Enhance Resistance Spot Welding Quality Control: A Machine Learning Approach

Wei Zhang[a, 1], Dali Wang[b], Jian Chen[a], Hassan Ghassemi-Armaki[c], Blair Carlson[c], Zhili Feng[a, *]

[a]Materials Science and Technology Division, Oak Ridge National Laboratory, Oak Ridge, TN, USA

[b]Environmental Sciences Division, Oak Ridge National Laboratory, Oak Ridge, TN, USA

[c]General Motors, Warren, MI, USA

Abstract

The Resistance Spot Welding (RSW) process is vital in the automotive industry, favored for its cost-effectiveness, short cycle time, and robustness. However, optimizing the quality of robust joints is challenging due to the complex interplay of various factors. Machine learning has emerged as a promising tool to predict joint quality and develop welding technologies.

In this on-going collaborative project between Oak Ridge National Laboratory and General Motors, we have developed a machine-learning based framework to quantify the weld quality as function of weld attributes. The framework utilizes an expandable deep learning model with a unified architecture for predicting weld attributes to quality. It includes a method to address the data scattering issue inherent in welding procedures. It is also used for training-friendly RSW data processing, to search for the optimal weld schedule. The deep neural network modeling framework include functions to uncover the complex relationship between in-situ welding conditions and weld quality prediction factors, which greatly improve the accuracy and reliability of ML based model for weld quality detection and quality improvement in RSW of EV battery enclosures.

Keywords: resistance spot welding; machine learning, neural network; welding physics-guided; weld quality prediction

[1] Corresponding author: Zhili Feng (fengz@ornl.gov), Wei Zhang (zhangw4@ornl.gov)

Introduction

Resistance spot welding (RSW) is a widely used joining process in various industries, particularly in automotive manufacturing, due to its high efficiency, cost-effectiveness, and suitability for high-volume production [1, 2]. By applying pressure and passing electrical current through the metals to be joined, RSW creates localized heat, which fuses the materials without requiring additional filler material. This process is especially advantageous for applications requiring fast and robust joints, as it enables high-speed automation and minimizes material waste. In recent years, the need to join dissimilar materials, particularly aluminum and steel, has grown significantly as industries strive to reduce vehicle weight for improved fuel efficiency and reduced emissions [3]. Their differing thermal and electrical conductivities, melting points, and metallurgical properties can lead to issues such as brittle intermetallic compounds, poor weld strength, and inconsistent weld quality. The development of optimized welding parameters for dissimilar material joints is critical but highly complex, requiring design over high dimensional welding variable space, such as current, weld time, electrode force, electrode cap shape, and other process variables.

Traditional methods of process development often rely on trial and error, which can be both time-consuming and costly. Moreover, these methods may not capture the full range of variability in material properties and welding conditions. This is where machine learning (ML) techniques can play a transformative role. By analyzing large datasets generated during welding trials, machine learning algorithms can identify complex relationships between process parameters, weld attributes, and weld quality outcomes. This enables the prediction and optimization of welding conditions, reducing the reliance on empirical testing and significantly improving process efficiency [4-10].

This paper investigates the application of machine learning to enhance process design, optimize weld parameters, and ensure consistent weld quality. We present an extensible ML framework that leverages a unified neural network architecture designed to assimilate knowledge from a broad spectrum of welding process scenarios. The architecture is extensible, enabling it to incorporate data from diverse sources, including different materials, welding parameters, and real-time process monitoring signals. Initially, the framework was developed to predict weld quality based on weld attributes, such as nugget size, expulsion, indentation, etc. However, its extensibility allowed us to broaden its capabilities to include predictions of process-to-quality relationships. By mapping welding parameters like current, welding time, electrode force, and electrode shape to quality outcomes, the framework helps identify optimal settings that improve the efficiency and reliability of the welding process.

Methodology

In this work, we present a machine learning framework for predicting weld quality in resistance spot welding (RSW). The model was developed and trained using a sizeable experimental dataset provided by General Motors. This section discusses the feature selection, neural network model, and the training and testing process.

