------------------------------------|-----------------|-----------------|------------------|-----------|
| Nugget width IF2-3 | P_0 Gaussian Processes (GP) | 9.45524e-05 | 0.0124435 | 0.0445792 | 0.956107 |
| | Automatic Machine Learning (H2O_AML) | 9.78066e-05 | 0.0129139 | 0.0461134 | 0.954042 |
| | R_0 Kriging (KR) | 0.000160396 | 0.0213153 | 0.0756228 | 0.844137 |
| | N Artificial Neural Network (ANN) | 0.000139746 | 0.0187695 | 0.0658868 | 0.896551 |
| | 3F_0 Radial Basis Functions (RBF) | 8.76586e-05 | 0.0116325 | 0.0413289 | 0.951108 |
| EP_0 Stepwise Regression (STEP) | 9.59356e-05 | 0.0127153 | 0.0452313 | 0.954854 | |
| | | | | | |
| Model | Training Progress | Mean Abs. Error | Mean Rel. Error | Mean Norm. Error | R-squared |
| Nugget width IF1-2 | P_0 Gaussian Processes (GP) | 0.000104831 | 0.0136620 | 0.0455788 | 0.943705 |
| | Automatic Machine Learning (H2O_AML) | 0.000262615 | 0.0344235 | 0.114180 | 0.650919 |
| | R_0 Kriging (KR) | 0.000167137 | 0.0221968 | 0.0726684 | 0.854913 |
| | N Artificial Neural Network (ANN) | 0.000278997 | 0.0370893 | 0.121303 | 0.501218 |
| | 3F_1 Radial Basis Functions (RBF) | 0.000108246 | 0.0143748 | 0.0470635 | 0.933447 |
| EP_0 Stepwise Regression (STEP) | 0.000117370 | 0.0153990 | 0.0510303 | 0.932480 | |



UHLC = 150 designs
 Train data = 80% UHLC = 120 designs
 Test data = 20% UHLC = 30 designs

— SF-MF Model
 ■ ML Model

SUMMARY

RSM evaluation identified **Gaussian Process** as the most accurate metamodel, with strong agreement between **SF-MF model** results and ML predictions.

