GREAT DESIGNS IN STEEL

Enhanced Resistance Spot Welding Quality Control: A Machine Learning Approach

Zhili Feng, PhD

Oak Ridge National Laboratory, Group Leader, Materials Joining

Team Members

Oak Ridge National Laboratory
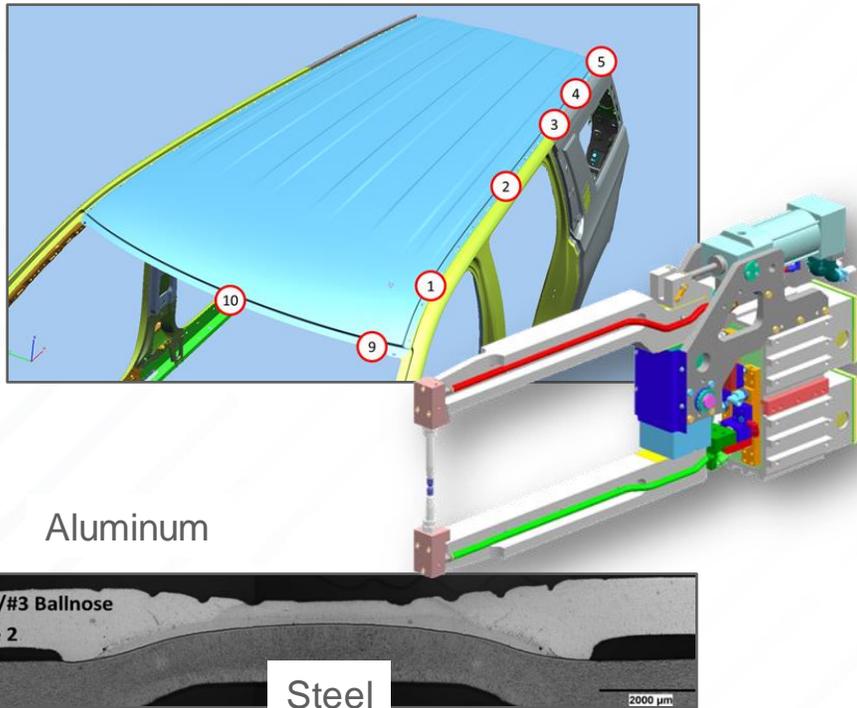
- Zhili Feng
- Wei Zhang
- Dali Wang
- Jian Chen