Feature Selection and Engineering

An important component of this approach is the application of domain knowledge in feature engineering. The model's ability to predict weld performance was enhanced by purposely selecting and engineering features rooted in the physics of dissimilar Al-steel RSWs. In welding dissimilar materials such as aluminum and steel, intermetallic compound (IMC) layers play a pivotal role in determining failure modes and joint performance. During welding process, localized heat leads to non-uniform thermal distributions, creating gradients in microstructure and material properties [11-13]. These spatial variations complicate the relationship between weld sub-locations and overall joint quality. To capture these effects, zone-based features were engineered to represent the spatial distributions of material hardness and IMC thickness, which vary across different regions such as the weld nugget, heat-affected zone, and base materials. Additional features, including nugget size, material indentation, button size, and the presence of expulsion, were also incorporated as model inputs. The flow of ML framework is presented in Figure 1. The model's output responses focused on key weld quality metrics such as peak load and total energy, as determined through coach peel tests.

Integration of Material Specifications

Base material properties, such as resistivity, strength, ductility, thickness, and surface coating, were included as input variables to account for the influence of material characteristics on weld performance. The inclusion of these material specifications serves two purposes: (1) expanding the model's scope to include a wide variety of stackups, even those with limited data representation, and (2) providing critical insights into the material behaviors that influence weld outcomes. By integrating material properties, the model gains a deeper understanding of the complex interactions between the materials and welding process, leading to improved generalization.

Weld Process and Joint Quality Variability Handling

Based on foundation ML framework, we have expanded the model with inputs of process conditions to explore the relationship between welding process conditions and joint performance properties. One major challenge in RSW is addressing the variability in weld quality observed under identical process conditions. Welds made under the same settings can exhibit different strengths, toughness, and fatigue resistance due to subtle variations in material properties, environmental factors, or process dynamics. To capture this variability, we developed a customized neural network system capable of not only predicting weld quality but also quantifying the variability across replicate welds. This was achieved by integrating process condition variables such as electrode cap shape, polarity, pre-heat, clamp load, welding current schedule, and adhesive type as input streams. These inputs, along with material specifications and post-weld conditions (e.g., baking, aging), were used to predict both the weld performance properties and their variability.

Neural network model

The proposed approach employs a single ML framework with a unified neural network architecture, which is designed to learn the material-associated weld attribute-performance relationship and weld process-performance relationship, as shown in Figure 1. The ML model consisted of a 2- or 3-layer artificial neural network with 32 to 256 neurons on each layer for each individual task. The Rectified Linear Unit (ReLU) activation function was selected for its ability to enhance training efficiency without compromising generalization accuracy [14]. The dropout layer was introduced after each hidden layer to mitigate the risk of overfitting. Given the differences in magnitude among input variables, we applied Min-Max normalization to standardize the range of predictor variables. This normalization ensured balanced node weighting during training, preventing instability due to disproportionate feature scaling.

Training and Validation

Central to our methodology is the utilization of a sizable dataset comprising Al-steel resistance spot welds spanning over 20 weld stackups. By training on this diverse dataset, the model learns to encapsulate the interplay between material characteristics, weld quality attributes, weld process conditions, and joint performance. The training dataset included a total of 4,756 individual welds. To ensure robust performance and avoid overfitting, we employed a five-fold cross-validation (CV) strategy. The dataset was randomly shuffled and divided into five folds, with four folds used for training and the remaining fold for validation. This process was repeated to validate model performance across all data splits.

