Virtual Welding Quality Assessment and AI-driven welding parameter optimization

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Outline

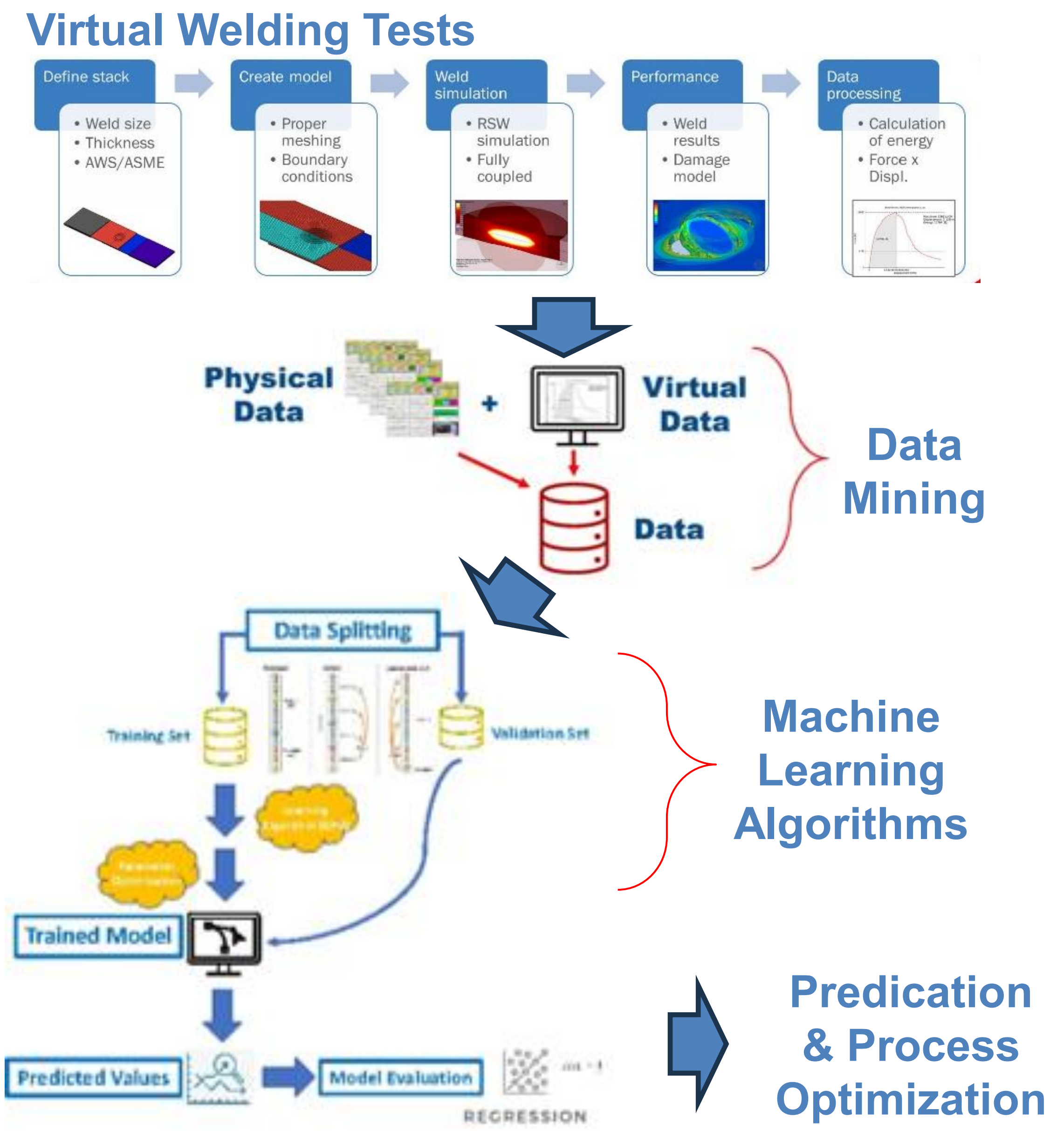
- ## Background
  Industry evolution, high stack ratio welding challenges, and impact on ICE & BEV body construction

- ## 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



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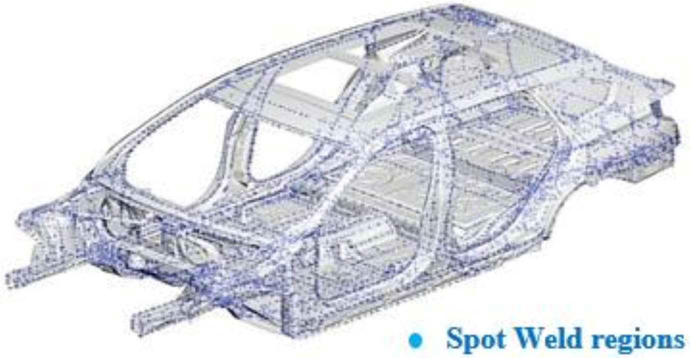
Background: Industry Context & Motivation

1 ICE & BEV BIW Implications

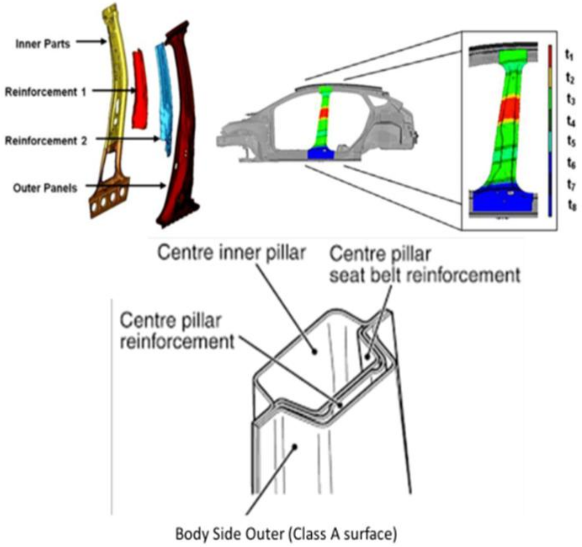
1. BIW designs are shifting toward **stronger, lighter**, and more **complex structures**.
2. ICE programs are expanding **advanced high-strength** and **hot-stamped materials**.
3. BEVs are accelerating demand for **higher stack-ratio joints** and more complex **3T/4T weld applications**.



- 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:

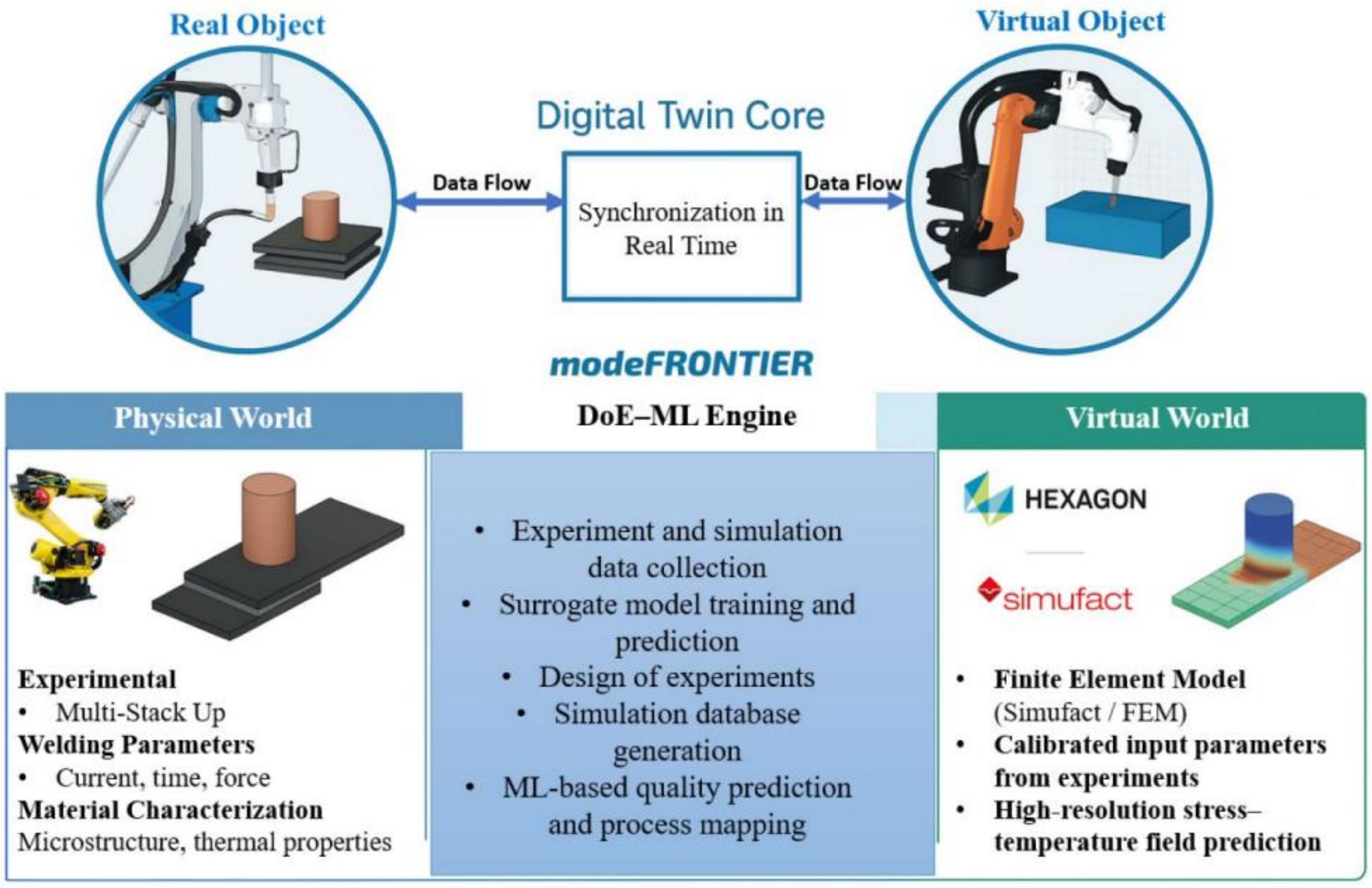
- ➢ Optimize RSW via simulations
- ➢ Automate for consistent quality
- ➢ Streamline efficient welds