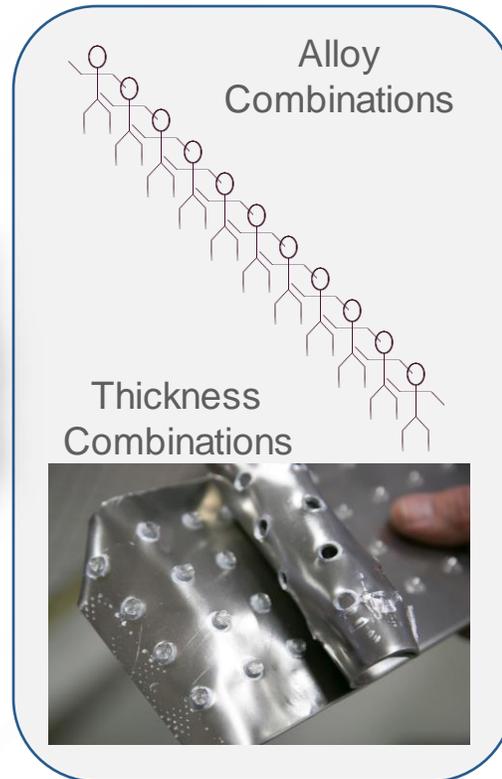General Motors LLC

- Blair Carlson
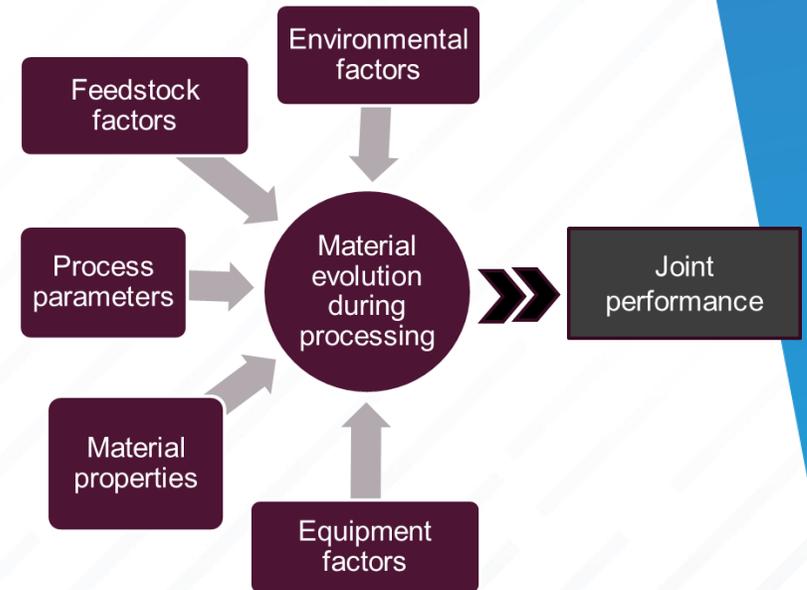- Hassan Ghassemi-Armaki

Background and Motivation

Dissimilar Material Joints to Enable Lightweighting for Greenhouse Gas Reduction

Today: Months of Experimental Development

Tomorrow: AI/ML Approaches to Enable High Quality Joints

Aluminum

MRD/#3 Ballnose
Stage 2

Steel

2000 µm

Alloy Combinations

Thickness Combinations

Feedstock factors

Environmental factors

Process parameters

Material properties

Material evolution during processing

Equipment factors

Joint performance

An Extensible ML Model Framework with Unified Architecture

Deep neural network
Physics-driven, unified architecture,
expandable, flexible

Materials & Process conditions	→	Weld attribute	→	Joint properties
Base materials		Button sizes		Coach peel properties
Sheet dimensions		Indentation		Lap-shear properties
RSW schedule parameters		Expulsion		Cross-tension properties
Post-weld treatment		Nugget size		
Inline signals		IMC thickness		
		Hardness		
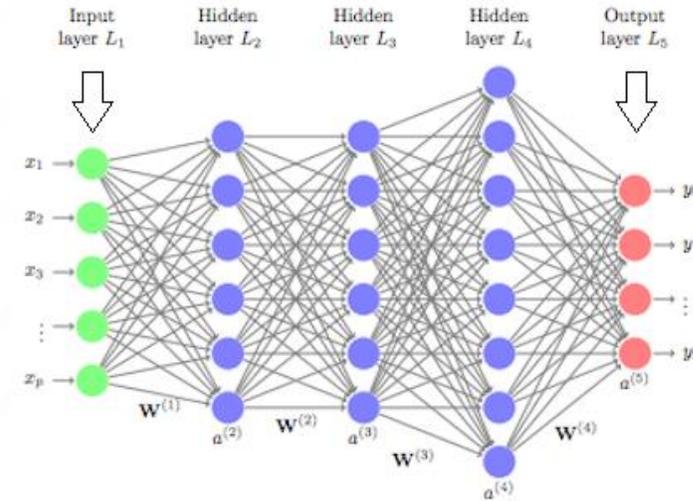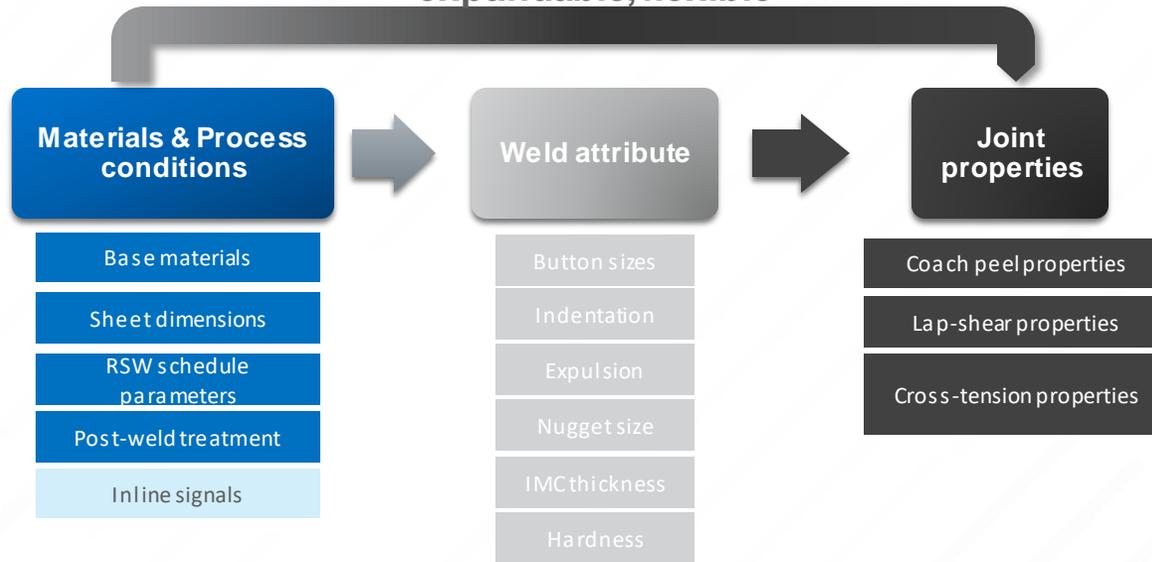
- Unified architecture (DNN based):
  - One model architecture to cover all RSW welds (Unified data representation, One ML network design, One training strategy)
  - No separate models for different stackups (no different ML design, no separate training)
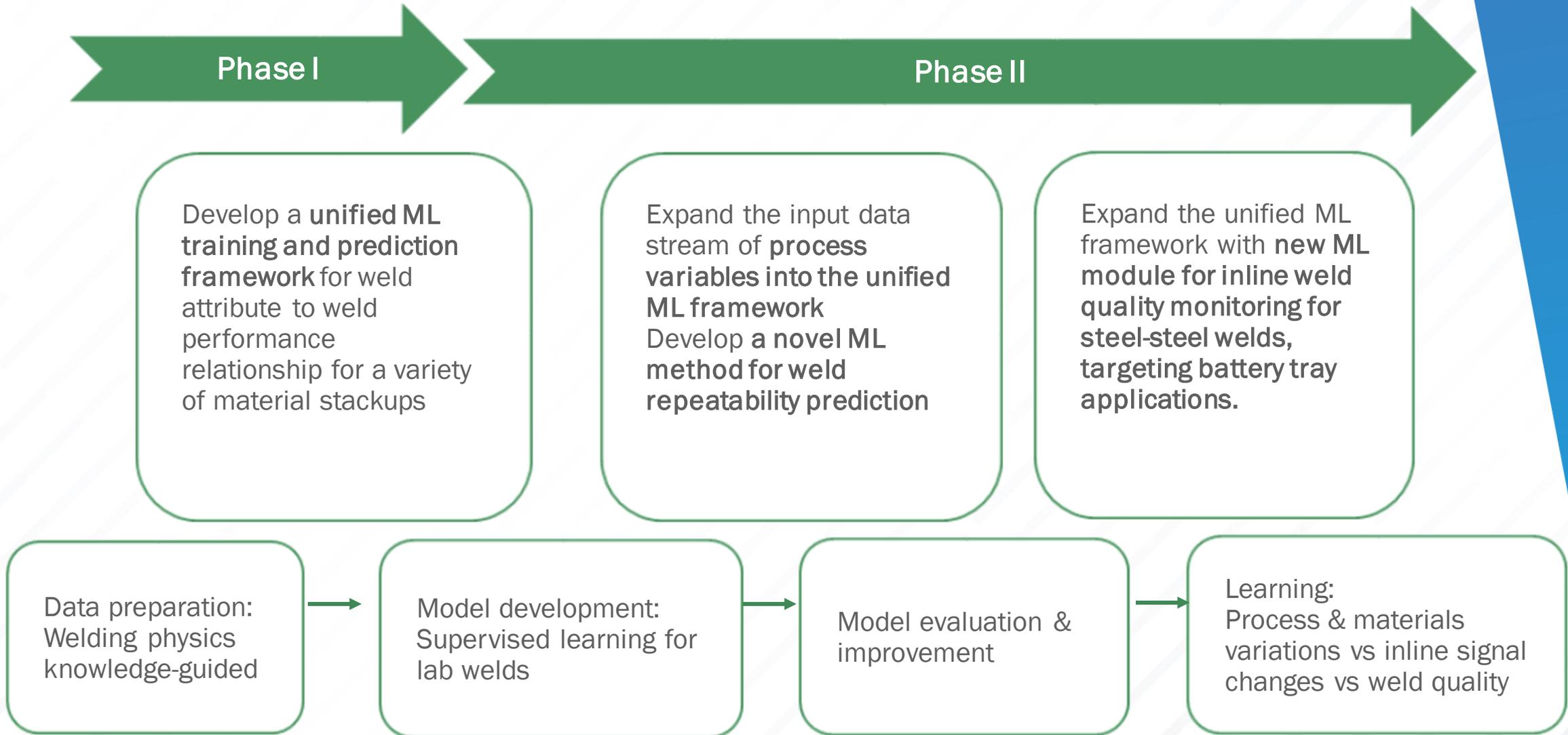- Extensible:
  - Designed to allow the addition of new capabilities and functionality:
  - Add new materials, thickness, and other conditions as they become available
  - Versatile to guide RSW process development for "unknown" materials, thickness combinations
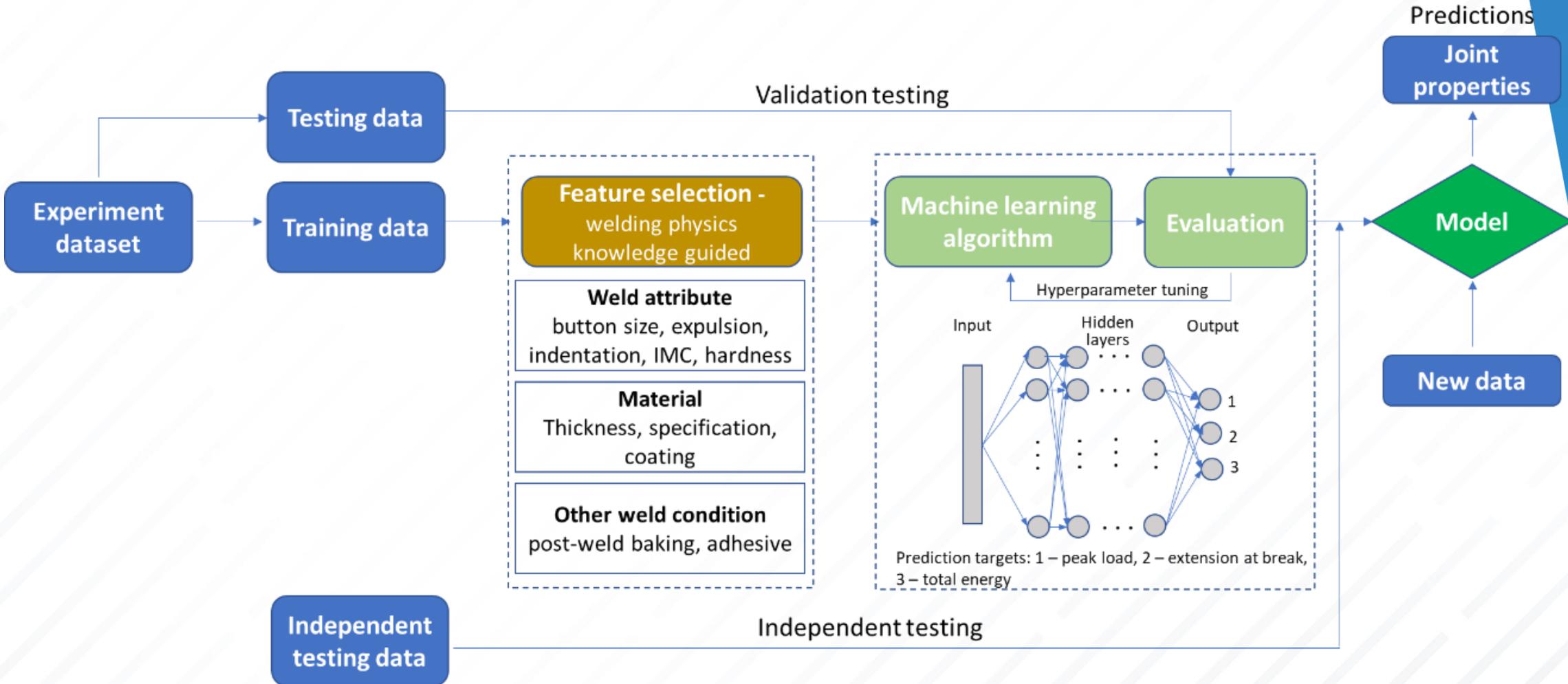
- Over 150 GB of resistance spot welding data, and more from GM
  - Al-steel dissimilar material welds
  - Steel-steel resistance spot welds (both lab and plant data)
    - Inline signals of dynamic resistance, current, load, and displacement available in addition to the setup process parameters

Progression of ML Model Development

Phase I → **Phase II**

Develop a **unified ML training and prediction framework** for weld attribute to weld performance relationship for a variety of material stackups

Expand the input data stream of **process variables into the unified ML framework**
Develop **a novel ML method for weld repeatability prediction**

Expand the unified ML framework with **new ML module for inline weld quality monitoring for steel-steel welds, targeting battery tray applications.**

Data preparation: Welding physics knowledge-guided → Model development: Supervised learning for lab welds → Model evaluation & improvement → Learning: Process & materials variations vs inline signal changes vs weld quality

Basic Machine Learning Pipeline: Prediction of Weld Property from Weld Attributes

Predictions

Validation testing

Testing data

Experiment dataset

Training data

Feature selection - welding physics knowledge guided

Weld attribute button size, expulsion, indentation, IMC, hardness

Material Thickness, specification, coating

Other weld condition post-weld baking, adhesive

Machine learning algorithm

Evaluation

Hyperparameter tuning

Input   Hidden layers   Output

1
2
3

Prediction targets: 1 – peak load, 2 – extension at break, 3 – total energy

Independent testing data

Independent testing

Joint properties

Model

New data

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# Weld Quality/Attributes to Performance

High correlation coefficients indicate DNN model learns high dimensional correlations between weld attributes and properties
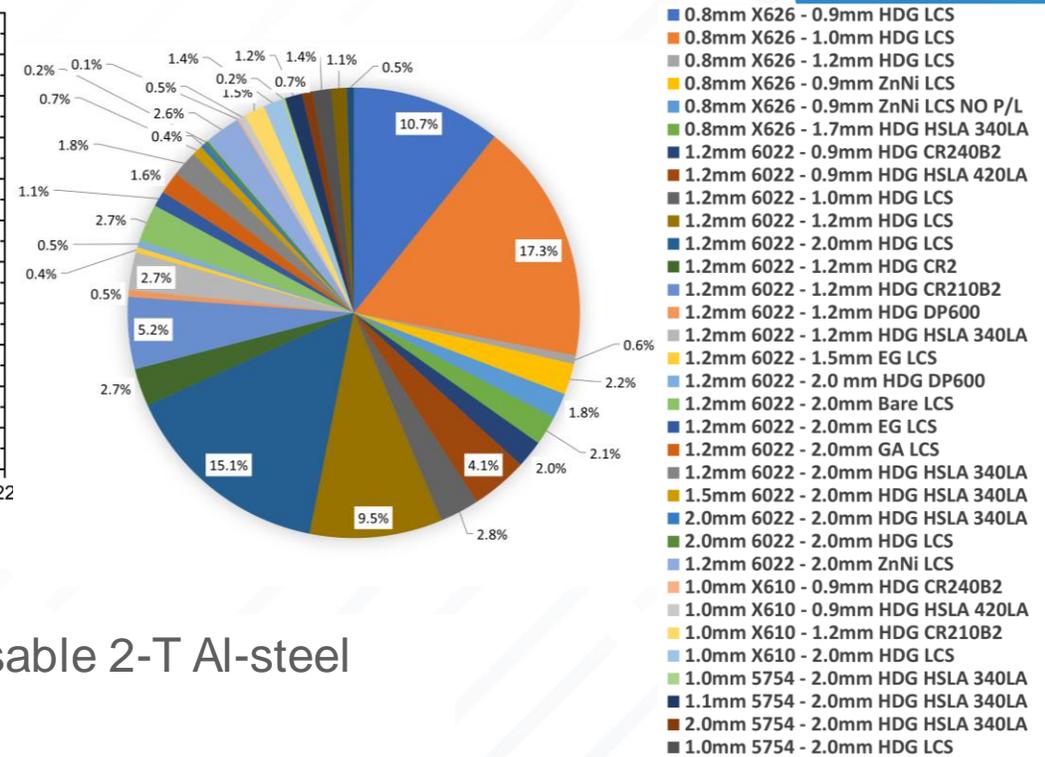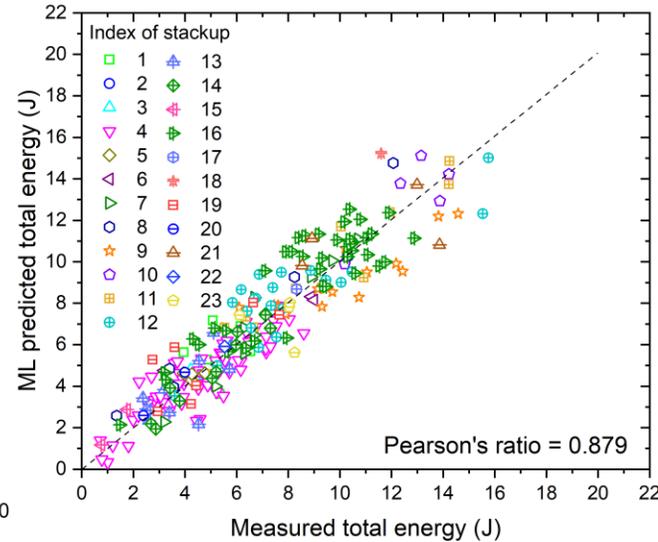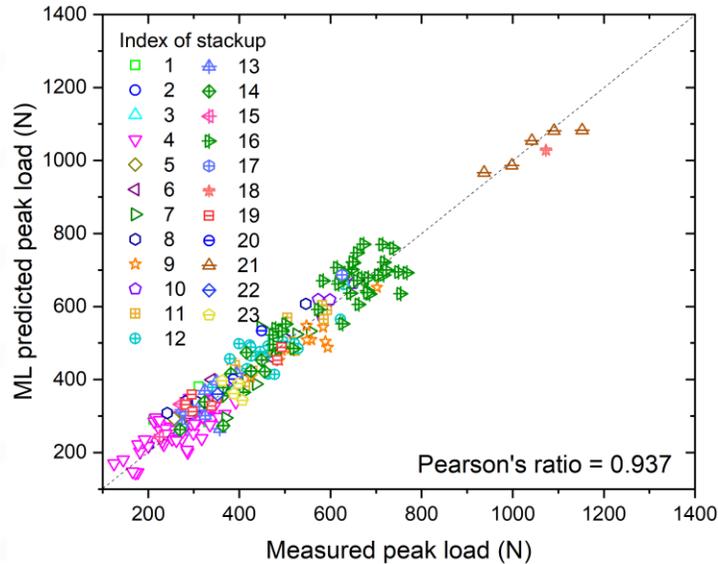
- Our patent pending NDD ML model has covered ~90% of usable 2-T Al-steel weld dataset from GM, over 800 unique weld conditions
  - Three objectives (peak load, extension at break, total energy)
 - Capable to guide RSW process development for "untrained" materials & thickness combinations