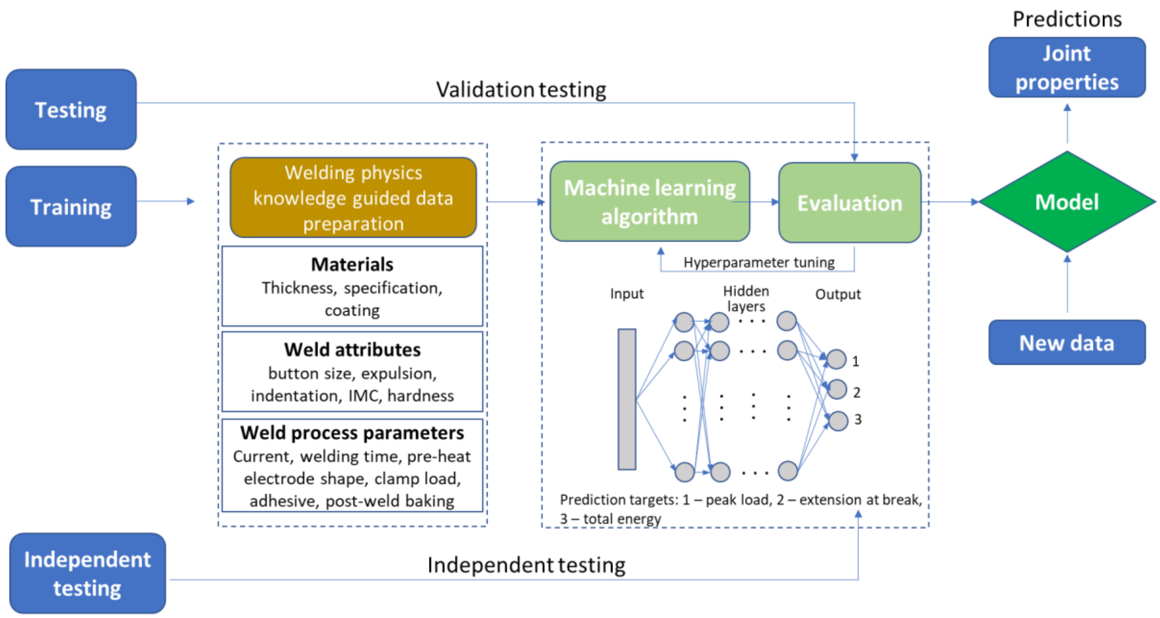

Figure 1 Flow of the machine learning framework for RSW quality prediction.

Results and Discussion

ML prediction of joint quality based on weld attributes: The performance of the machine learning (ML) model in predicting joint properties was evaluated by comparing its predictions to experimental measurements. Figure 2 plots the regression analysis between predicted and measured peak load and total energy for validation test welds. The predicted and measured values were located around the perfect prediction line (i.e., y=x) in a scattered manner. The Pearson's correlation coefficients between the measured and predicted values for peak load and total energy were calculated as 0.937 and 0.879, respectively. The high correlation coefficients suggest a strong relationship between predicted and measured data, that is, the DNN regression model identified the high dimensional correlations among the welds attributes and joint performance properties. It was noted that the predictions of total energy exhibited increased error and larger variation, which could be attributed to the complicated nature of the fracture process. The challenges were partially addressed in our study, laying the groundwork for future improvements. Despite occasional limitations in predicting total energy for certain weld stackups, the neural network model consistently delivered satisfactory performance in predicting weld quality metrics, validating its ability to capture high-dimensional correlations between weld attributes and joint performance properties.

ML prediction of joint quality from weld process parameters: The ML model was expanded to explore the relationship between welding process parameters and joint quality. The novel neural network design enables the prediction of both joint performance and the associated variability under different welding process conditions. Figure 3 summarizes the model's predictions of the statistical mean, minimum, and maximum joint peak load, compared to experimental measurements. The model provided accurate quantitative predictions of both the average peak load and the range of variability (minimum and maximum) across the entire dataset, which included welds produced under approximately 650 process conditions. The ability of the model to handle weld stackups with limited data is particularly notable. Even in cases where data representation was sparse, the model leveraged the comprehensive learning framework to make reliable predictions. This demonstrates the effectiveness of our unified ML training strategy, which allows the model to generalize effectively across different process conditions and material stackups. The insights gained from these results suggest potential for further improvements by incorporating additional data sources or sensing variables, which could enhance the model's ability to predict weld quality metrics.