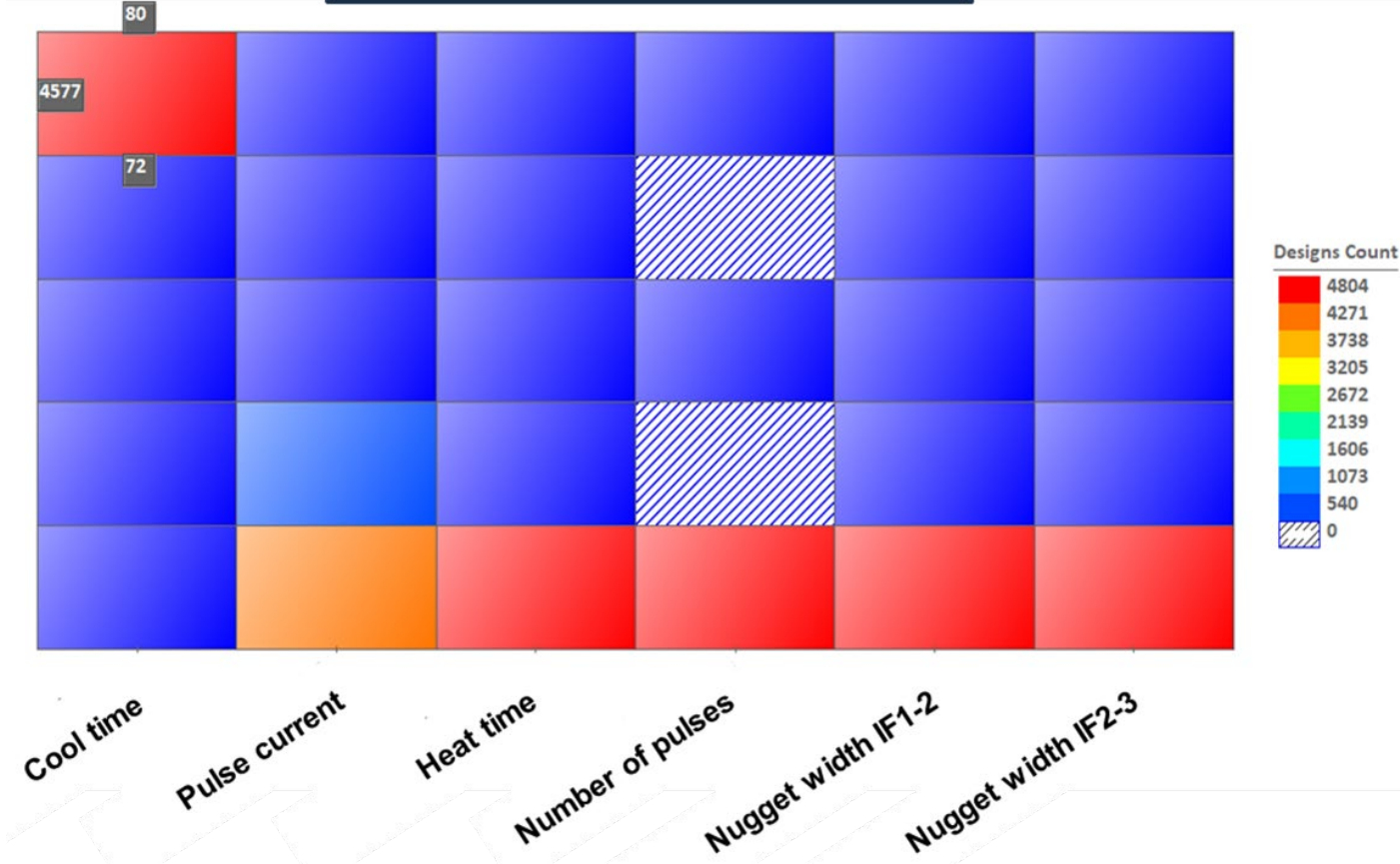


Results & Discussions: Virtual Optimization

Metamodel comparison identified the most accurate model

Design Distribution Chart

- **Efficiency:** RSM-based virtual optimization, using GP metamodels, **completes 5,000 simulations in under a minute and scales to millions.**
- **Speed:** RSM-based virtual optimization outpaces traditional **SimuFact simulations** by leveraging metamodels instead of real solvers.
- **Scalability:** Enables rapid design computations, revolutionizing optimization workflows.