Mean Absolute Prediction Accuracy of Peak Load and Extension for 40 Al-steel Weld Stackups

- Training dataset:
  - 90% for peak load
  - 86.2% for extension at break
- Validation testing dataset
  - 89.4% for peak load
  - 85.9% for extension at break
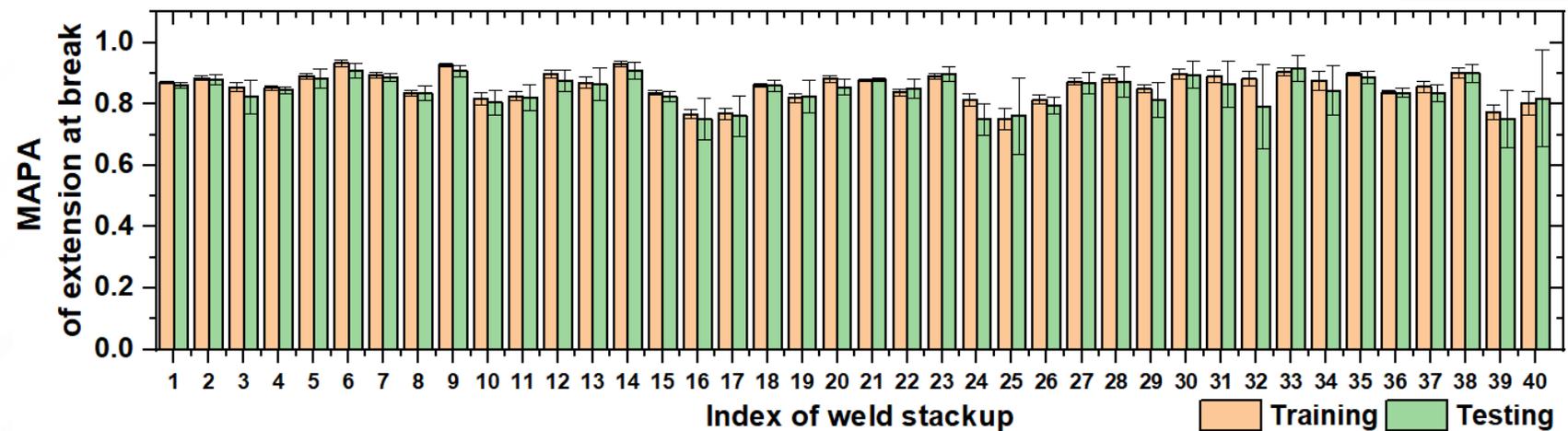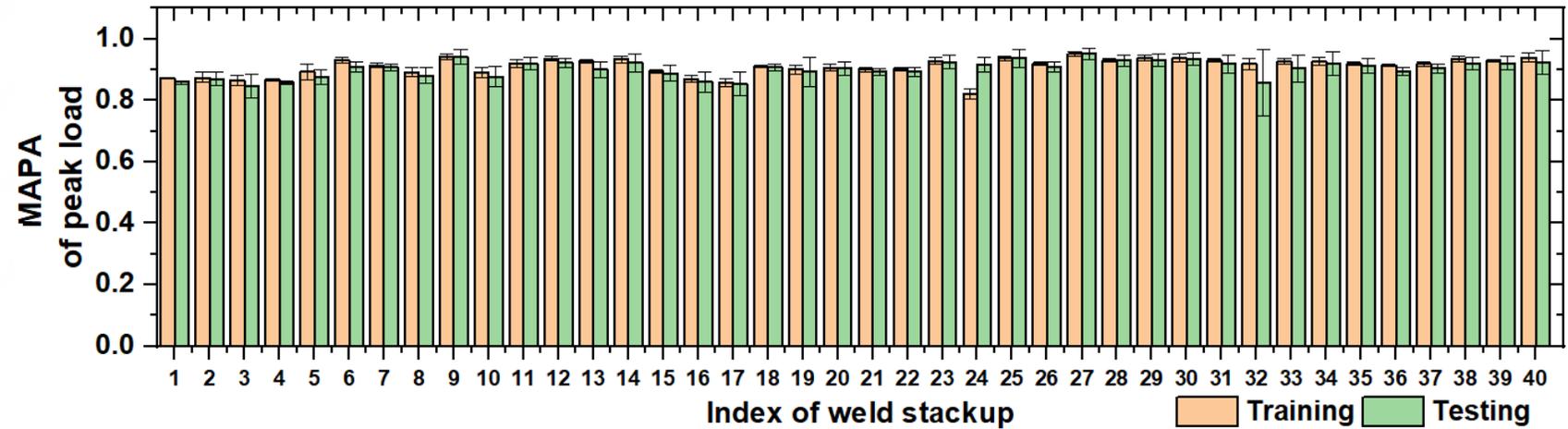
ML Predictions of Peak Load for an Independent Dataset of Welds

- Independent dataset: dataset not used in ML training
  - 1.2 mm AA6022 – 1.4 mm Bare LCS

- The ML model predicted the peak load with greater than 80% accuracy for over 90% independent testing welds.
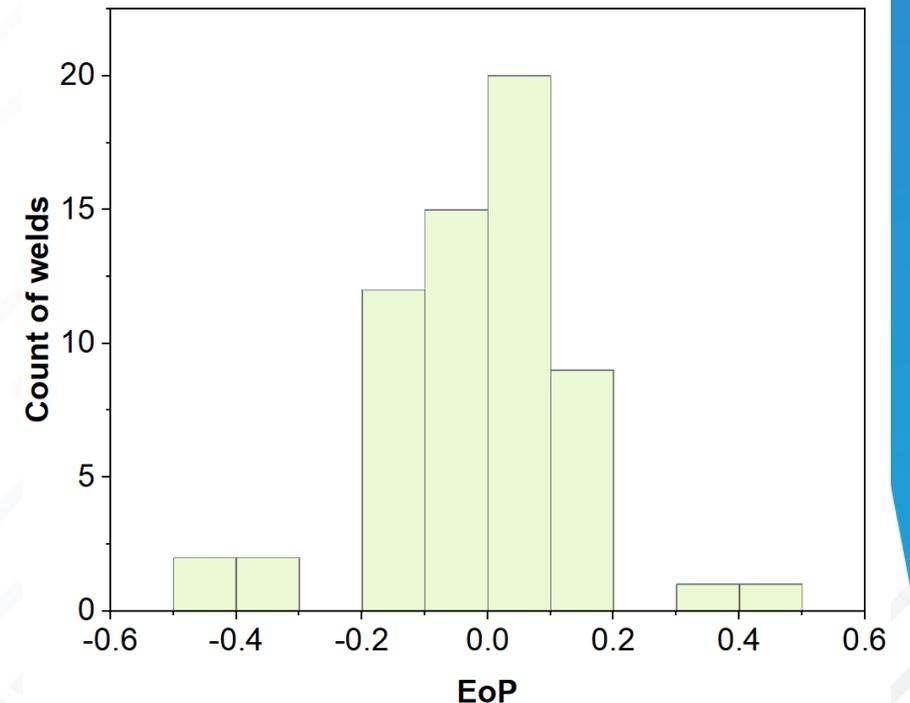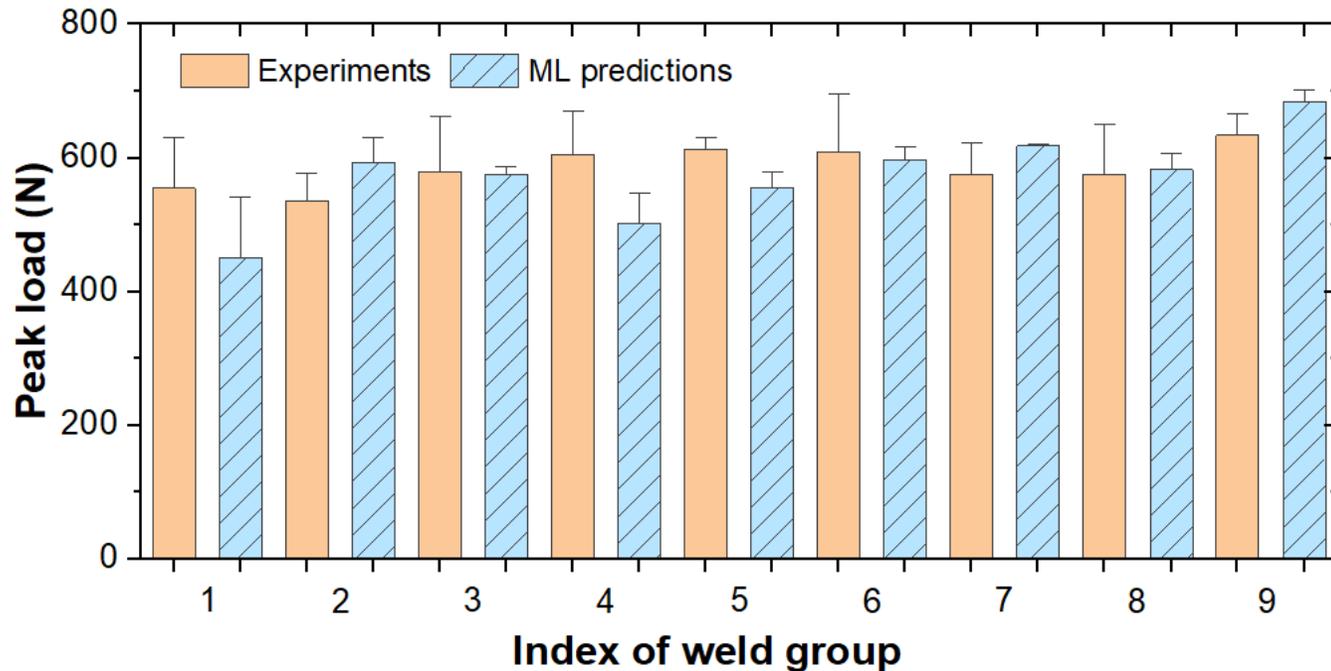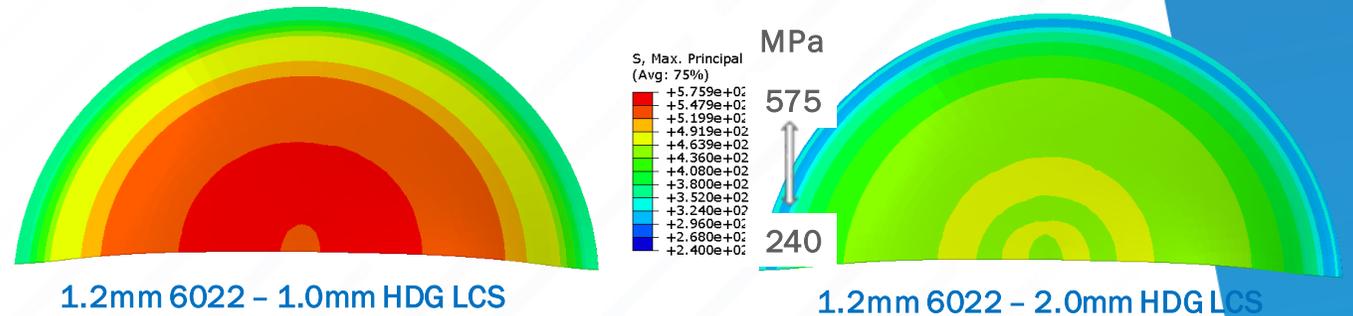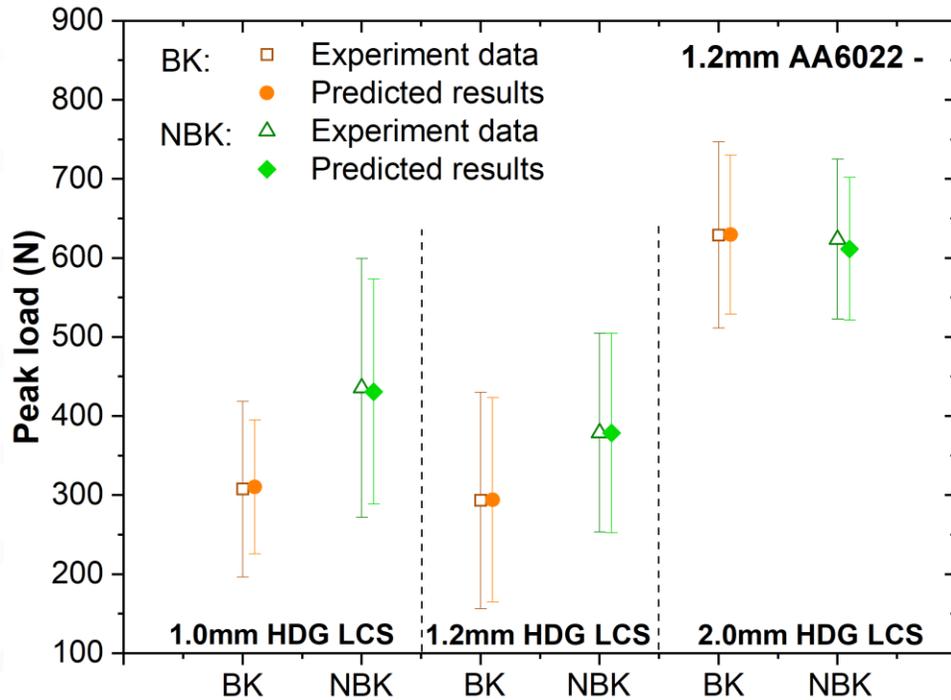
Learning from ML Model: Thickness-dependent Baking Effects