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



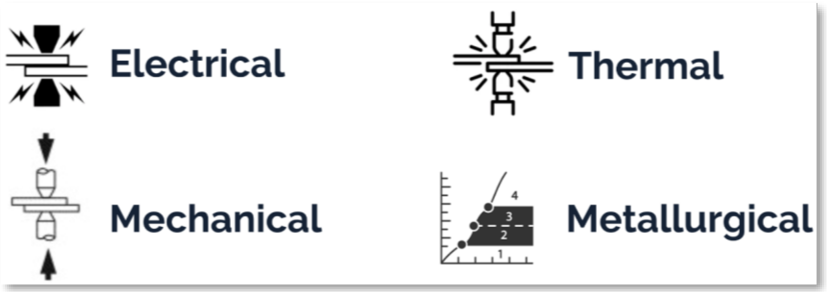
(Aminzadeh & Belgasam et al., 2026, Welding in the World)

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.

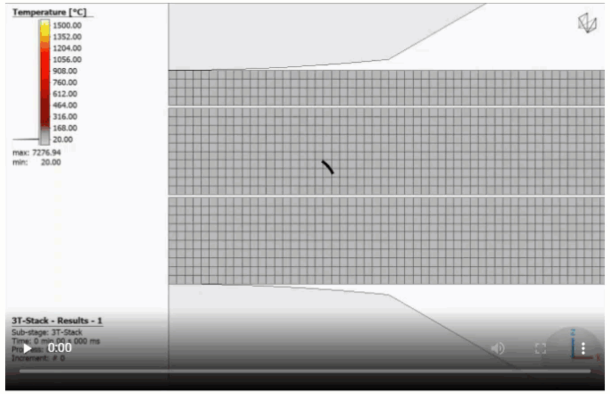
Methodology and Approach: RSW Simulation

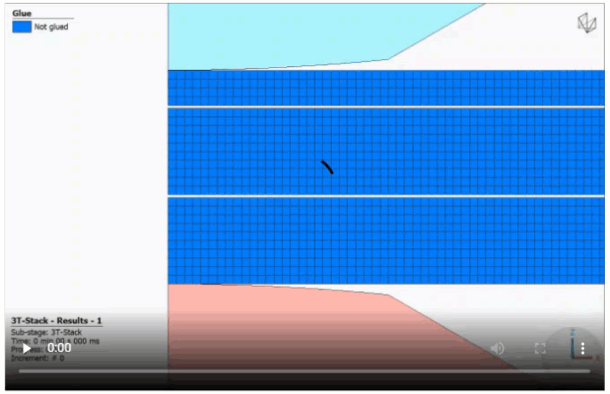
Weld Simulation Approaches

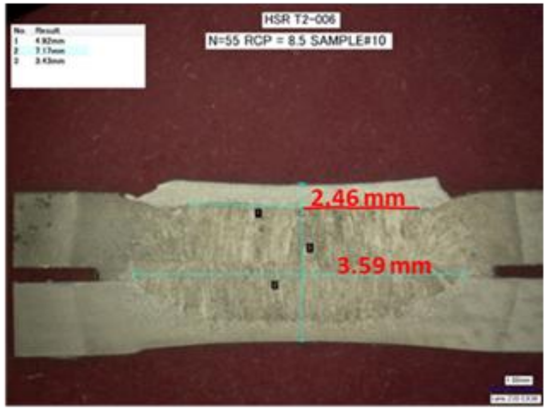
- **Simufact (SF)** digital tool simulates the complicated RSW process which involves the interaction of four phenomena:

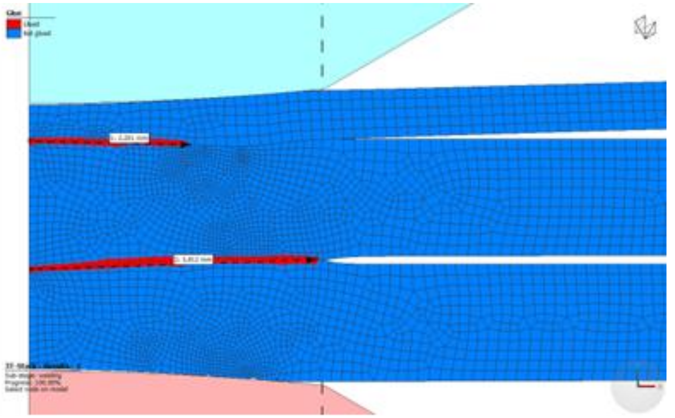


- **Simufact** simulations enable optimization of nugget size and welding parameters, reducing dependance on extensive physical experiments
- **2D Axisymmetric** is used for fast analysis and weld schedule development
- **3D Analysis** is used for tensile test and strength prediction









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

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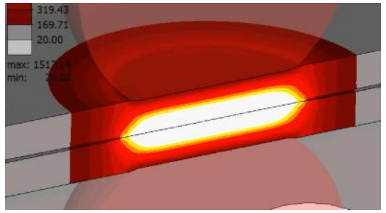
Methodology and Approach: RSW Simulation

Weld Tensile Testing Approach

Welding Analysis

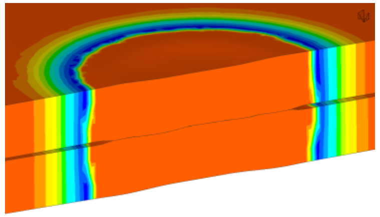
Baseline RSW model (stack, materials, schedule, electrode)

Simple material data (base hardness, phase fractions)



Nugget

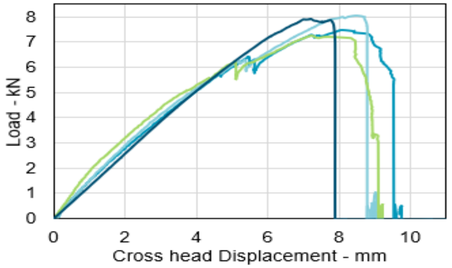
RSW Thermal-Mechanical Analysis



Hardness Map

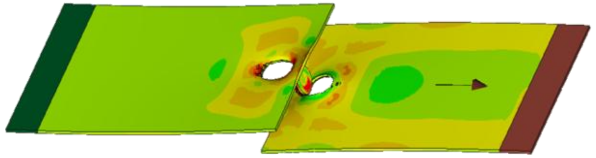
Hardness map

Tensile Test Analysis



Fxd Curve

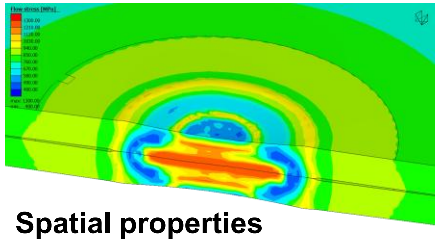
Failed Sample (FxD curve, failure mode)



Tensile Test

Tensile Test Transient Analysis

Spatial dependent damage criteria (strain based)



Spatial properties

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.