Figure 4 presents four example cases, illustrating how the ML model predicts joint performance while quantifying the variability of weld quality under different welding scenarios. The model's predictions ranged from high strength with good repeatability to low strength with poor repeatability. For each case, the model provided both the statistical average peak load and a probability distribution describing the variation of peak load across replicate welds. A narrower probability distribution indicated more consistent weld quality under specific welding conditions, while a broader distribution signified greater variability. The close agreement between the predicted and actual measurements suggests that the model effectively captures the inherent variability in weld quality, allowing manufacturers to optimize welding parameters for both performance and consistency. By predicting the probability distribution of weld quality outcomes, the model provides valuable insights for improving process control and ensuring reliable product quality in industrial settings.

To enhance the practical utility of the ML framework, we connected the fully trained DNN model to an optimization scheme aimed at identifying optimal welding process windows. This approach enables the determination of process conditions that produce welds meeting specific target performance criteria for a given material stackup. Figure 5 illustrates the weld schedule optimization approach and presents the optimized ranges of welding process conditions necessary to achieve high performance and good repeatability for two material stackups: (1) 0.8 mm X626 – 0.9 mm HDG LCS: Target performance – Peak load > 300 N, Coefficient of Variation (CV) < 12% and (2) 1.2 mm AA6022 – 2.0 mm HDG LCS: Target performance – Peak load > 550 N, CV < 12%. These predictions assume ideal welding conditions without special fit-up issues, such as electrode misalignment or sheet gaps. Part of the predicted process conditions have been validated with the training dataset. While the ML model also predicted new process conditions that haven't been tested experimentally, this allows manufacturers to explore a broader range of settings to achieve their performance targets without the need for extensive trial and error. The results demonstrate the potential of the unified ML framework to guide the development of resistance spot welding for different Al-steel combinations. While the results are promising, further independent testing is desirable to validate the model's effectiveness across a broader range of material stackups and process conditions.

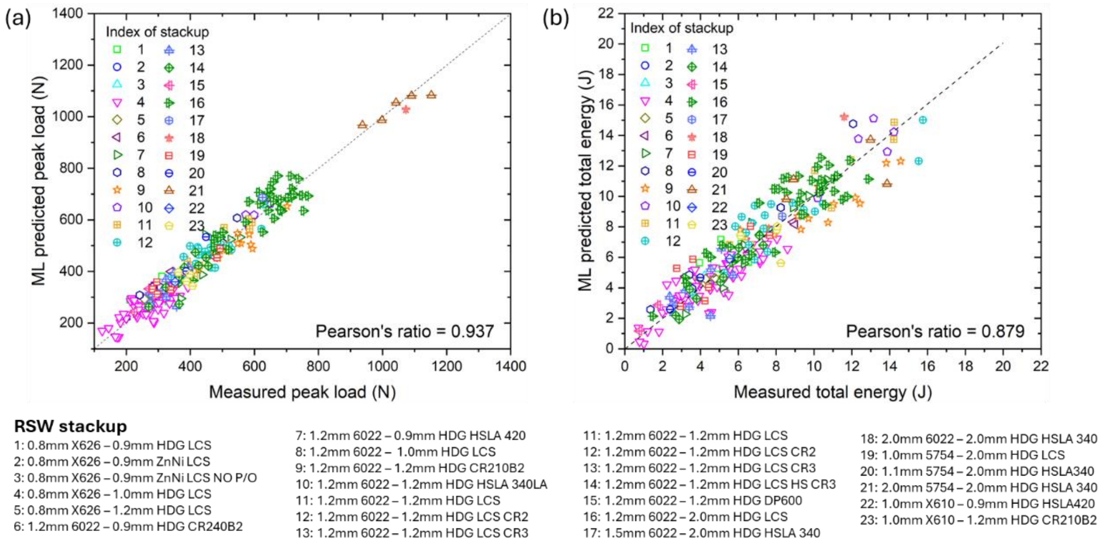

Figure 2 Comparison between ML predicted and experimentally measured (a) peak load and (b) total energy for validation test welds.