ML model identified:

Baking worsens the mechanical performances of RSWs made by thinner steel plates

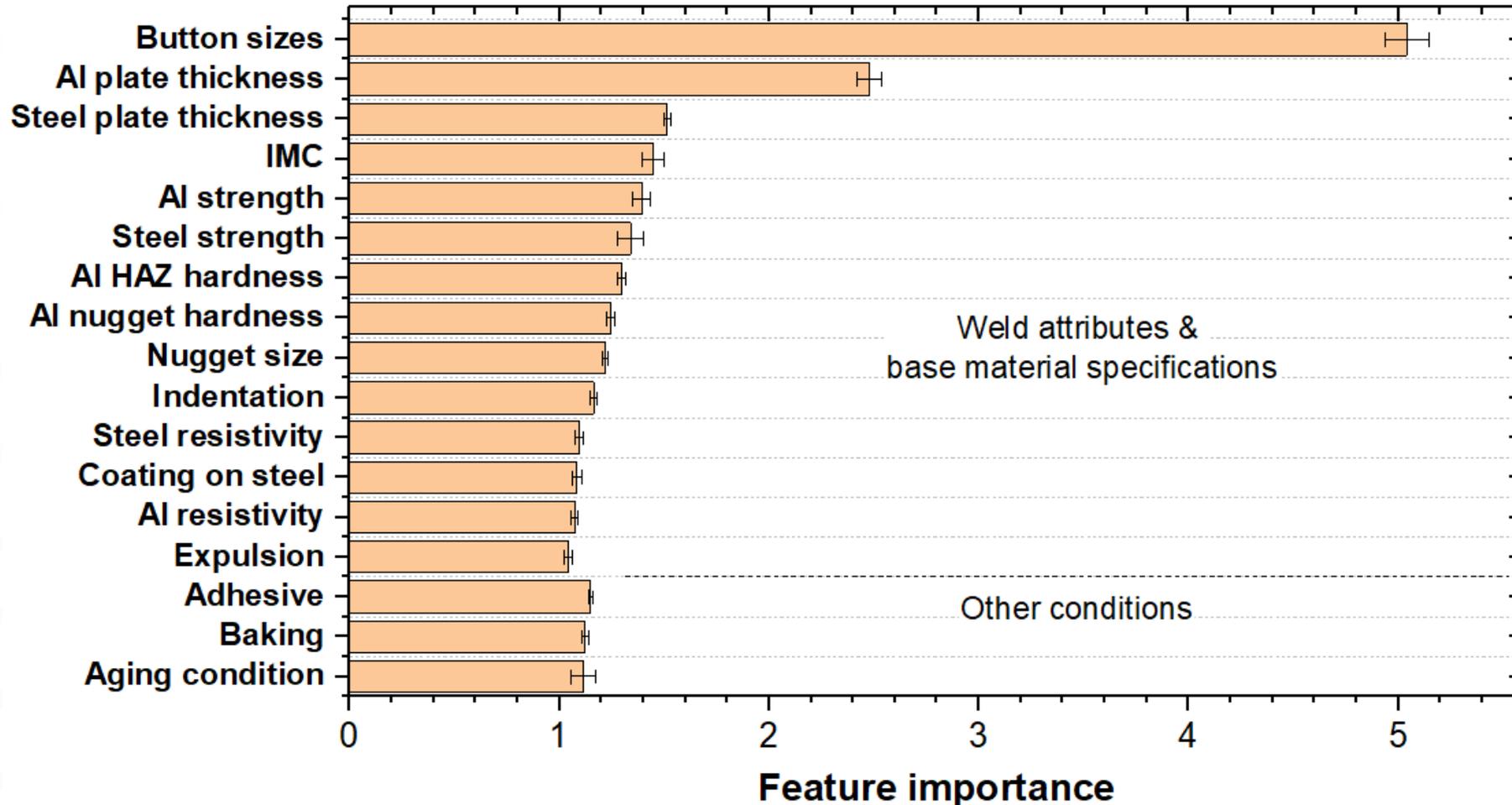Baking does not have significant effect on RSWs made by thicker steel plates

ICWE model was used for mechanistic understanding of baking effect

1.2mm 6022 – 1.0mm HDG LCS

1.2mm 6022 – 2.0mm HDG LCS

- **Root cause: Mismatch of thermal expansion** of Al and steel during baking generates high stress on IMC layers and may potentially break the bond. Thicker steel reduces the interfacial stress on IMC layer

Zhang, W, Wang, D, Chen, J, Ghassemi-Armaki, H, Carlson, B, Feng, Z. (2023) A New Perspective of Post-Weld Baking Effect on Al-Steel Resistance Spot Weld Properties through Machine Learning and Finite Element Modeling. Journal of Manufacturing and Materials Processing,

Feature Importance
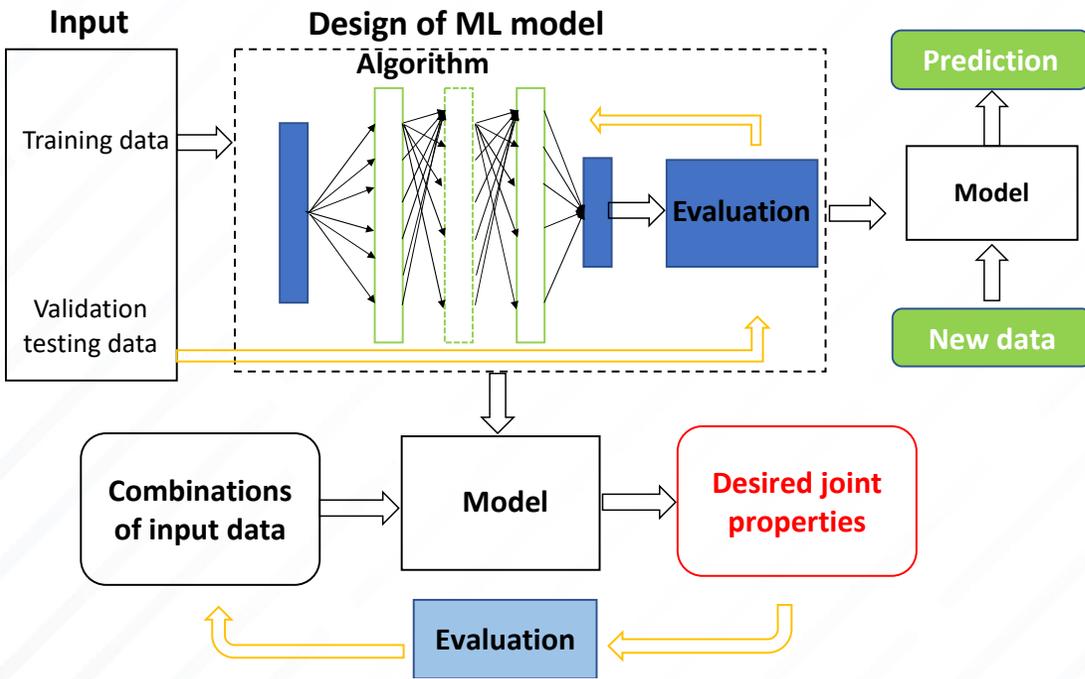
- Ranking of variables on weld strength

Model Application: Identify Weld Attribute to Achieve Target Performance (ORNL)

Example:

Identify a set of weld conditions to achieve performance target: peak load >= 750.0N and total energy >= 14.5J for a material combination **not yet tested experimentally**