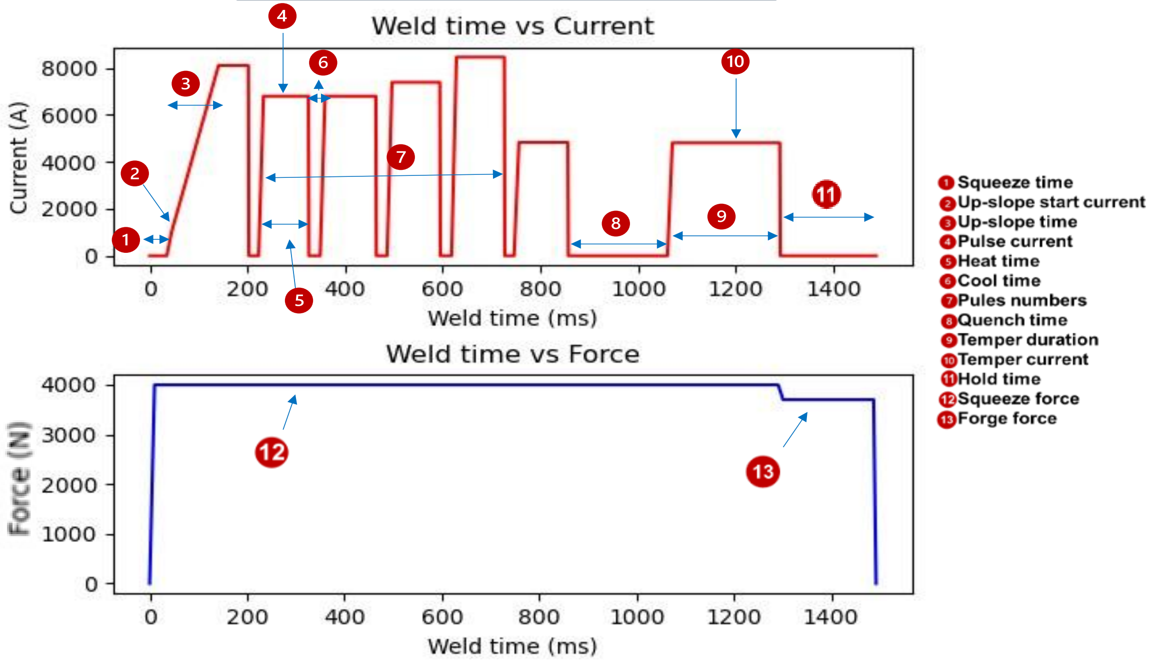
2. Weld Quality Responses

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

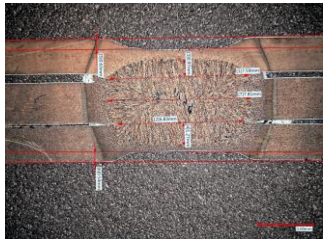
1. **Nugget size response**
2. **Interface behavior**
3. **3T and 4T stack-up weld performance**

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

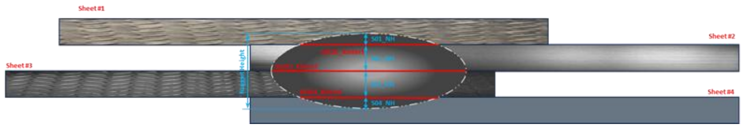
Parametrized Welding Schedule



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.

Methodology and Approach: Process Automation and Optimization Tool

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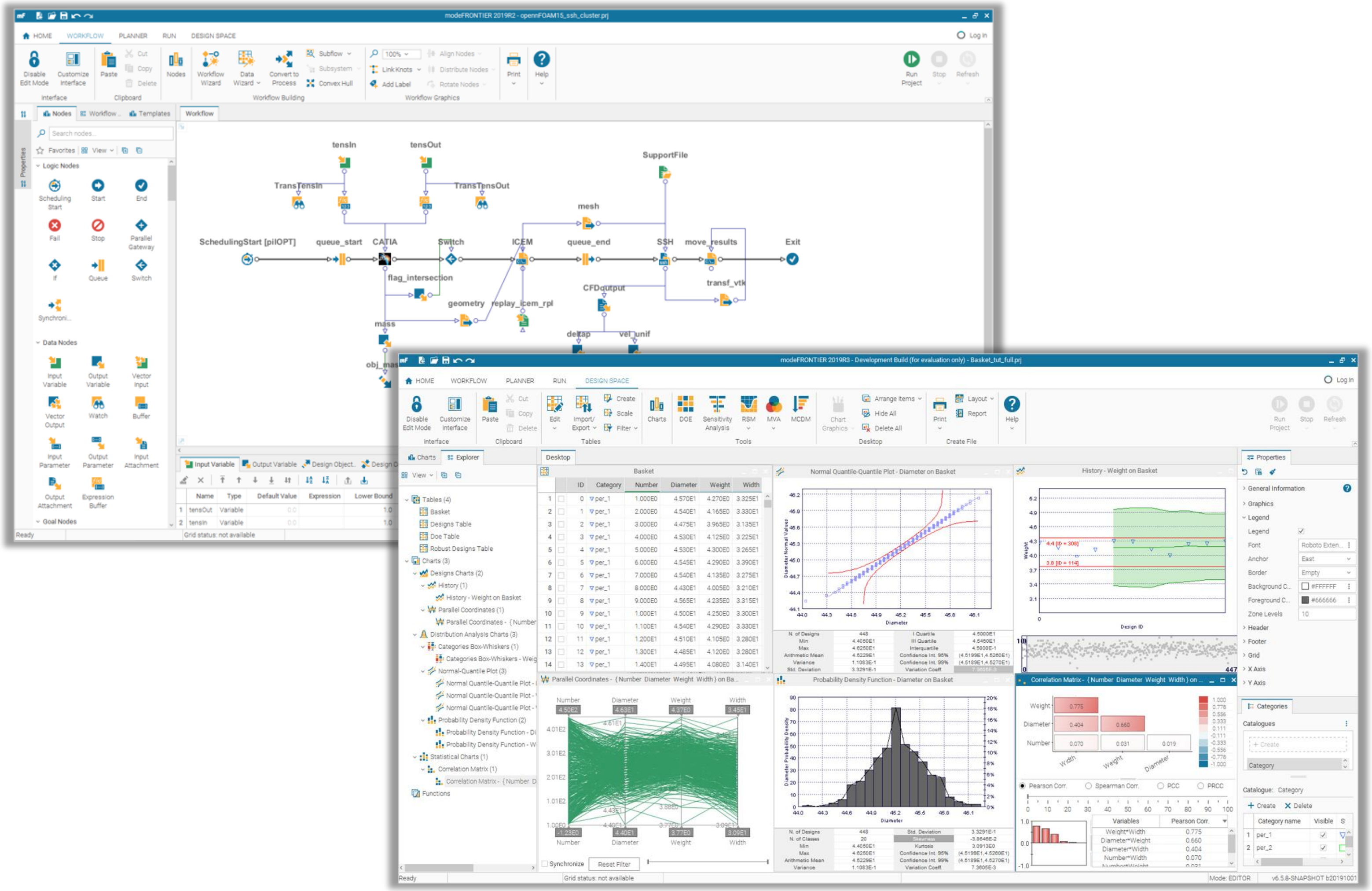
modeFRONTIER



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:

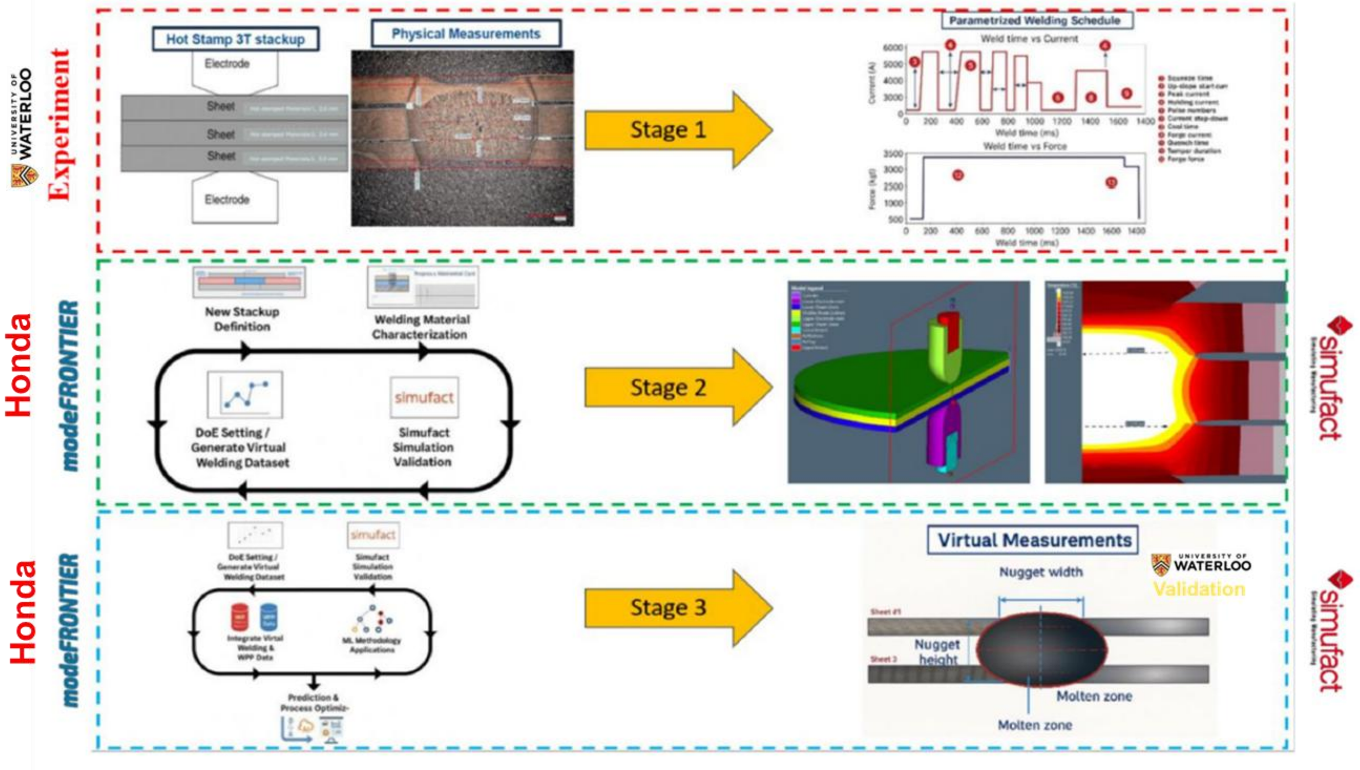
The VWQA workflow steps for new weld stack-ups involving new material grades, configurations, or welding techniques covers:

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)

Virtual welding quality assessment (VWQA) workflow

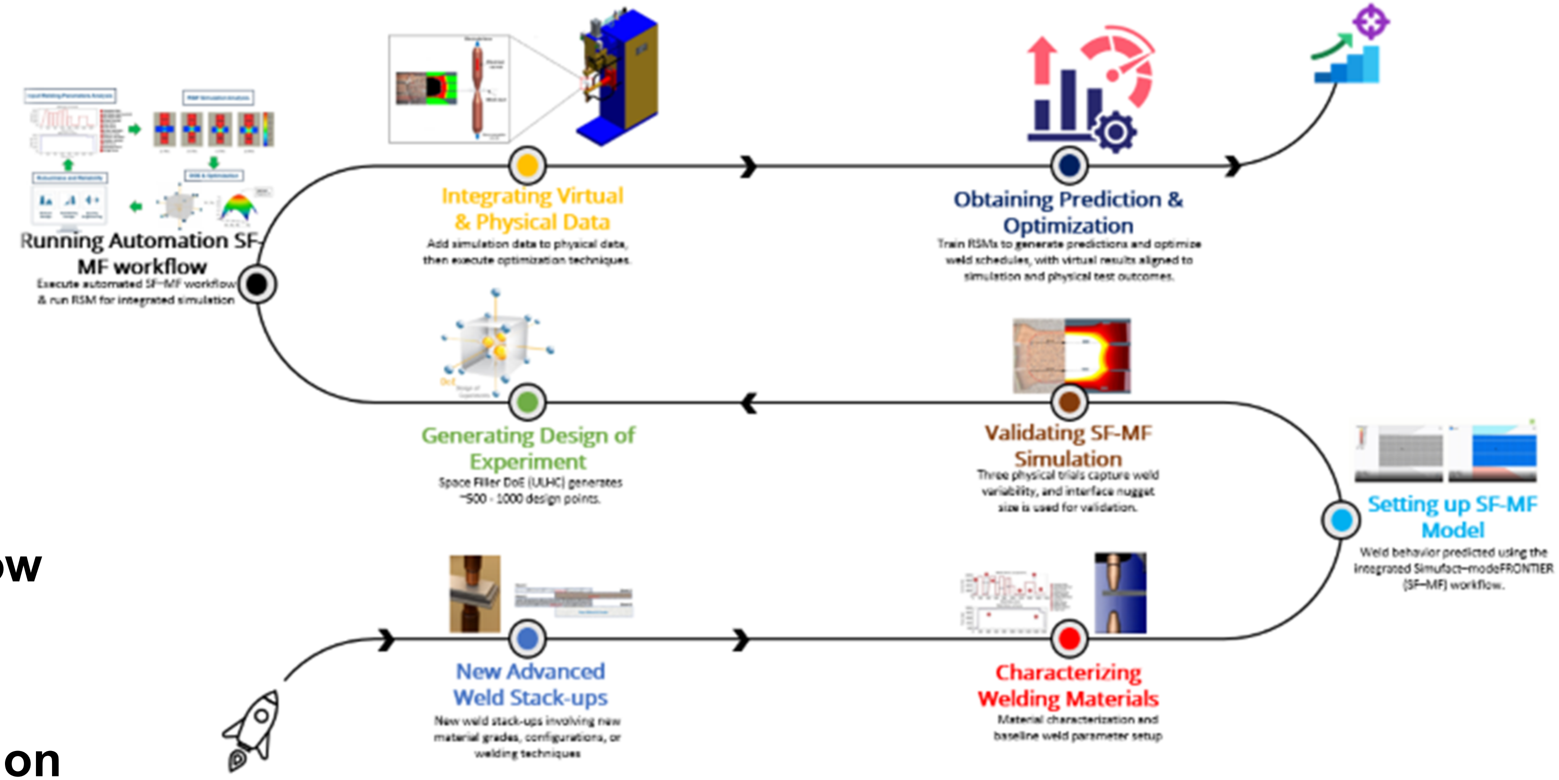


Structured VWQA workflow transitions from **physical baseline** to **simulation, ML-driven exploration**, and **validated optimization**.

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.

Results & Discussions: MCC Calibration Performance

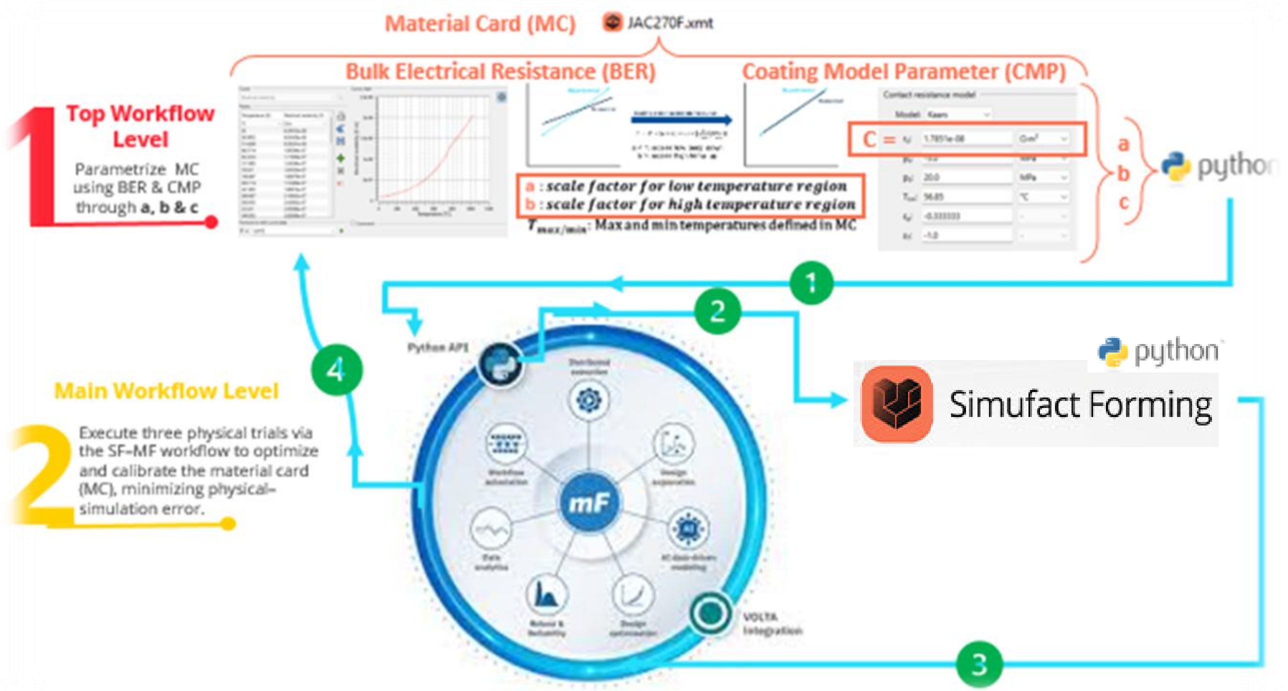
Automated Workflow for RSW Material Card Calibration (MCC)
Enabling robust digital–physical correlation

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

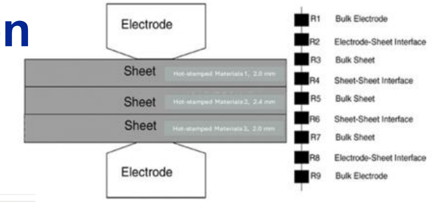
④ **Correlation Readiness:**
Automated calibration improves correlation and enables reliable digital–physical alignment



SUMMARY **Automated MCC calibration** strengthened **digital–physical alignment**—ensuring reliable weld prediction across complex hot-stamped stack-ups.