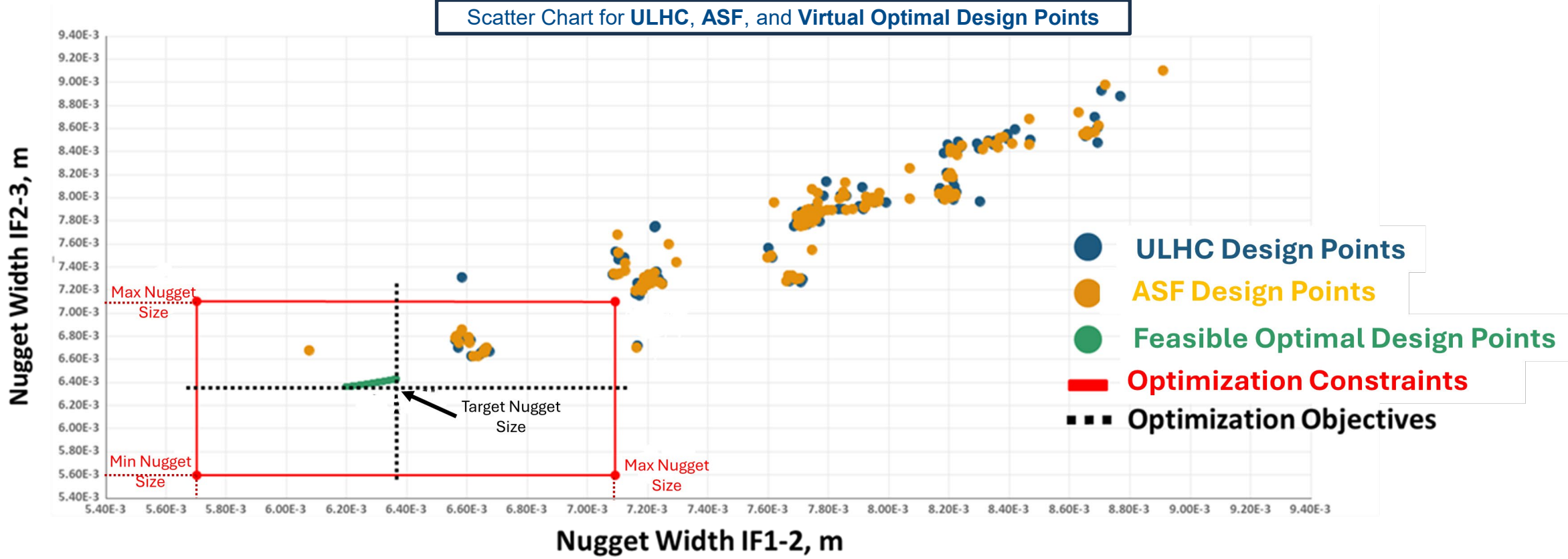
SUMMARY

RSM-based virtual optimization revolutionizes workflows by delivering rapid, scalable simulations (5,000 in under a minute) and outpacing traditional methods through the use of efficient GP metamodels.

Results & Discussions: Virtual Optimization

Optimization Constraints and Objectives

- Optimization constraints & objective based on Honda Standards $Nugget\ Size > min\ size$
- **Approach1:** any design satisfying the constraints is optimal $Min < Nugget\ Width\ IF1-2\ \&\ IF2-3 < max$
- **Approach2:** minimize the difference between virtual nugget width and target nugget size, $Target = objective = ((min + max)/2)$



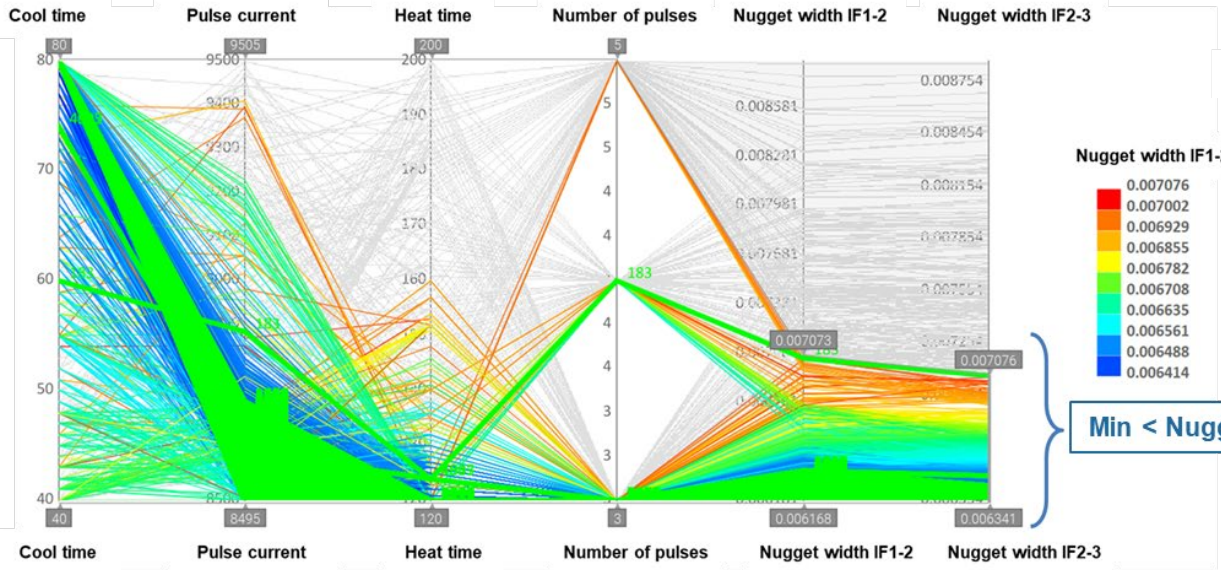
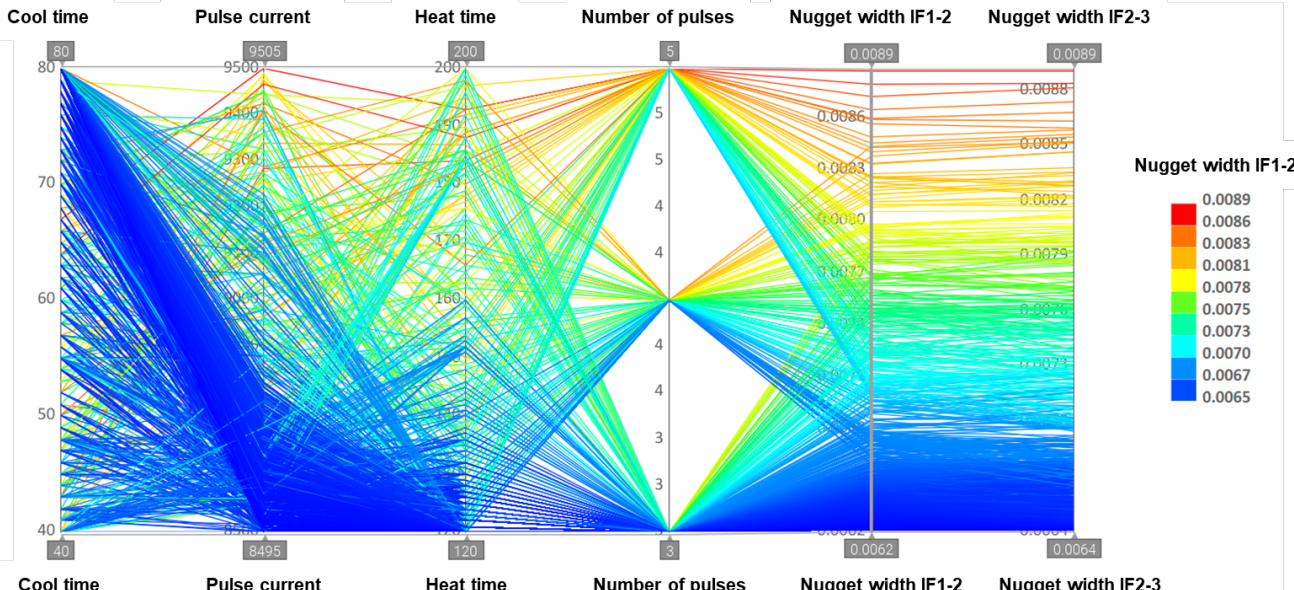
SUMMARY