Input

Design of ML model
Algorithm

Training data

Validation testing data

Prediction

Model

Evaluation

New data

Combinations of input data

Model

Desired joint properties

Evaluation

	Stackup-1: 1.2mm 6022 – 2.0mm HDG LCS		Stackup-2 (outside training dataset): 1.1mm 6022 – 2.0mm HDG LCS
	Identified range		Identified range
Min button size	6.2~8.4 mm (Exp: 6.5-7.4mm)	Min button size	7.958~8.4 mm
Max button size	7.9~8.9 mm (Exp: 7.9-8.0mm)	Max button size	8.9 mm
Indentation	0.062~0.373mm (Exp: 0.3-0.32mm)	Indentation	0.062~0.124mm
Expulsion	N, IXS (Exp: N)	Expulsion	N, IXS

Highest properties:

| Peak load	813.25 N
Total energy	16.20 J

Highest properties:

Peak load	759.44 N
Total energy	15.12 J

* Welds manufactured without adhesive and post-weld baking

GDIS

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Novel ML Algorithms Capable of Predicting Scatter of Weld Quality

- One group of weld process conditions result in varying weld qualities
  - How to predict from one to many?
  - Our ML tool aims to be able to predict not only the "statistic average/mean", but also the scattering (quality variability), and associate them with welding process conditions, with high level of confidence
- We developed a novel ML learning methodology for such type of problem
  - Under patent filing
  - Applicable to the "broadly" one-to-many ML training and prediction

Higher strength, good repeatability
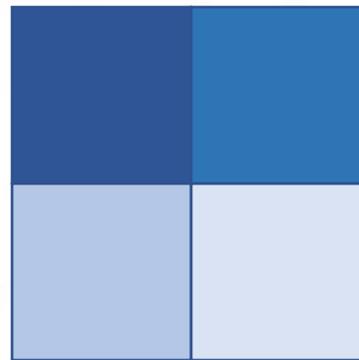
Poor repeatability under same prescribed welding conditions
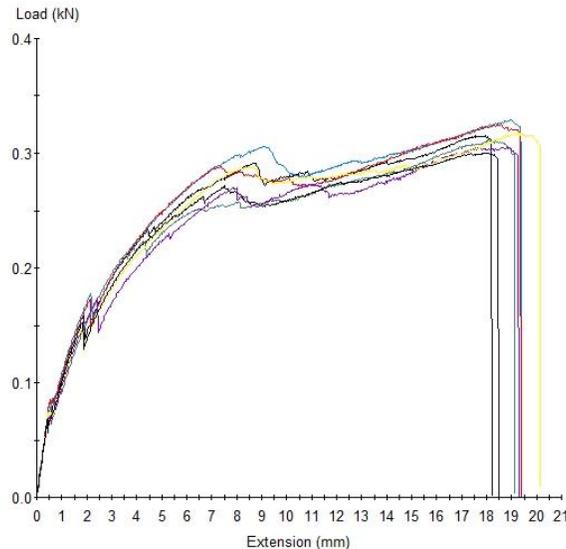
C238-1: 1.2mm 6022 - 1.0mm HDG LCS
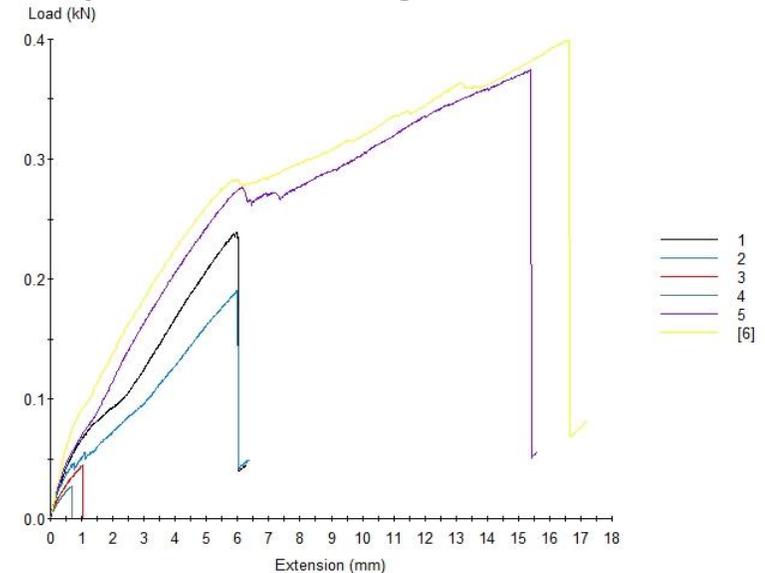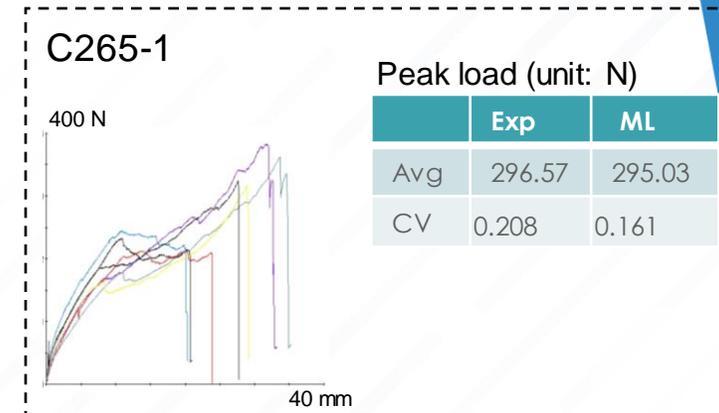
C139-1, 1.2 mm 6022 – 2.0 mm Zi-Ni LCS

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Model Validation: Qualify Both Statistic Means and Consistence of Weld Strength Under a Variety of Materials and Welding Conditions
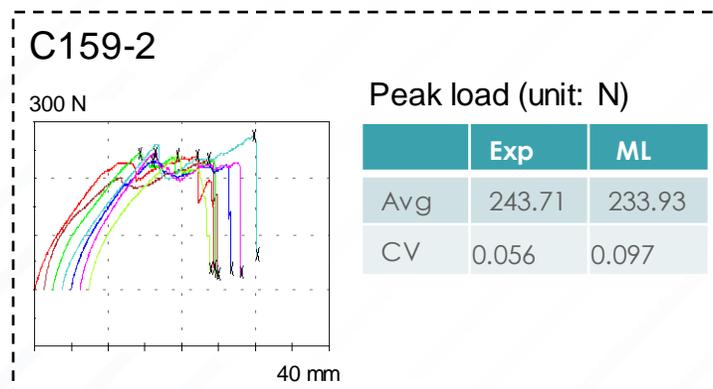
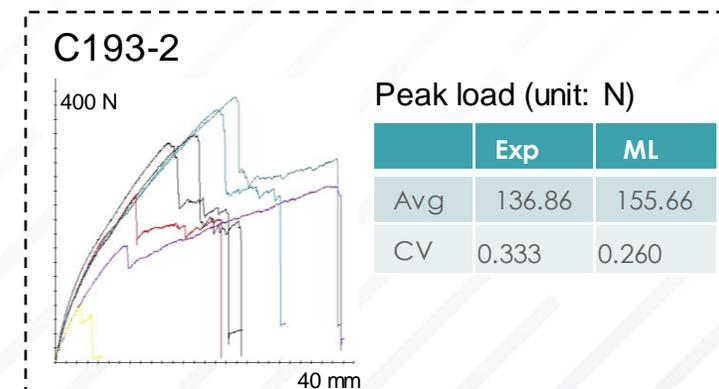**Higher strength, good repeatability (small variation)**

C274-1BK

400 N

Load – extension curves

40 mm

Peak load (unit: N)

	Exp	ML
Avg	327.57	305.62
CV	0.091	0.100

CV (coefficient of variation)
$$CV = STDEV/AVG$$
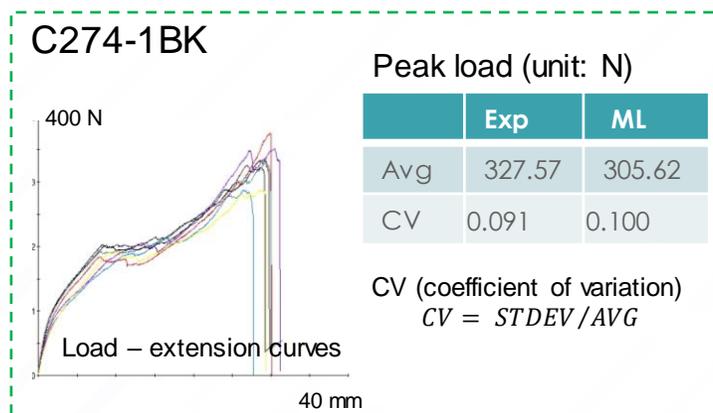
Higher strength, poor repeatability (large variation)

C265-1

400 N

40 mm

Peak load (unit: N)

	Exp	ML
Avg	296.57	295.03
CV	0.208	0.161

Lower strength, good repeatability

C159-2

300 N

40 mm

Peak load (unit: N)

	Exp	ML
Avg	243.71	233.93
CV	0.056	0.097

Lower strength, poor repeatability

C193-2

400 N

40 mm

Peak load (unit: N)

	Exp	ML
Avg	136.86	155.66
CV	0.333	0.260

High strength
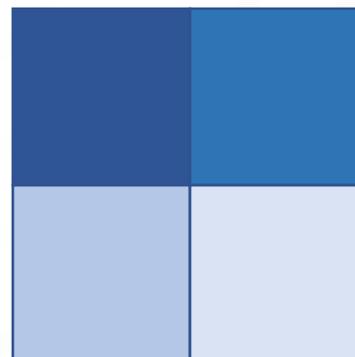
Low strength

small variation → large variation

Patent under preparation

# ML Predicted Joint Performance with a Confident Range

- ML provided both **joint quality** (e.g., peak load) and **weld repeatability** predictions for most welds