Results & Discussions: MCC Impact Assessment

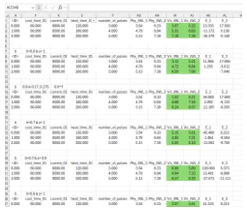
Driving efficiency and accuracy in weld prediction



Before MCC

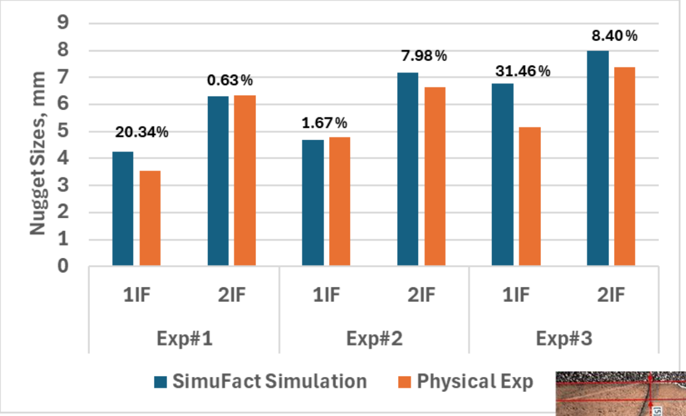
- Run more than 300 simulation to calibrate material card manually
- Best lowest error compared to 3 physical trails for IF1-2:

  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%



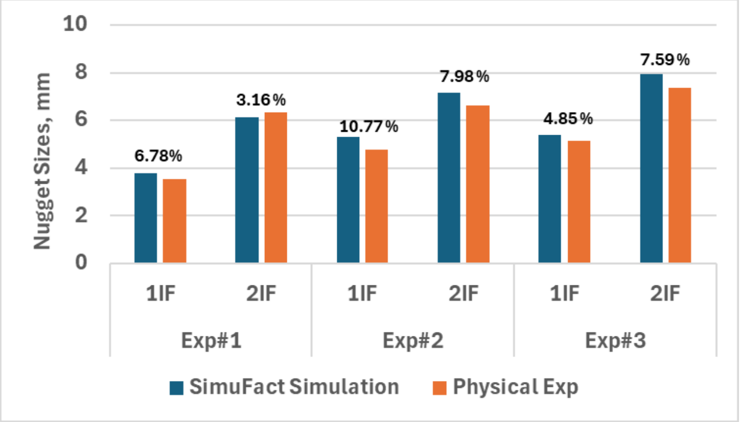
After MCC

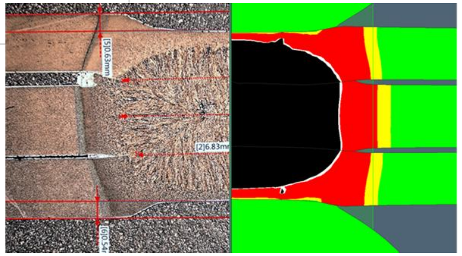
- Run less than > 50 simulation to calibrate material card via MCC
- Best lowest error compared to 3 physical trails for IF1-2:

  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

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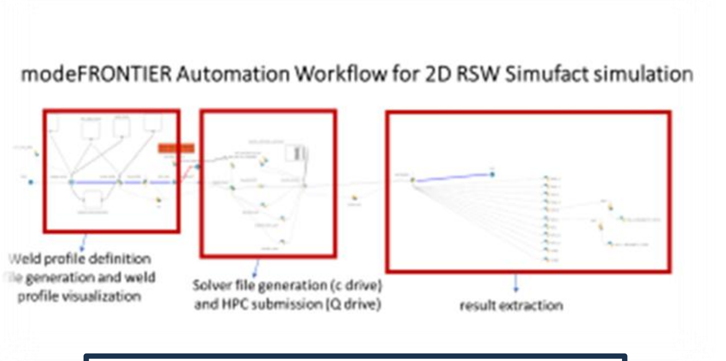
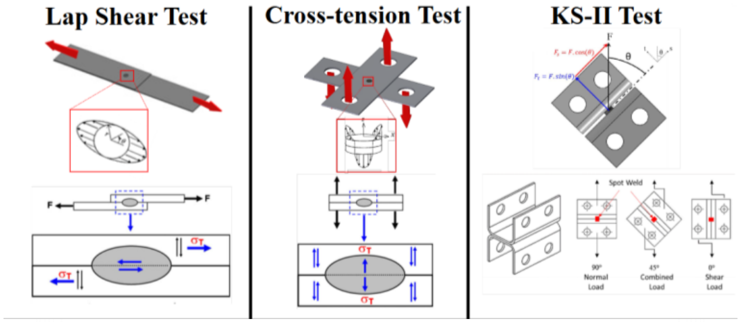
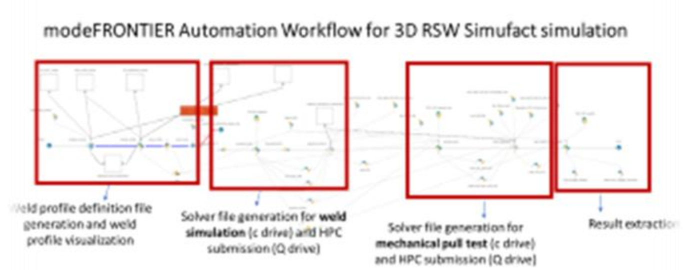
SimuFact–modeFRONTIER integration enabled scalable automation, optimization, and validation readiness

- 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



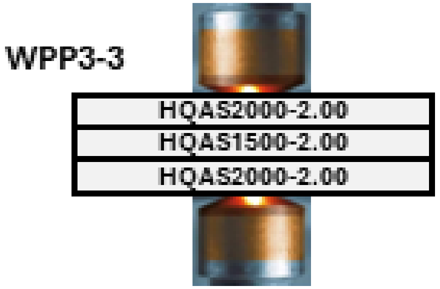


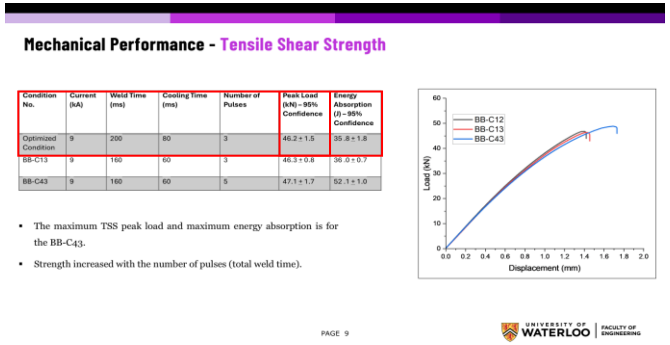
SUMMARY

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

3D RSW Lap Shear Simulation – Peak Load Prediction

- **Automated 3D workflow** was successfully applied to the hot-stamped materials stack-up for tensile shear prediction.
- Simulation showed good agreement with UW physical test data, strengthening confidence in mechanical performance prediction.
- Peak load prediction error was approximately 3.3%, with simulation showing close agreement to UW physical test data.
- Total end-to-end runtime exceeded 1.5 hours on HPC, highlighting the need for further efficiency improvement.





Mechanical Performance - Tensile Shear Strength

Condition No.	Current (kA)	Weld Time (ms)	Cooling Time (ms)	Number of Pulses	Peak Load (kN) – 95% Confidence	Energy Absorption (J) – 95% Confidence
Optimized Condition	9	200	80	3	46.2 ± 1.5	35 .8 ± 1.8
BB-C13	9	160	60	3	46.3 ± 0.8	36 .0 ± 0.7
BB-C43	9	160	60	5	47.1 ± 1.7	52 .1 ± 1.0

- The maximum TSS peak load and maximum energy absorption is for the BB-C43.
- Strength increased with the number of pulses (total weld time).