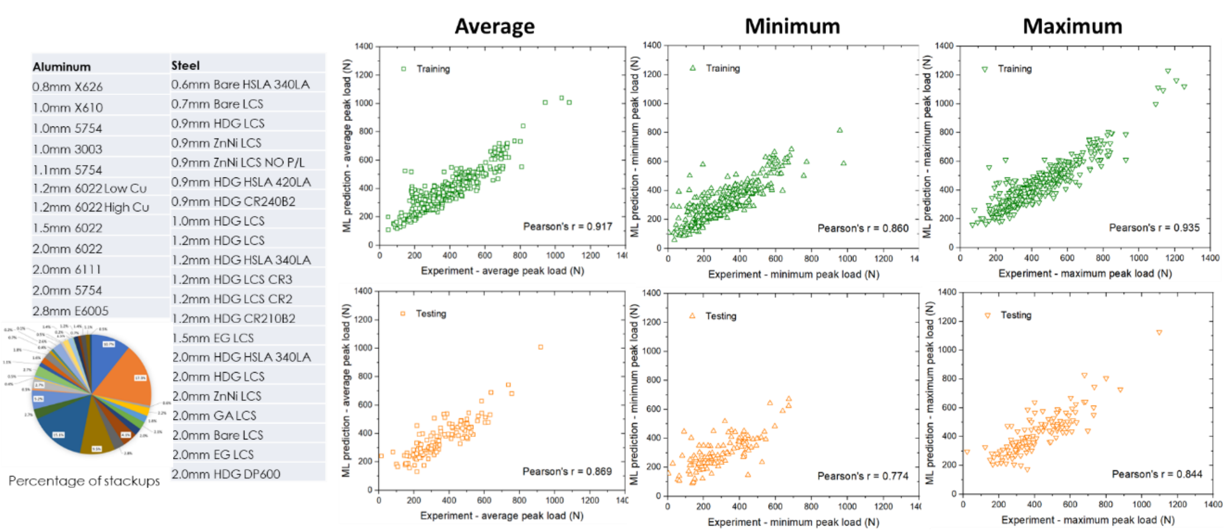

Figure 3 ML model provided quantitative prediction for mean, minimum and maximum joint peak load for a variety of material combinations.