- ML predicted welds made with adhesives with larger error, due to the insufficient learning from the limited available data of welds fabricated with adhesives
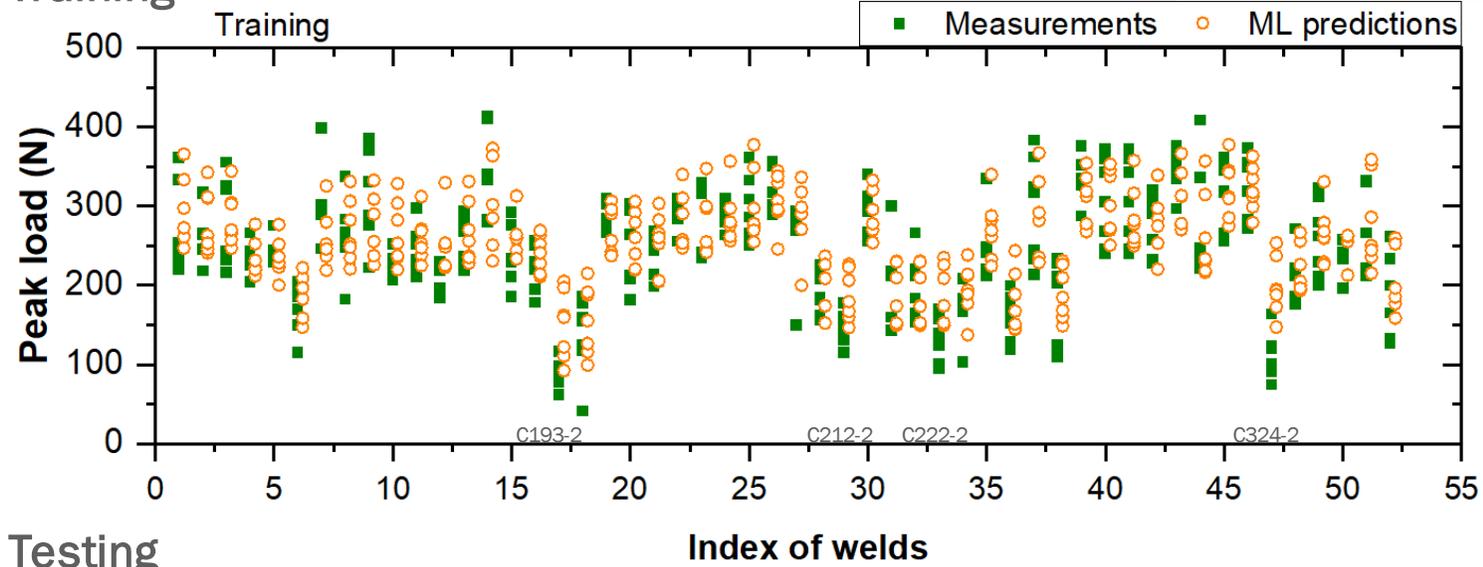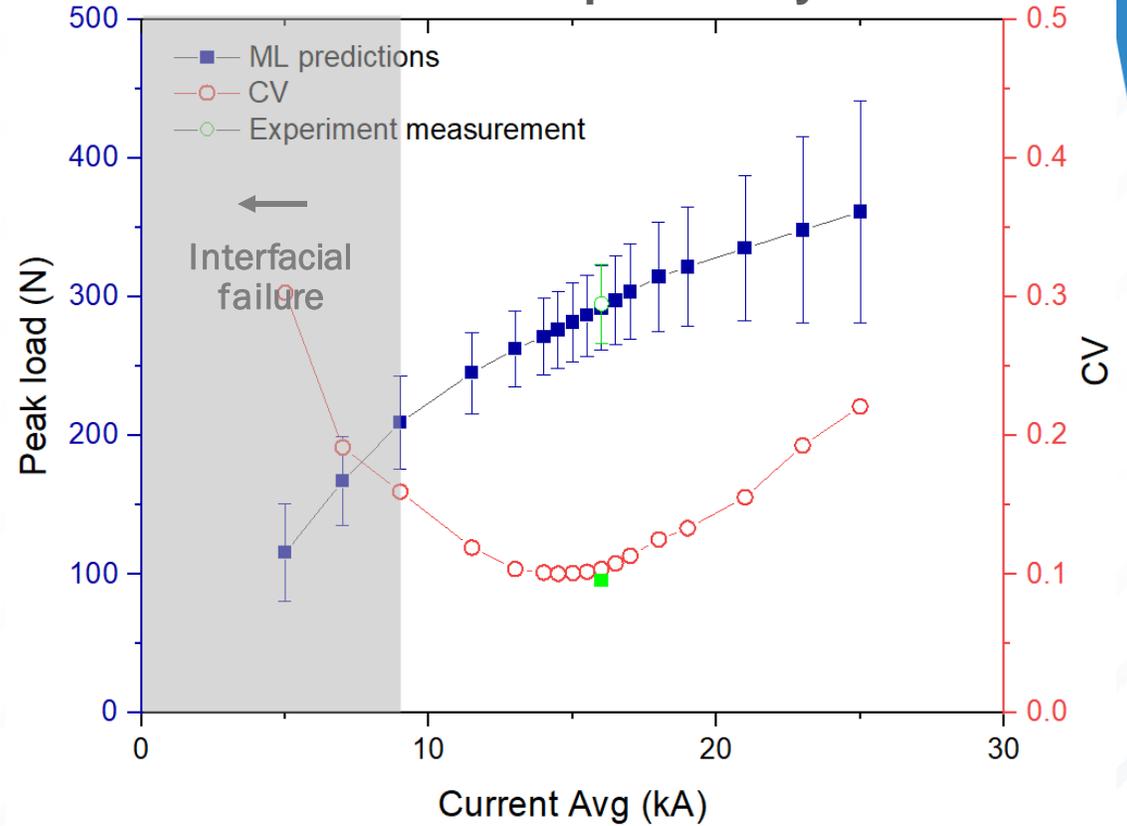
Weld stackup: 0.8 mm X626-0.9 mm HDG LCS

- Training

- Testing
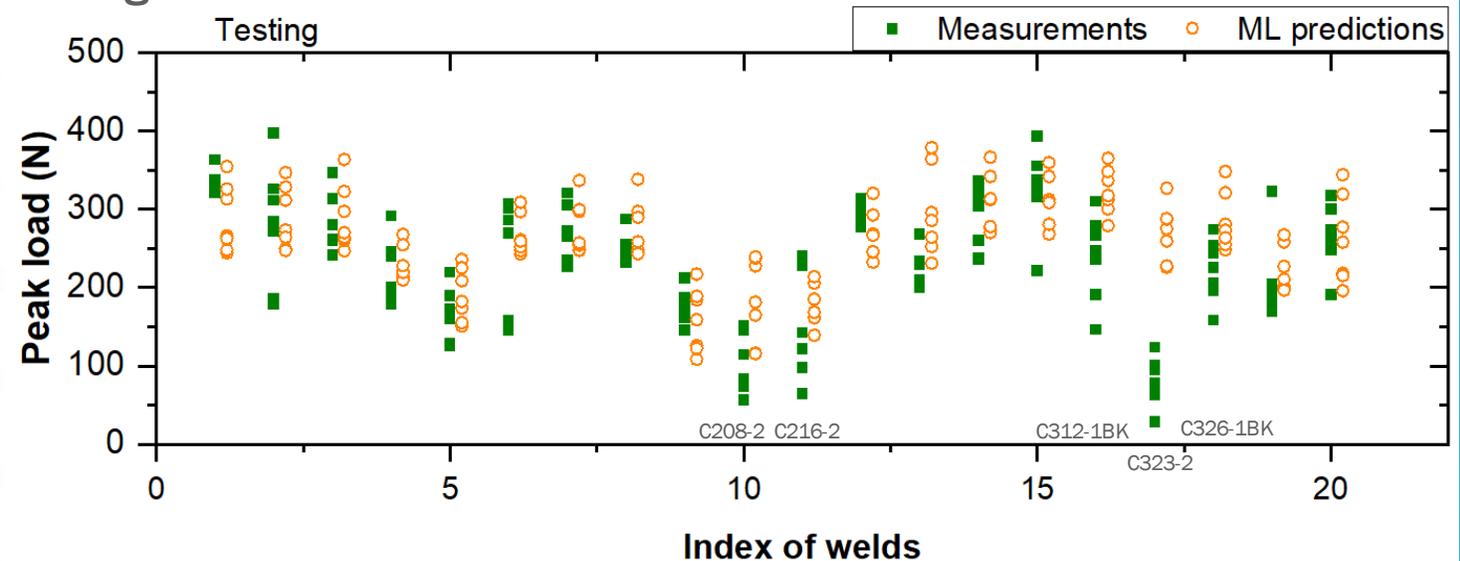
- Weld stackup: 0.8 mm X626 - 0.9 mm HDG LCS

Adhesive Suffix	Op. Code	Operator	Stackup	Polarity	Anode (+)	Cathode (-)
-1 MAN A		AH	0.8mm X626 - 0.9mm HDG LCS	AP	0.8mm X626	0.9mm HDG LCS

Welder	Anode (+) Cap	Cathode (-) Cap	Weld Order	CP/LS Coupon Width in.	Bake
stand 2	6148-B-MRD	6148-G-5mm	Shunt		1.5 NB

Clamp Load (lb)	Pre-Heat	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
800			10p 60h 30c 14.5-17.5kA			

Example: Current (kA) - welding duration (ms)

— Current Avg 7kA (virtual data out of GM dataset)   — Current Avg 16kA (within GM dataset)   — Current Avg 21kA (virtual data out of GM dataset)

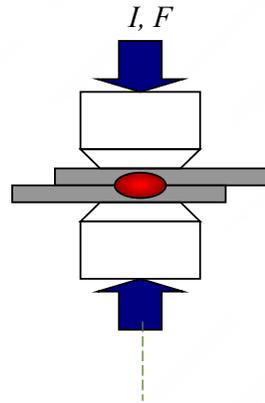- **Effects of welding current on joint peak load and repeatability**
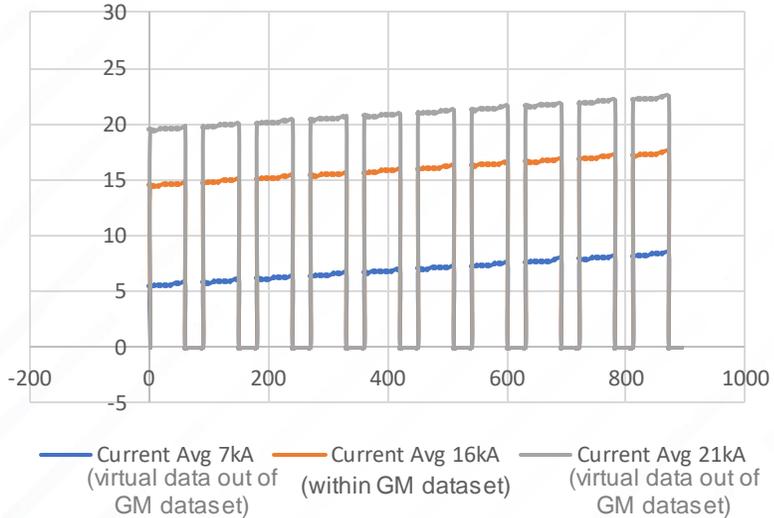
Extending ML Framework for Inline Weld Quality Monitoring (Steel RSWs in Battery Tray Application)

Materials

- Material specification
- Coating thickness

Welding Schedule

I, F

Process uncertainties

Sheet gap, electrode angle, edge weld, electrode wear, etc.