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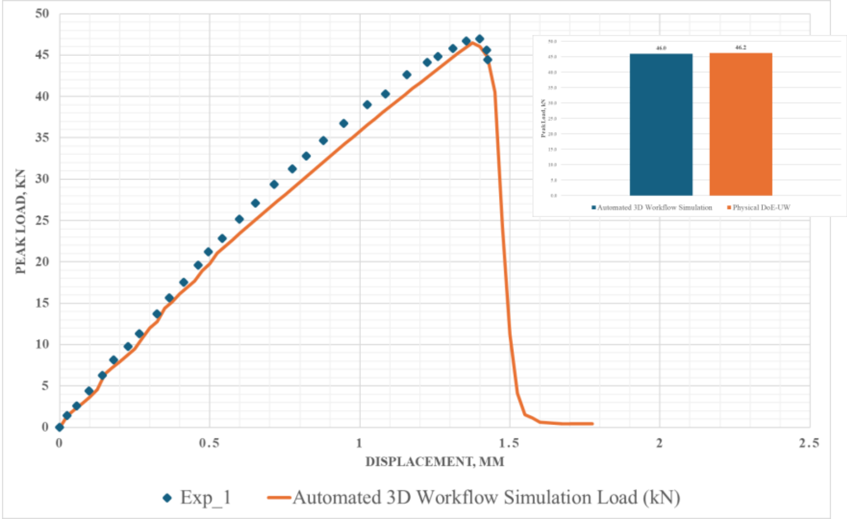

SUMMARY

Automated 3D RSW workflow predicted lap shear peak load with **~3.3% error** versus UW test data, demonstrating strong mechanical correlation, while >1.5-hour HPC runtime highlightsthe need for further efficiency improvement.

Results & Discussions: Identify Most Influential Variables

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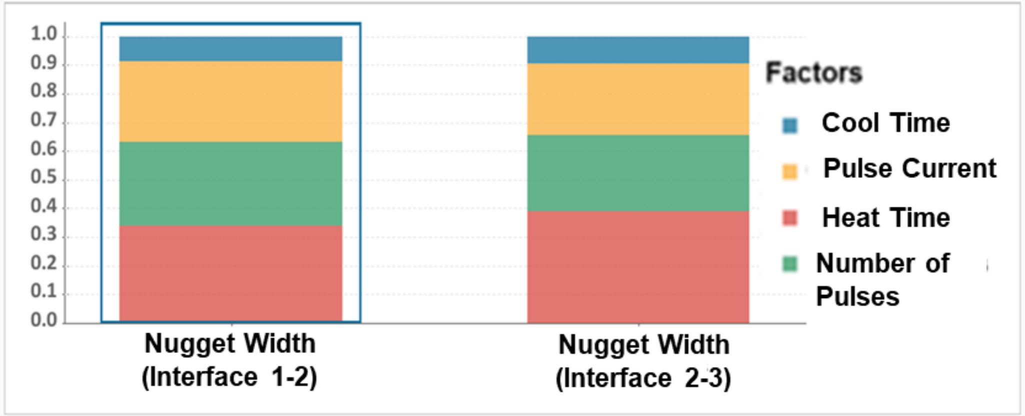
Distributed Random Forest-based Sensitivity Analysis

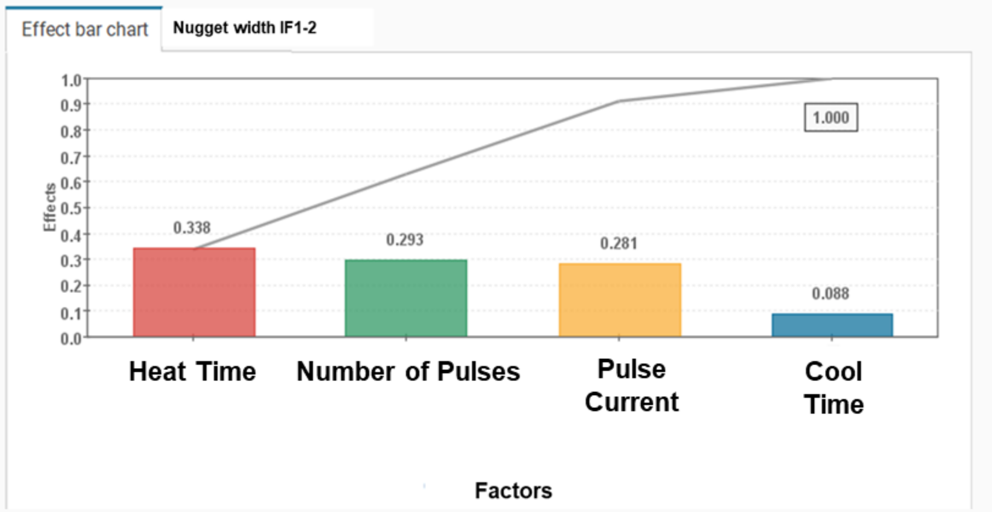
- **DRF algorithm** detects which **welding schedule parameters** contribute most to the nugget width and which contribute the least.
- **Heat time, number of pulses and pulse current** are most effective factors in nugget width between sheets

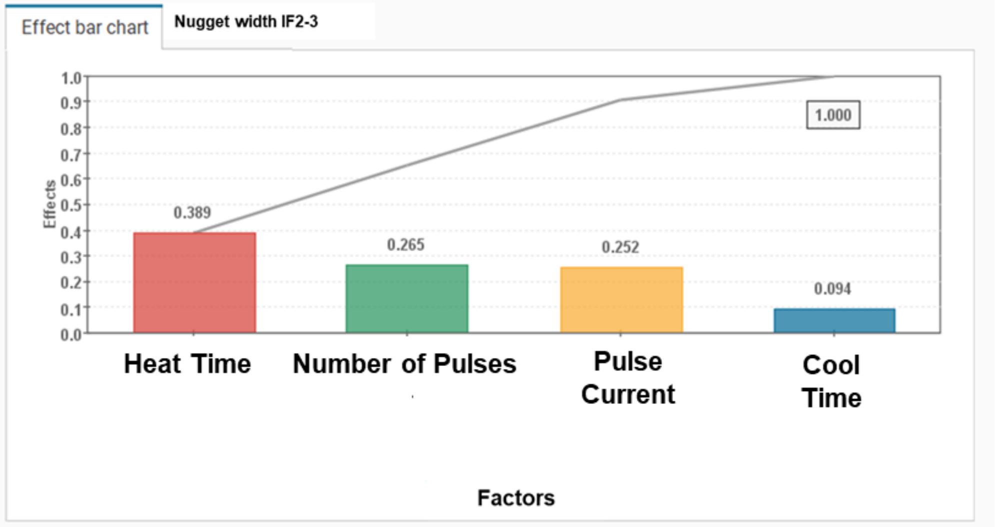
Performance Indices

	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).

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Results & Discussions: RSM Model Performance

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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

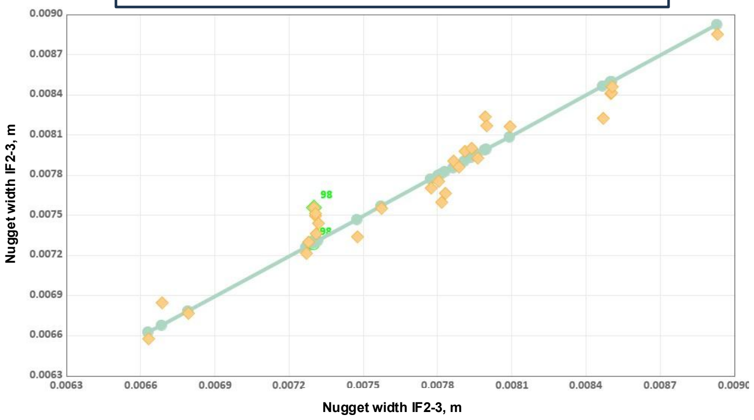
Nugget width IF1-2

	Mean Abs. Error	Mean Rel. Error	Mean Norm. Error	R-squared
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
Kriging (KR)	0.000160396	0.0213153	0.0756228	0.844137
Artificial Neural Network (ANN)	0.000139746	0.0187695	0.0658868	0.896551
Radial Basis Functions (RBF)	8.76586e-05	0.0116325	0.0413289	0.951108
Stepwise Regression (STEP)	9.59356e-05	0.0127153	0.0452313	0.954854

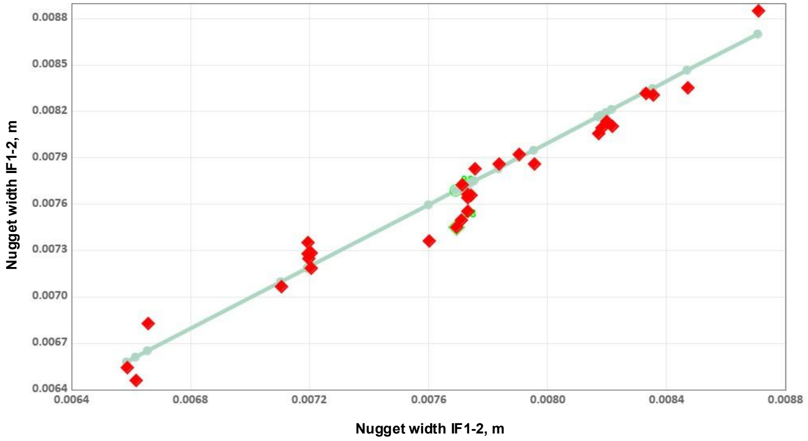
Nugget width IF2-3

	Mean Abs. Error	Mean Rel. Error	Mean Norm. Error	R-squared
Gaussian Processes (GP)	0.000104831	0.0136620	0.0455788	0.943705
Automatic Machine Learning (H2O_AML)	0.000262615	0.0344235	0.114180	0.650919
Kriging (KR)	0.000167137	0.0221968	0.0726684	0.854913
Artificial Neural Network (ANN)	0.000278997	0.0370893	0.121303	0.501218
Radial Basis Functions (RBF)	0.000108246	0.0143748	0.0470635	0.933447
Stepwise Regression(STEP)	0.000117370	0.0153990	0.0510303	0.932480

GP Distance Chart for Nugget Width IF2 -3 (Test Data)



GP Distance Chart for Nugget Width IF1 -2 (Test Data)



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.