Virtual optimization ensures compliance with Honda standards by either meeting defined constraints and minimizing deviation from the target nugget width.

Results & Discussions: Virtual Optimization

Parallel Coordinates chart

- The Parallel coordinates chart visualizes **5000 high-dimensional virtual designs**.
- High values are shown in red, whereas low values are shown in blue** in accordance with the color legend to the right of the chart.



View Constraint Limits

The chart provides extra information on **constraint axes**: a **dark line marks** the region where the designs are **feasible** and an **arrow marks** the **constraint type** (**greater than, less than or equal to**) and **limit**.

Min < Nugget Width IF1-2 & IF2-3 < max

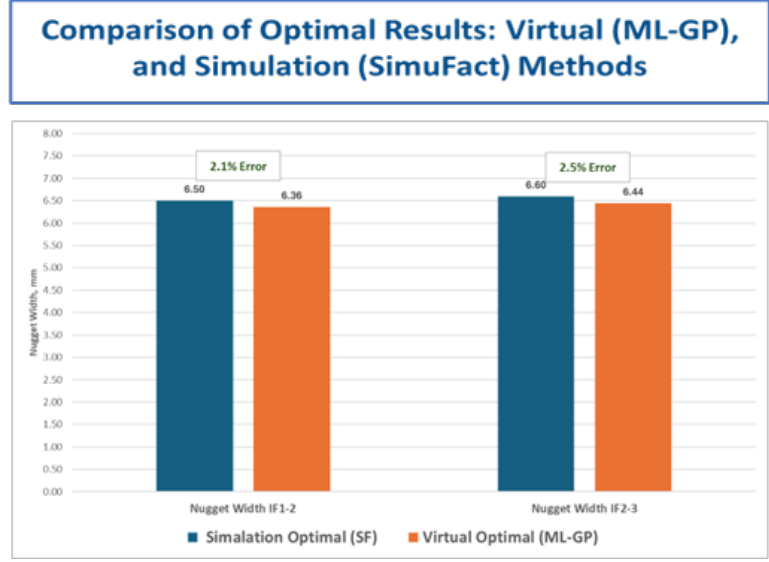
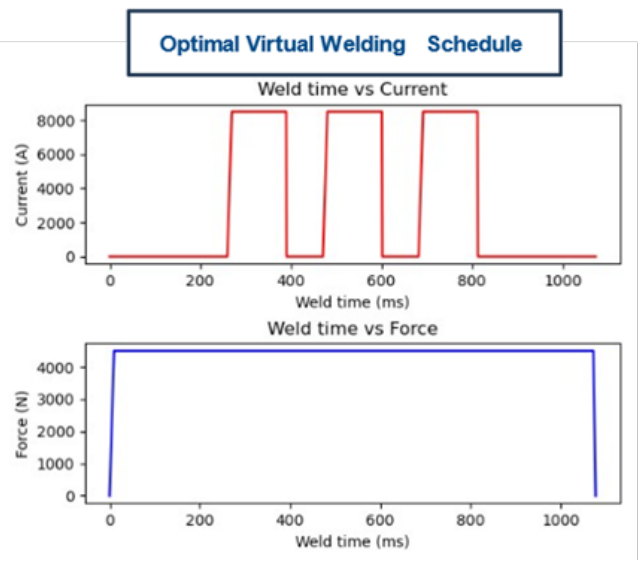
SUMMARY