Inline signals

- Current
- Dynamic resistance
- Power & Energy
- Force*
- Displacement*
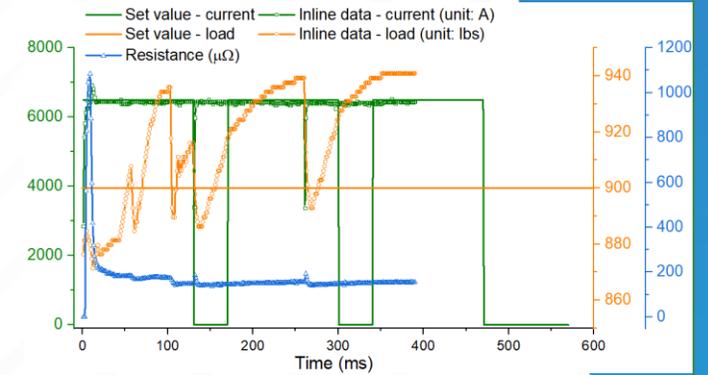
Prediction Model Targets

1. **No weld (zero mm nugget size) and Weld available (>0 mm) - Primary**
2. **Below Min nugget size= 4*sqrt(t) which t is lowest sheet thickness in between two sheets. – Primary**
3. **Nugget size prediction**

ORNL DNN, unified ML framework

DNN – inline signals

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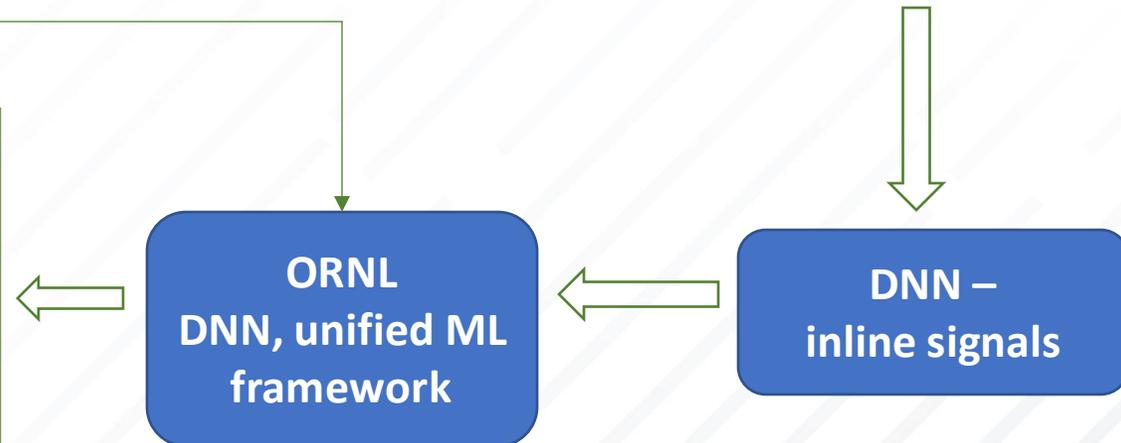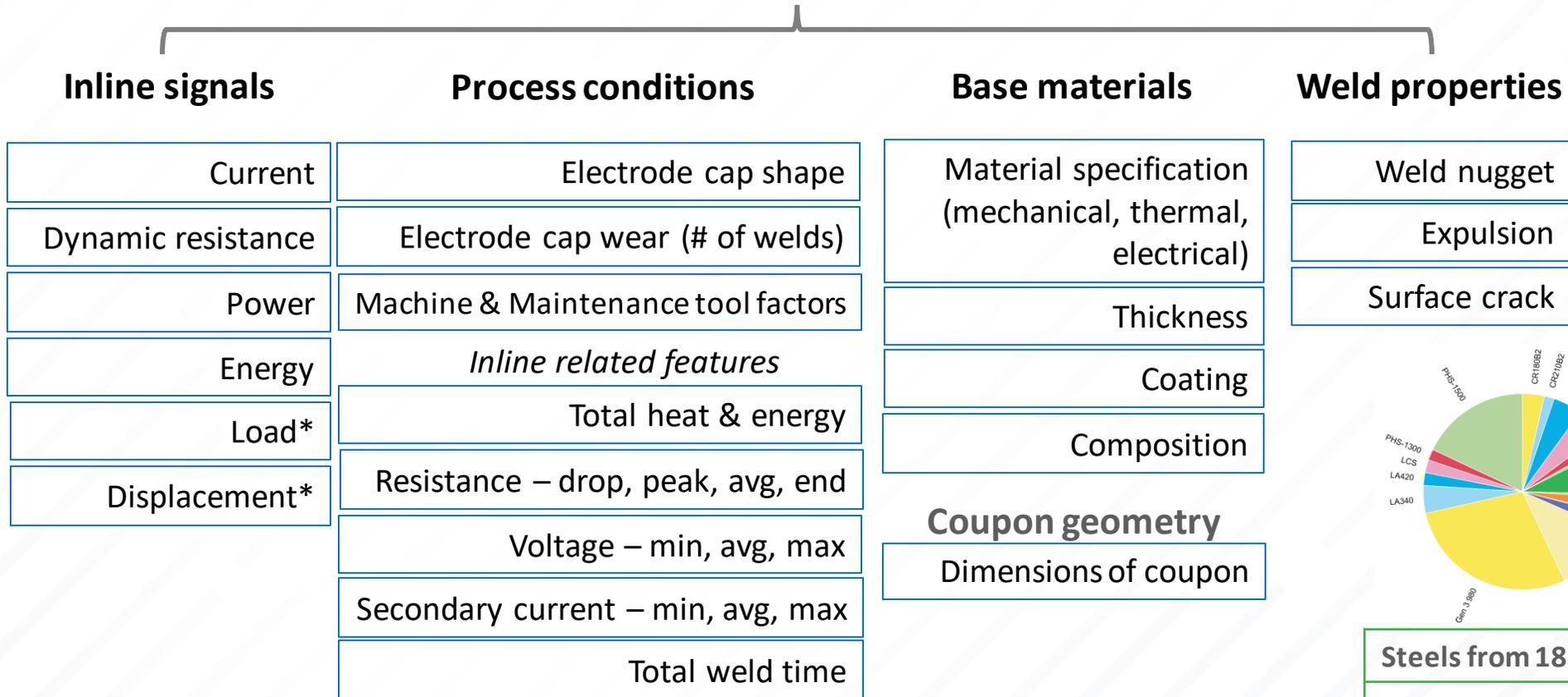# RSW Data for Training and Testing (GM)

- **Lab Data (7,500 welds & 18 DOEs)**
- **Plant Data (2,350,000 welds)**

Lab data

Inline signals	Process conditions	Base materials	Weld properties
Current	Electrode cap shape	Material specification (mechanical, thermal, electrical)	Weld nugget
Dynamic resistance	Electrode cap wear (# of welds)		Expulsion
Power	Machine & Maintenance tool factors	Thickness	Surface crack
Energy	*Inline related features*	Coating	
Load*	Total heat & energy	Composition	
Displacement*	Resistance – drop, peak, avg, end		
	Coupon geometry		
	Voltage – min, avg, max	Dimensions of coupon	
	Secondary current – min, avg, max		
	Total weld time		

Steels from 18 DOEs	Coating
• 14 different steels from low carbon steel to GEN III AHSS • Thickness ranging from 0.65 mm to 2.8 mm	• Bare • HDG, • EG, • AS-various grade

Plant data
Available data - inline signals and process conditions

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Deep Learning Model for Weld Nugget Prediction

ID CNN module for inline signals

Inline signals
Current, resistance, power, energy, load, displacement

Input layer → 1D convolutional layer (RELU / Dropout) → Max pooing → ⋮ → Flatten layer → Fully connected (RELU / Dropout) → Desirable features (RELU)

(,1315,4)

Unified DL framework

Base materials
(thickness, material, coating)
Welding schedule
Electrode shape

Other conditions
(electrode wear, etc.)

Input layer → Merged input → Fully connected (RELU / Dropout) → ⋮ → Fully connected (RELU / Dropout) → Nugget size

- **Data**: 2T welds, a total of 4323 welds (so far)
- **Prediction target**: nugget size
- **Training and testing**: 5-fold cross validation

Model Training and Testing: Prediction of Weld Nugget with > 98% Accuracy
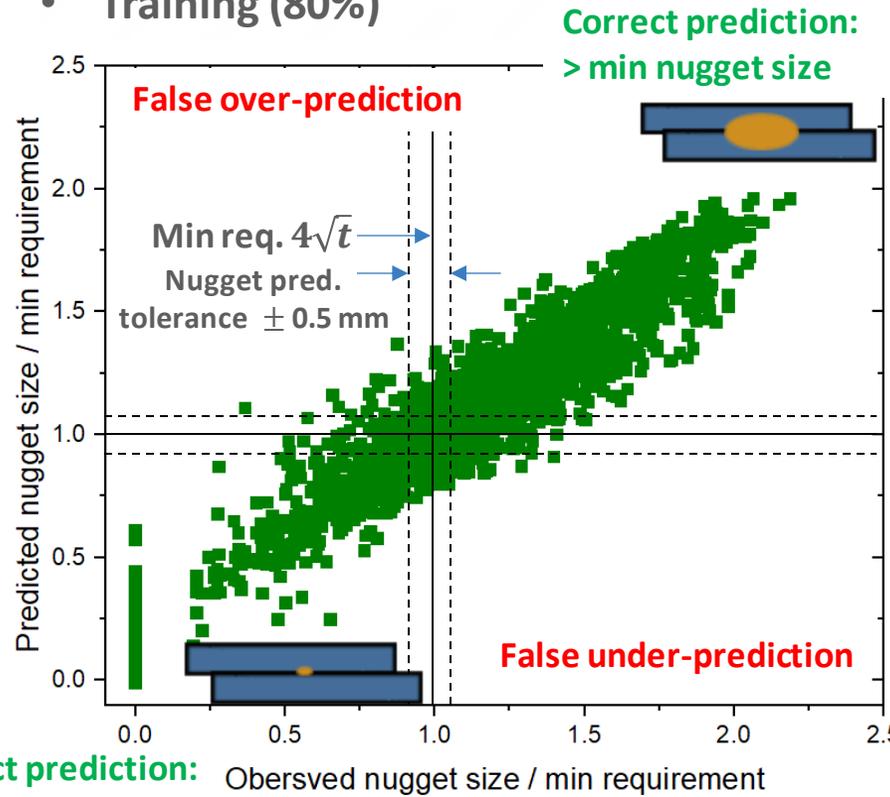
- **Model performance**

Training
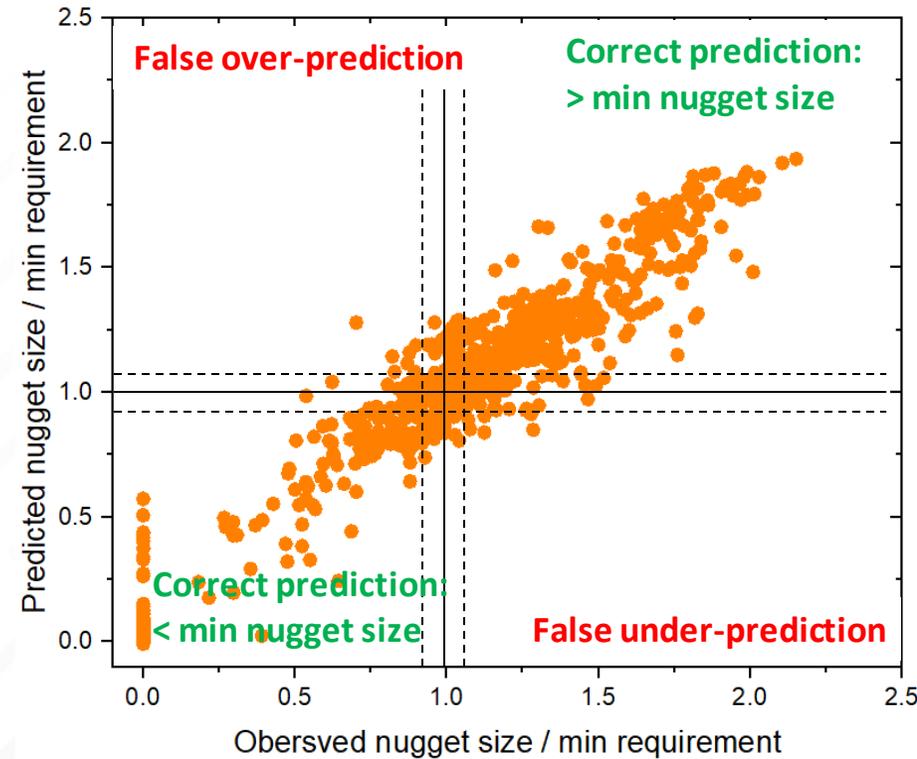
Prediction accuracy	False classification rate
99.2%	0.8%