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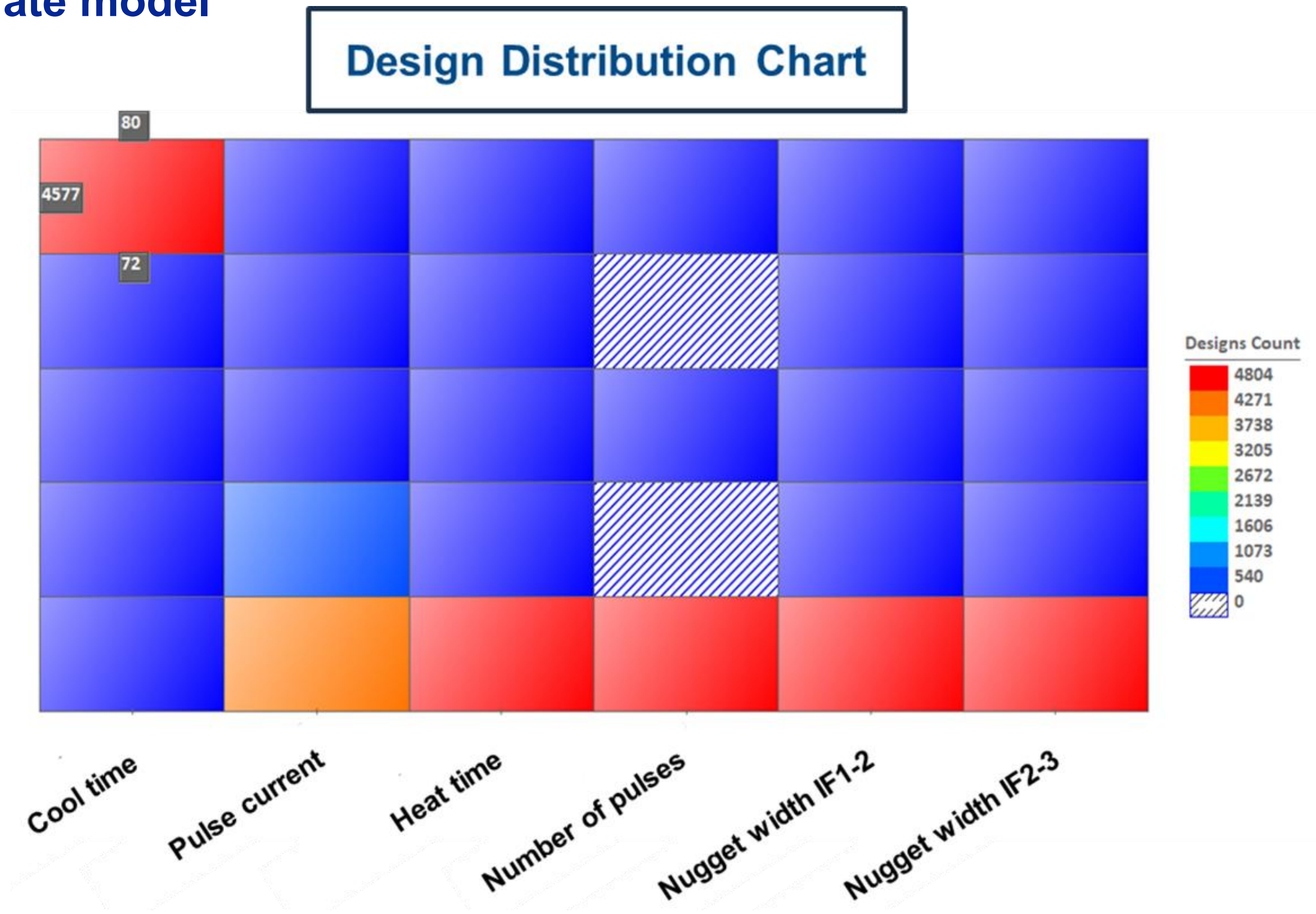
Results & Discussions: Virtual Optimization

Metamodel comparison identified the most accurate model

- **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.

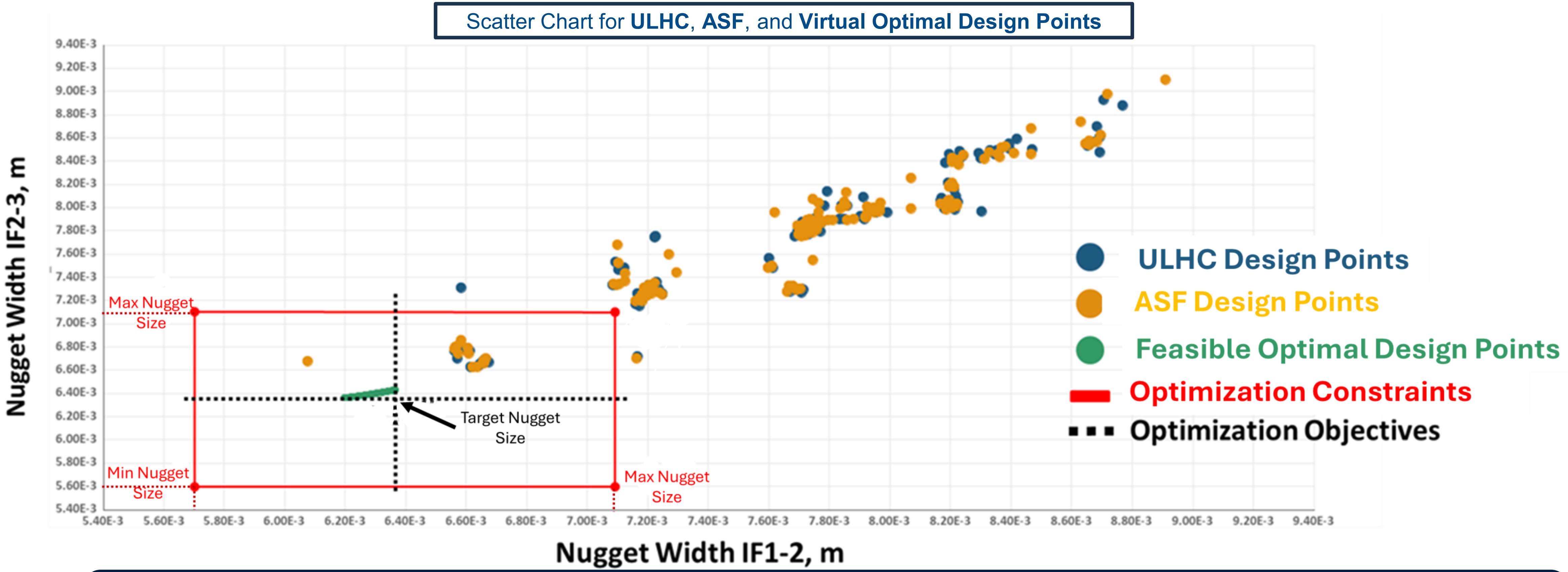


SUMMARY **RSM-based virtual optimization** revolutionizes workflows by delivering rapid, scalable simulations (**5,000 in under a minute**) and outpacing traditional methods through the use of efficient GP metamodels.

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.