The Parallel Coordinates Chart visualizes **5,000 designs**, highlighting high (red) and low (blue) values, and **marks feasible regions and constraint types for optimal analysis**.

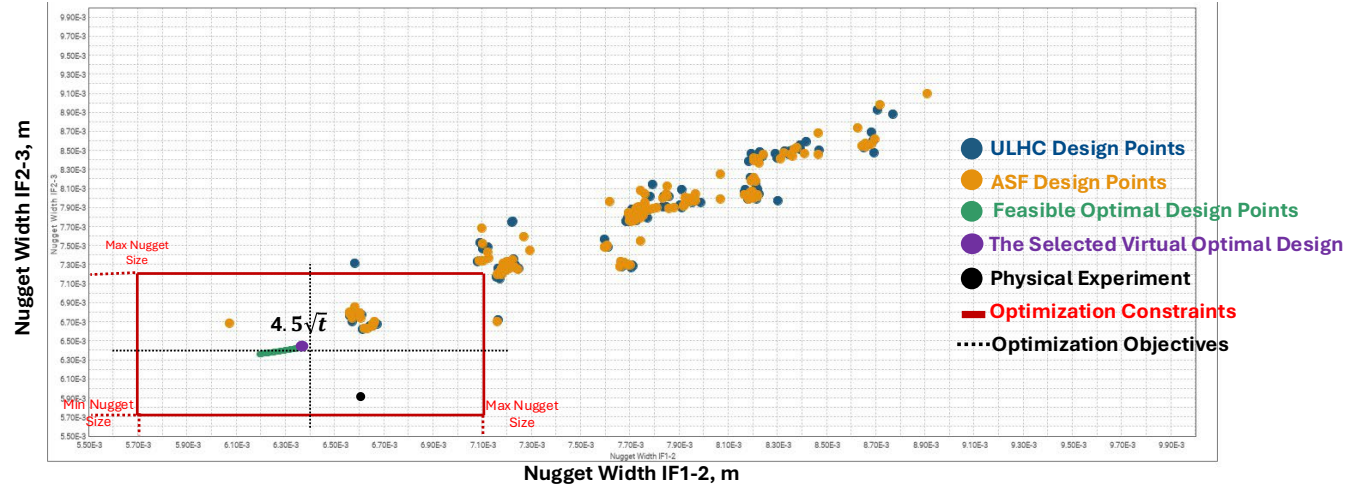
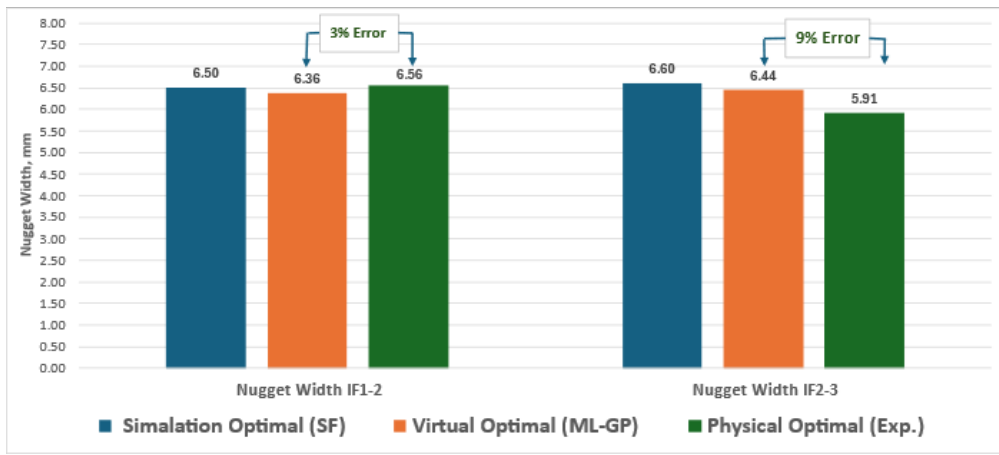
Results & Discussions: Virtual vs Physical Assessment