Testing

Prediction accuracy	False classification rate
98.6%	1.4%

- **Training (80%)**

Correct prediction: > min nugget size

False over-prediction

Min req. $4\sqrt{t}$

Nugget pred. tolerance $\pm$ 0.5 mm

Predicted nugget size / min requirement

False under-prediction

Correct prediction: < min nugget size

Obersved nugget size / min requirement

- **Testing (20%)**

False over-prediction

Correct prediction: > min nugget size

Predicted nugget size / min requirement

Correct prediction: < min nugget size
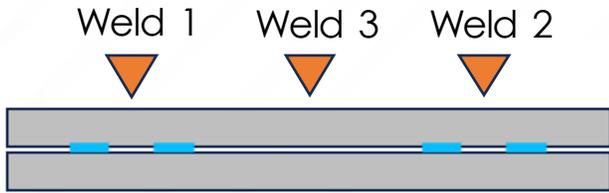
False under-prediction

Obersved nugget size / min requirement

- **Prediction targets: Min weld nugget requirement ($>4\sqrt{t}$) with acceptable tolerance of ± 0.5mm**
- Data: All labeled 2T welds, a total of 4323 welds

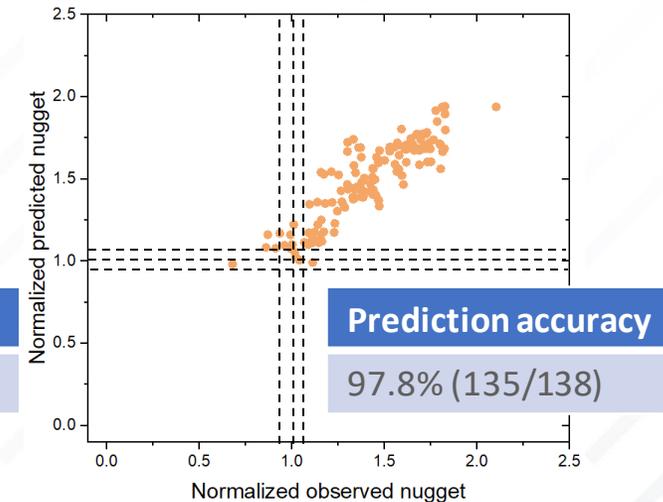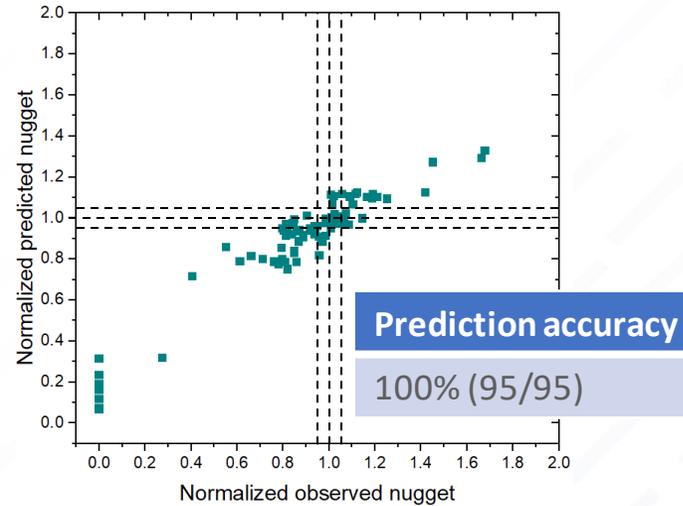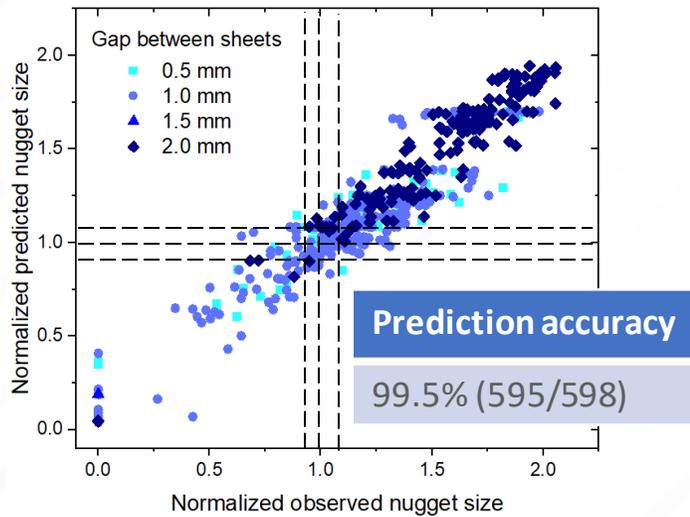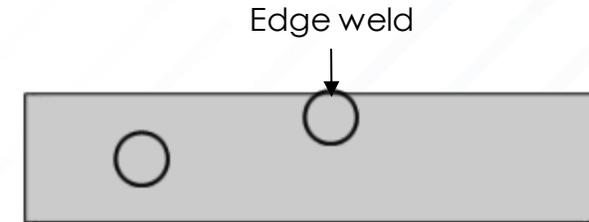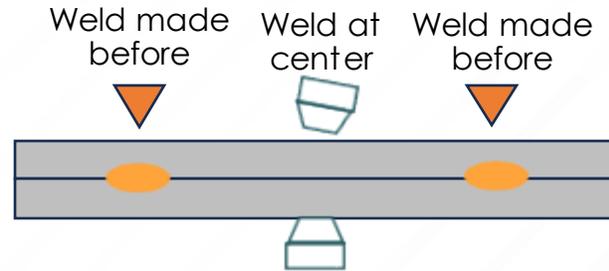# Model Performance Due to Production Uncertainties > 98%

- **Production uncertainty**
  - Sheet gap
  - Electrode angle
  - Edge weld
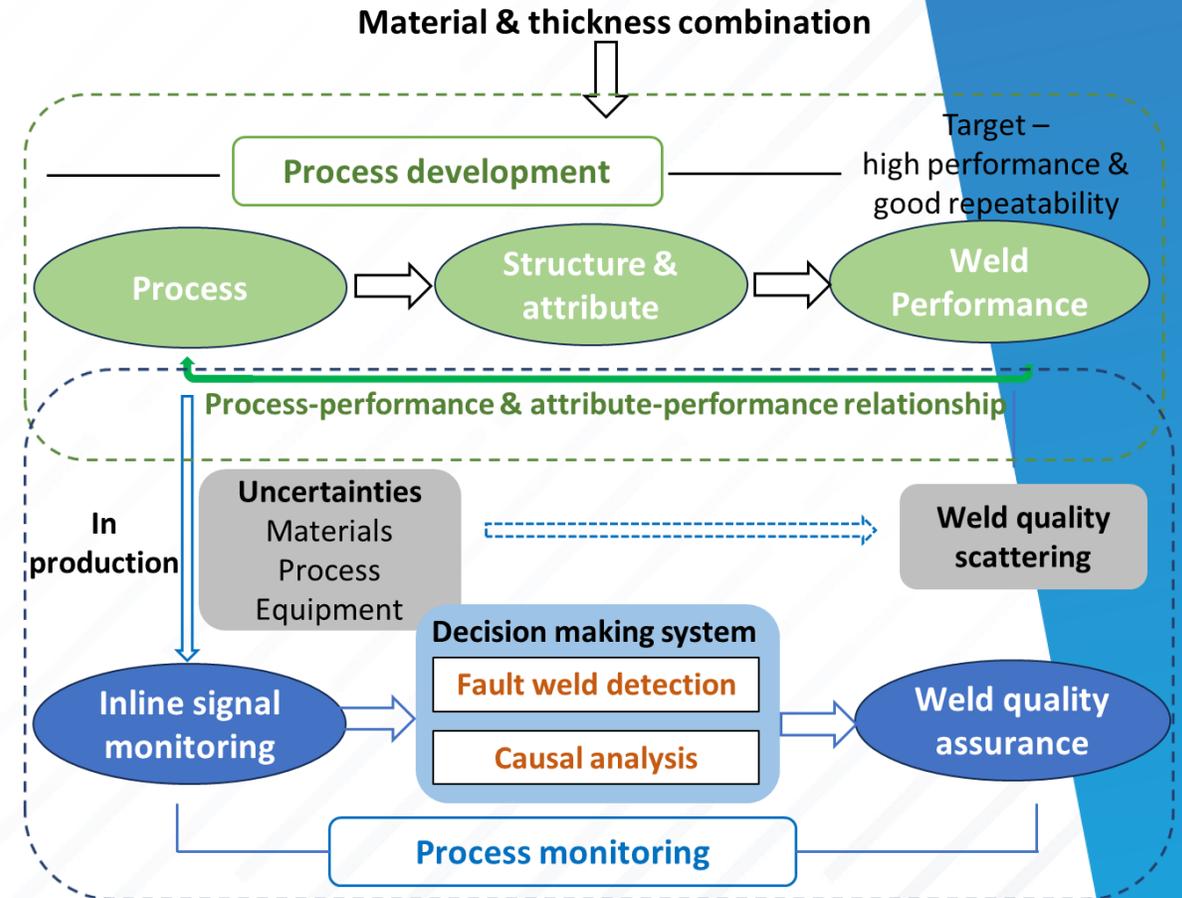
- **How do they impact the inline signal and nugget formation?** (production uncertainty not included as model inputs)

Weld 1   Weld 3   Weld 2

Weld made before   Weld at center   Weld made before

Edge weld

Prediction accuracy

99.5% (595/598)

Prediction accuracy

100% (95/95)

Prediction accuracy

97.8% (135/138)

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Summary

- **ML/AI framework for resistance spot welding from design to production**

- **Process design**: ML/AI framework can model complex relationships between RSW parameters, weld attributes and joint properties without computational models
  - ML model based on DNN have over 80% prediction accuracy

- **Inline weld quality monitoring**: ML model is capable to identify the signature data patterns and anomalies from inline signals, and reliably predict weld quality properties
  - Have over 98% prediction accuracy for high priority weld quality metrics required from industry
  - ML/AI framework demonstrates its capability to predict weld quality, even under abnormal welding conditions

Material & thickness combination

Process development

Target – high performance & good repeatability

Process → Structure & attribute → Weld Performance

Process-performance & attribute-performance relationship

In production

Uncertainties
Materials
Process
Equipment

Weld quality scattering

Decision making system
Fault weld detection
Causal analysis

Inline signal monitoring

Weld quality assurance

Process monitoring

For More Information

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