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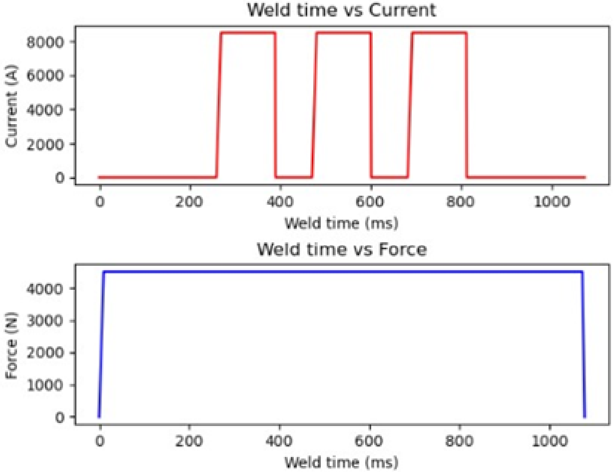
Results & Discussions: Virtual vs Physical Assessment

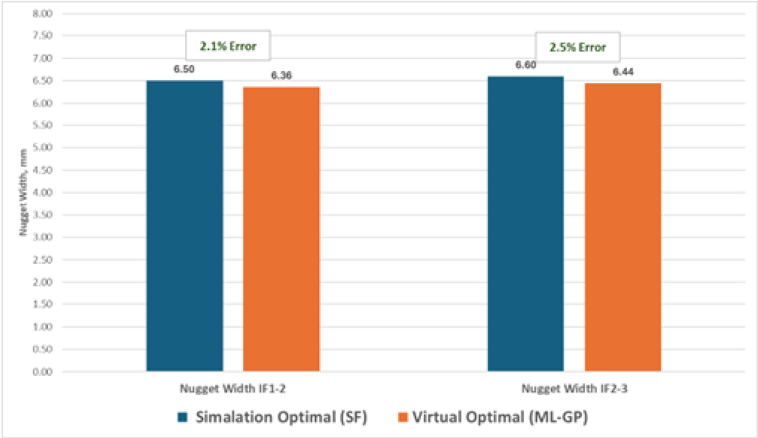
Virtual vs Physical

- 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.

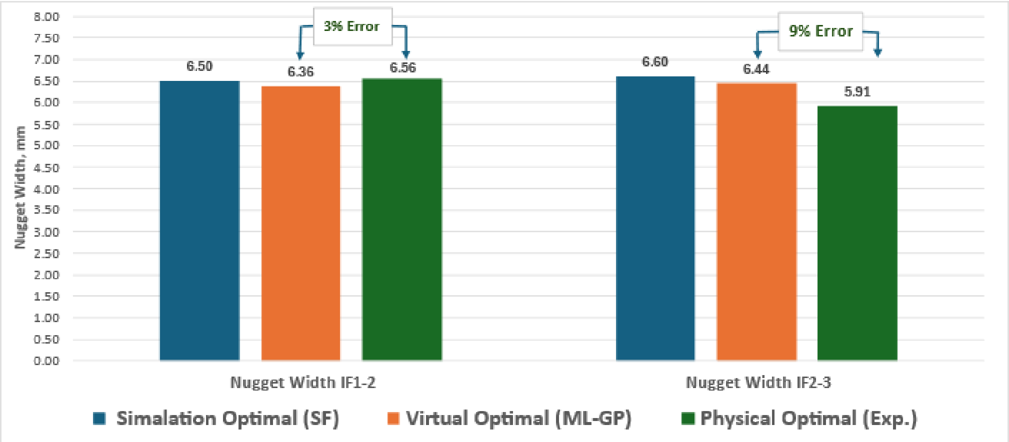
Optimal Virtual Welding Schedule

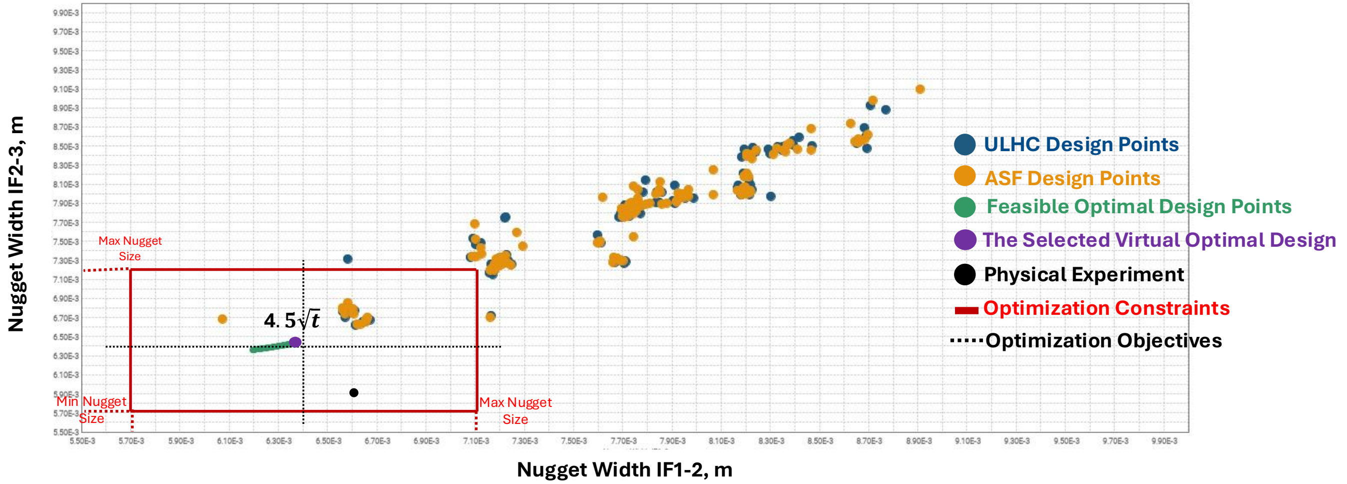


Comparison of Optimal Results: Virtual (ML-GP), and Simulation (SimuFact) Methods



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.

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Results & Discussions: Virtual vs Physical Assessment

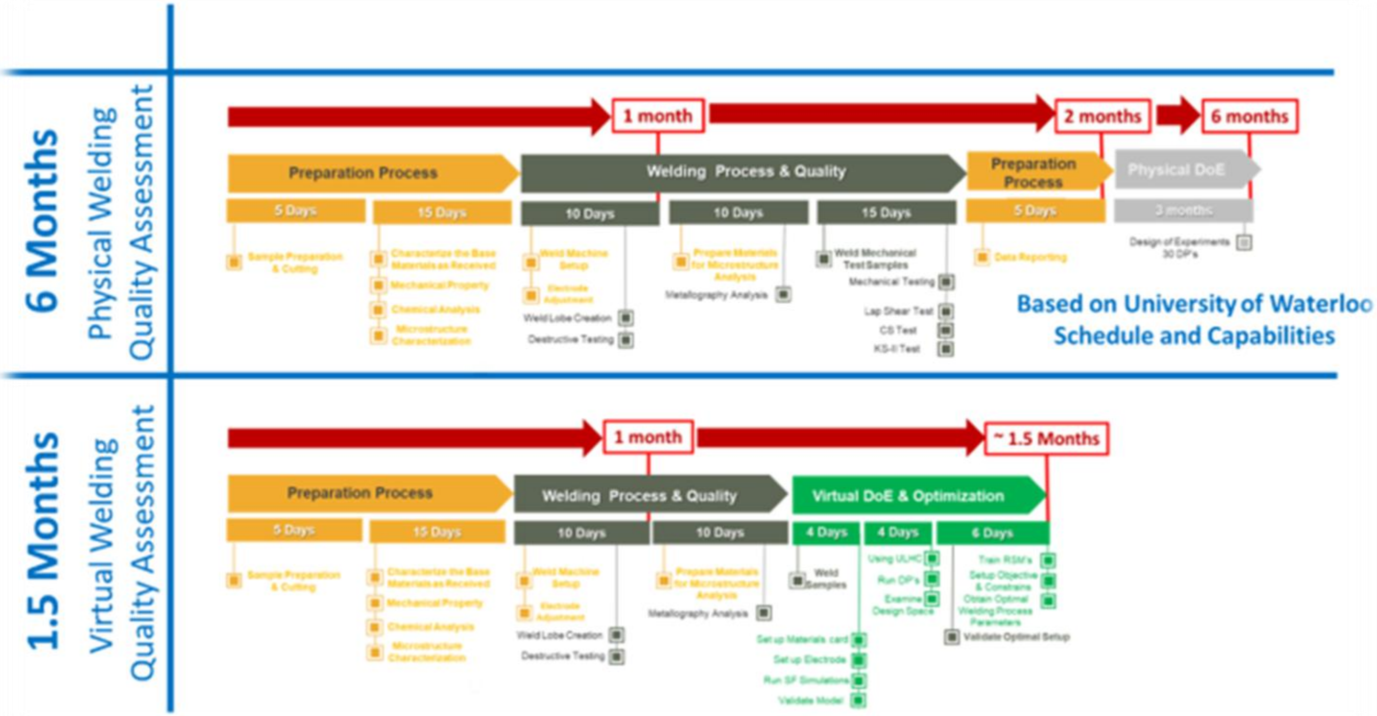
GDIS

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.

Takeaways

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.

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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.

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Q&A

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