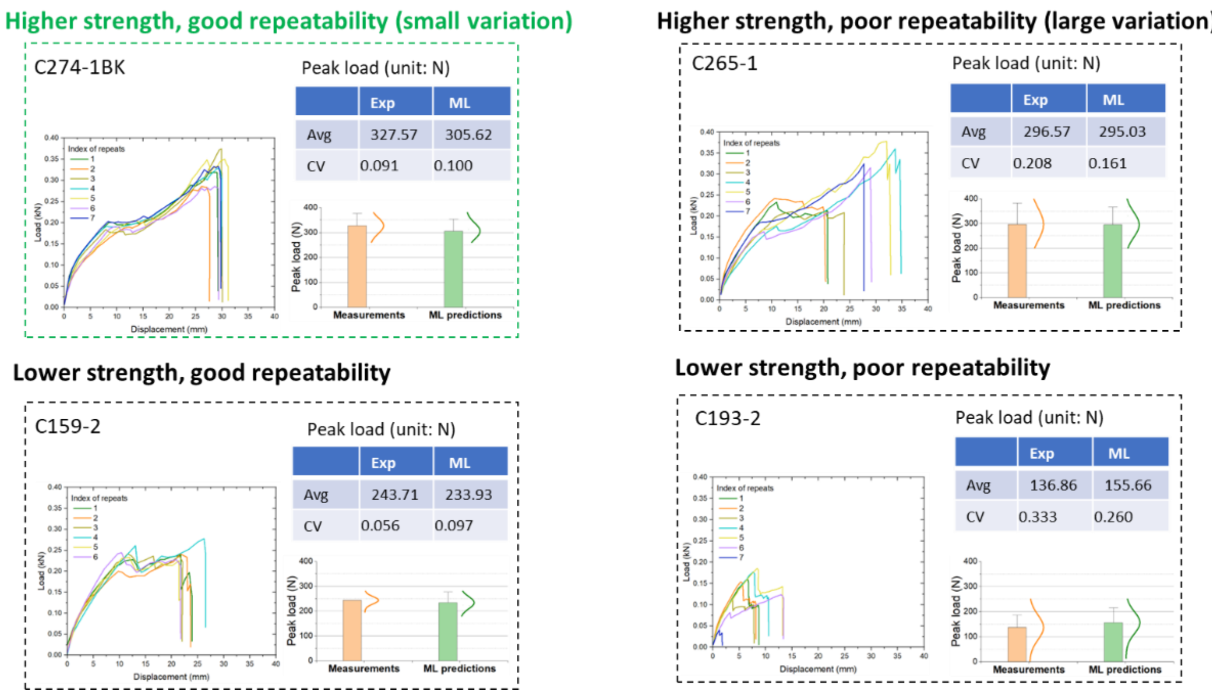

Figure 4 ML model predicted joint peak load and its variability under a variety of materials and welding conditions.

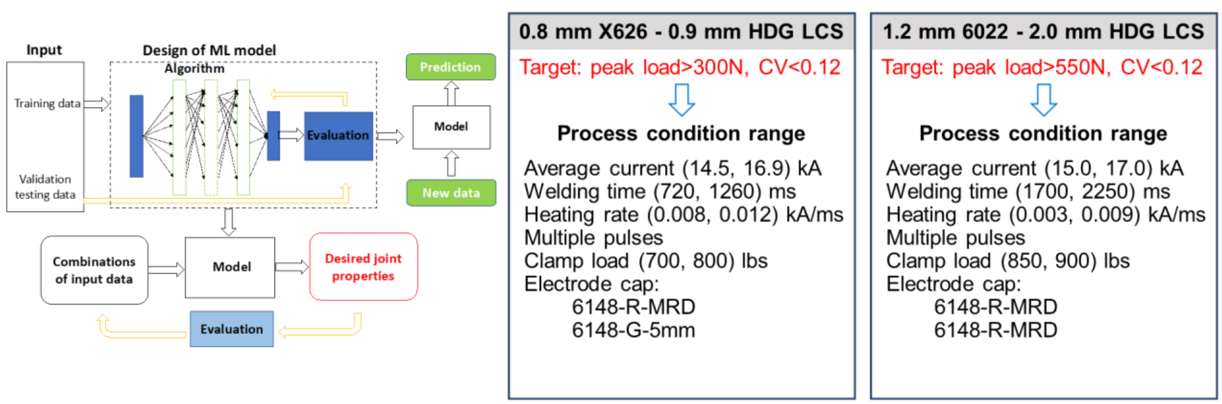

Figure 5 Leveraging the DNN model for welding process design to achieve joint target performance for two example weld stack-ups of 0.8mm X626 – 0.9mm HDG LCS and 1.2mm 6022 – 2.0mm HDG LCS.

Conclusion

This work presented an expandable ML based modeling framework to enhance process design, optimize weld parameters, and ensure consistent weld quality in RSW. By incorporating domain knowledge of welding physics, the model improved the prediction of key weld metrics such as peak load and total energy. Trained on a sizeable aluminum-steel weld dataset, the model accurately captured relationships between weld attributes, process conditions, and joint performance, while accounting for variability under different welding scenarios. The ML framework successfully predicted weld quality and variability, helping to optimize welding parameters for consistent performance. The model's integration with an optimization scheme demonstrated its practical utility in identifying optimal process windows for various material stackups. Future work will focus on improving integrating real-time inline signal data in our expandable ML model framework training and prediction to enable real-time weld quality prediction and adaptive process control. Expanding the dataset and refining the model will further improve its accuracy and applicability across diverse welding conditions, making it a practical tool for industrial applications.

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