Virtual vs Physical

- Comparison of virtual optimization (ML-GP), SF-MF model, and physical experiments for weld nugget width (IF1-2 and IF2-3) shows strong alignment, confirming the accuracy of digital predictions.
- Bar Charts Shows minimal error margins (2-9%) between physical, virtual, and simulated nugget width results, confirming the reliability of virtual models.



Comparison of Optimal Results: Physical (Experimental), Virtual (ML-GP), and Simulation (SimuFact) Methods



SUMMARY The VWQA showcased exceptional alignment between virtual simulations and physical test results, enabling a user-friendly automated weld schedule optimization pipeline with closely matched virtual predictions, simulations, and physical tests for critical welding KPIs.

Results & Discussions: Virtual vs Physical Assessment

VWQA ROI / Benefit



Physical WQA (6 Months):

Covers preparation, welding, quality testing, and physical DoE with detailed material and mechanical analysis



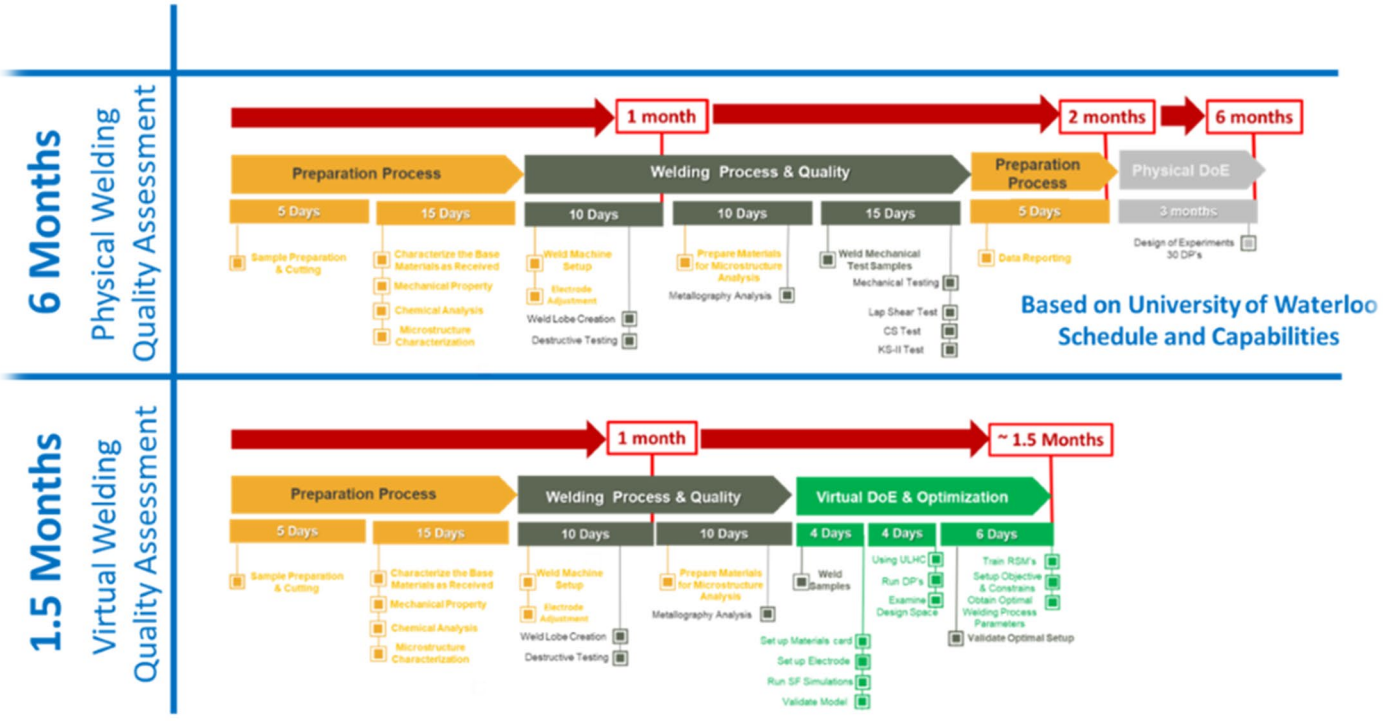
VWQA (1.5 months):

Optimizes DoE with simulations, predictive modeling, and weld validation, saving time and cost



Workflow:

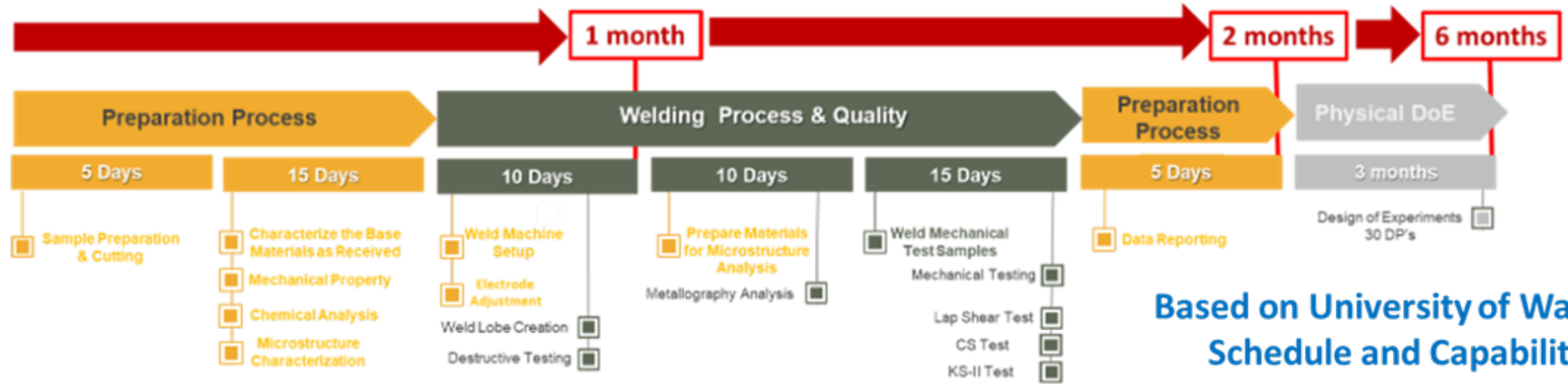
Our process matches our university partner's schedule, making sure we can adapt and work efficiently using physical Design of Experiments techniques.



Based on University of Waterloo Schedule and Capabilities

6 Months

Physical Welding Quality Assessment



Based on University of Waterloo
Schedule and Capabilities

1.5 Months

Virtual Welding Quality Assessment



Results & Discussions: Virtual vs Physical Assessment

VWQA ROI / Benefit



Physical WQA (6 Months):

Covers preparation, welding, quality testing, and physical DoE with detailed material and mechanical analysis



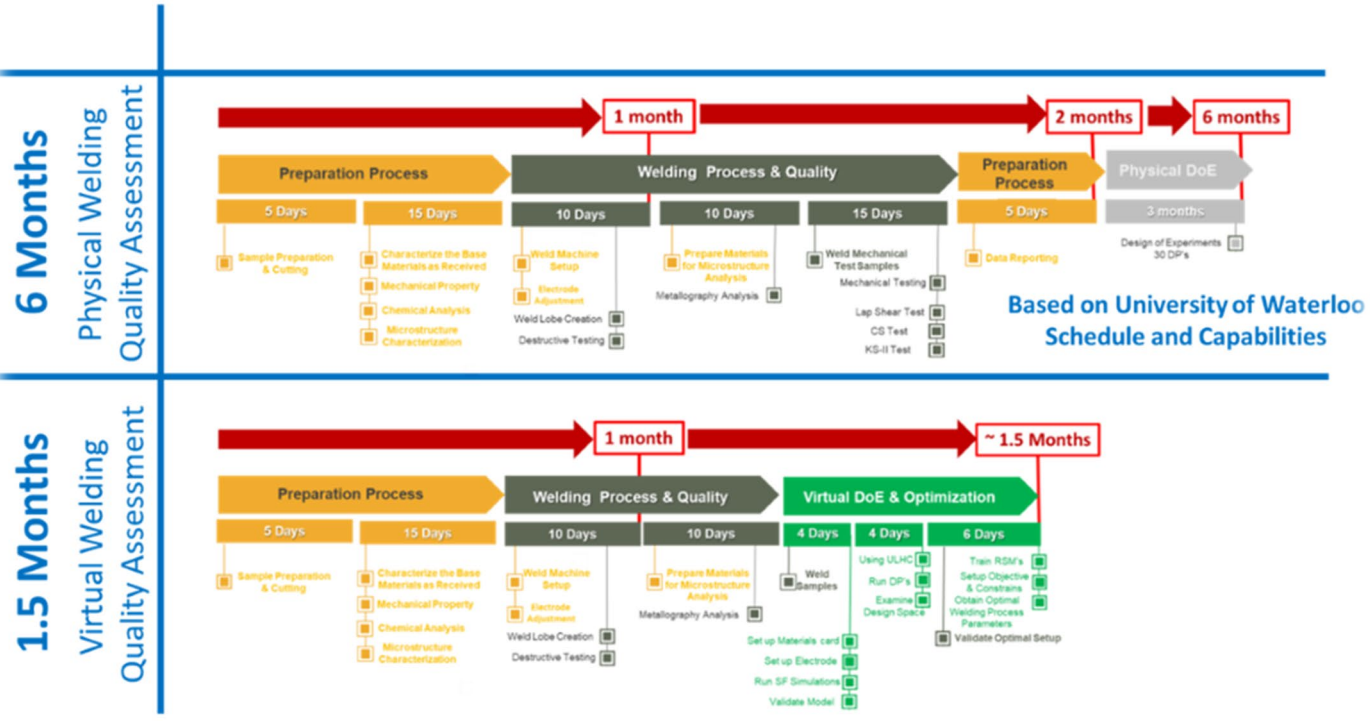
VWQA (1.5 months):

Optimizes DoE with simulations, predictive modeling, and weld validation, saving time and cost







Workflow:

Our process matches our university partner's schedule, making sure we can adapt and work efficiently using physical Design of Experiments techniques.



SUMMARY The VWQA, using GP models, aligns closely with physical experiments, reducing welding optimization timelines from 6 months to 1.5 months while maintaining accuracy.

- 01**  The integration of **virtual simulations and metamodeling** has significantly optimized resistance spot welding (RSW) processes, **reducing testing resource use and improving efficiency.**
- 02**  The use of **Gaussian Process (GP)** models ensured **high accuracy**, closely aligning with experimental results, especially in estimating nugget width for complex stack-ups.
- 03**  Implementing virtual assessments accelerated the optimization timeline **from 6 months to just 1.5 months**, demonstrating substantial time and cost savings.
- 04**  The **developed workflow** allows for **streamlined parametric studies**, **enabling reliable optimization, robustness**, and reliability analyses to enhance BEV welding quality.

Honda gratefully acknowledge the outstanding support and collaboration from:



Zhendan Xue, PhD
Sr. Application Engineer
ESTECO North America Inc

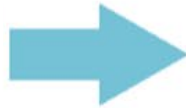


For his technical assistance and continuous support with optimization and workflow automation tools.

cā dence



Fernando Okigami, PhD
Product Engineering Manager
Cadence Design Systems



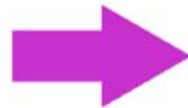
For providing advanced simulation solutions and expert guidance throughout the project.

cā dence



Nicholas Avedissian
Product Manager
Cadence Design Systems

Honda - University of Waterloo Research Project Team



For research partnership, academic insights, and valuable contributions to physical methodology development.

**THANK
YOU**

Q&A

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If you have more questions or would like to discuss any of the topics in more detail, please feel free to reach out.



